Receptiveness to Advice, Cognitive Ability, and Technology Adoption *

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Abstract

We construct a model of technology adoption with agents differing on two dimensions: their cognitive ability and their receptiveness to advice. While cognitive ability unambiguously speeds adoption, receptiveness to advice may speed adoption for individuals with low cognitive ability, but slow adoption for individuals with high cognitive ability. We conduct economic experiments measuring US farmers' cognitive ability and receptiveness to advice and examine how these characteristics impact their speed of adoption of genetically modified (GM) corn seeds. The empirical analysis shows that early adopters are those who are both quite able cognitively and not receptive to advice.

Keywords: technology adoption, learning, receptiveness to advice, responsiveness to advice, advice-taking, cognitive ability, economic experiments, genetically modified 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 (Comin & Hobijn 2010, Klenow & Rodríguez-Clare 1997). Limited access to credible information has been shown to be a major deterrent to technology adoption (Jack 2013). And yet, recent studies also find that increased advice and information sometimes have small impacts on technology adoption (Karlan et al. 2015, Ryan 2015).

The potential under-performance of advice and information provision may, in part, arise because individuals are unable to process information effectively and/or they are not receptive to advice. How these two dimensions interact is not well understood. Previous studies focus on how adoption is shaped by the identity of the advice-giver (Banerjee et al. 2013, Beaman et al. 2015, Kim et al. 2015, Maertens 2017) and how best to incentivize advice-givers (BenYishay & Mobarak 2015).

While there is significant research looking at the ideal identity and incentives of advice-givers, there is much less research on differential receptiveness of advice-receivers. Coffman & Niehaus (2015) find that the literature's focus on the advice-givers (in their setting these are the sellers) may not be well-placed. They find that "buyer fixed effects explain more of the variation in our data than do seller fixed effects, product fixed effects, and order effects combined." Given this result, they argue that "it may be as important to understand what makes a person *persuadable* as to understand what makes them persuasive" and "the evidence for *persuadable* types is stronger than the evidence for *persuasive* types" (emphasis as in the original). Recent papers in the experimental literature have shown that individual-level receptiveness to advice is stable across settings (Ambuehl & Li 2015, Buser et al. 2016, Coffman & Niehaus 2015) but technology adoption studies have not explored this character trait.

This article addresses this gap by examining which individuals are most receptive to advice and how receptiveness interacts with cognitive ability to shape the patterns of adoption of a profitable technology. Specifically, we present a Bayesian technology adoption model in which individuals vary on two dimensions: cognitive ability and receptiveness to advice. Individuals with high cognitive ability are good at 'learning from doing,' which in the model means they interpret the signals they get from experimentation with higher precision. Individuals who are highly receptive to advice are good at 'learning from advice,' which in the model means they have a subjective belief that the advice signal they receive is more precise.

Advice influences technology adoption when individuals respond to advice. Thus, when analyzing advice taking, we distinguish between two related concepts: responsiveness, a measure of how much the individual changes his prior when presented with advice; and receptiveness, the focus of this paper, a measure of how precise an individual believes advice to be. Our model shows that responsiveness to advice depends on both cognitive ability and receptiveness, and so our paper focuses on those two traits as more fundamental determinants of technology adoption.

Consistent with previous empirical findings on schooling and cognitive ability (Aldana et al. 2011, Feder et al. 1985, Foster & Rosenzweig 2010), the model predicts that high cognitive ability individuals will adopt before low cognitive ability individuals. The model also reveals that being receptive to advice can slow adoption for high cognitive ability individuals, because these individuals have greater incentives to wait for additional information from others.

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 to test the model's predictions empirically. We designed a game that allows us to estimate both cognitive ability and receptiveness to advice. This incentivized game is a variant of a typical "advice-taking" experiment found in the industrial and organizational psychology literature. Bonaccio & Dalal (2006) offer a review of this class of games.

First, to measure the farmer's cognitive ability, we have him play multiple rounds of an individual learning game in which he learns about how a signal translates into an outcome. All else equal, individuals who have higher cognitive ability (i.e., those who are better at learning from doing and those who interpret their signals with more precision in the individual learning game) will have more accurate predictions by the end of the first game. Next, to measure responsiveness and receptiveness to advice, we have each participating farmer play multiple rounds of an advice-taking game in which he predicts the outcome, is given the prediction of a more experienced player, and is given the opportunity to change his prediction.

Many studies compare actual behavior with optimal behavior and show that individuals are not as receptive to advice as they ought to be (Stone & Zafar 2014, Weizsäcker 2010). Other studies measure receptiveness multiple times or in multiple ways and show that it is a stable character trait which varies across people. Ambuehl & Li (2015), Buser et al. (2016), and Peterson et al. (1965) find that individuals have heterogeneous levels of receptiveness to information that is consistent within individual across games.[1] In Buser et al. (2016) this trait

[1] Similarly Moore & Healy (2008) find that overprecision (excessive precision in one's beliefs) has high

predicts entry into a competitive task. Receptiveness to advice is correlated with personality traits such as agreeableness and dependency (Dalal & Bonaccio 2010), expressivity (Feng & MacGeorge 2006), and autonomy (Koestner et al. 1999). Consistent with our results, others find that women are more responsive to advice than men[2] (Dalal & Bonaccio 2010, Feng & MacGeorge 2006, Mesoudi et al. 2014), providing further evidence that receptiveness to advice has a substantive 'fixed' component.

We find that individuals with higher cognitive ability are less responsive to advice, as predicted by the theory; but they are more receptive to advice (a relationship about which there is no theoretical prediction). This result stresses the importance of distinguishing between responsiveness (how much the individual's beliefs change in response to advice) and receptiveness to advice (how precise the individual believes the advice to be).

The empirical results support the predictions of the model showing that, conditional on farmers' underlying cognitive ability, being receptive to advice does not necessarily speed adoption of a good technology. While it tends to speed adoption for low cognitive ability individuals, it also slows adoption for high cognitive ability individuals.

We are not the only researchers to suggest that being receptive to information has a differential effect on low versus high cognitive ability individuals. In a very different setting, Buser et al. (2016) show that being 'conservative' (the opposite of being receptive to information) increases the payoffs of high cognitive ability subjects but decreases the payoffs of low cognitive ability subjects.

For research purposes, focusing on the timing of adoption for a technology which is superior for virtually all decision-makers is an ideal setting. In the United States, genetically modified (GM) corn fits that description. Since the introduction of GM corn seeds in 1996, there has been almost universal adoption by US farmers (Fernandez-Cornejo 2010) with almost no sustained disadoption. GM technology has contributed substantively to agricultural productivity, increasing mean yields and reducing variability (Chavas et al. 2014, Qaim 2009, Shi et al. 2013). It has also reduced time and management costs associated with pest and weed control. While 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.

test-retest reliability. Cesarini et al. (2009) find that overconfidence (in this case the difference between actual rank on a cognitive ability test and the individual's estimate of his rank) is correlated within both monozygotic and dizygotic twin pairs suggesting overconfidence is due to both genetic and environmental factors (with more due to genetics).

[2]Relatedly Niederle & Vesterlund (2007) and references therein show women are less overconfident than men.

Farmers get information from a myriad of sources including agricultural extension agents, seed dealers, and their peers. Most research in this area focuses on one specific information source. 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 & 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 (Banerjee et al. 2013, Conley & Udry 2010, Dupas 2014, Foster & Rosenzweig 1995, Miguel & Kremer 2007).

We only know of one other paper exploring which farmers are most likely to seek out and use advice. Cole & Fernando (2016) 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. Farmers do 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 are 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.

Our empirical analysis offers new insights into the role of advice in technology adoption. Our approach is novel in several ways. First, instead of studying how endogenous choices such as conversations with seed dealers or placement of extension agents impact adoption, we look at farmers' underlying receptiveness to advice. Second, we investigate how farmers incorporate information more generally rather than focusing on one specific source (e.g., seed dealers, extension agents, or peers). This makes it easier to identify the role played by receptiveness to advice. Finally, while much of the most relevant adoption literature is from developing countries, we use farm-level data from the developed world where education levels and school quality are relatively high. This reduces the potential range of variation in our key experimental measures likely to be accounted for by differences in participants' educational backgrounds. Based on these unique features, this paper makes new contributions to our understanding of the process of technology adoption.

We investigate the linkages between these experimental measures of cognitive ability and receptiveness to advice and the timing of GM corn adoption in the real world. One of our key findings relates to the interactions between cognitive ability and advice receptiveness. As predicted by the theoretical model, our empirical evidence shows that the earliest adopters have high cognitive ability. We also find that for high cognitive ability individuals, being an advice taker actually slows adoption.[3]

The paper is organized as follows. Section 2 presents a model of technology adoption, with a focus on the roles of cognitive ability and receptiveness to advice. Section 3 presents the GM technology, games, and survey data. Section 4 discusses the measurement of both cognitive ability and receptiveness to advice in our games. Section 5 analyzes the link between cognitive ability and receptiveness to advice in the experiment and actual adoption decisions made by the farmers on their farms. Section 6 probes correlations between experimental measures of receptiveness to advice and answers to survey questions regarding information use and on-farm experimentation. Finally, section 7 concludes.

2 Model and Intuition

We present a model of technology adoption which shows how cognitive ability and receptiveness to advice interact to influence timing of adoption. Specifically, this model predicts that having high cognitive ability speeds adoption for all individuals. Having a high receptiveness to advice may slow adoption for high cognitive ability individuals, but speed adoption for lower ability individuals.

The intuition behind the result is that individuals exhibiting high cognitive ability but low receptivity to advice rely more on their own experimentation to give them a relatively clear idea about the new technology. Because these individuals believe that external advice will be relatively uninformative, their main way to reduce uncertainty about the most profitable way to implement the new technology is to learn by doing. Thus they jump in early.

On the other hand, individuals exhibiting high cognitive ability and high receptivity to advice believe that they will receive informative advice signals in the future from which they can learn the best way to implement the new technology. They are then more likely to strategically wait, free ride and learn more about the idiosyncrasies of the technology from the earlier adopters. When they do finally adopt after a delay, they will use the technology

[3] We did not pre-register our experiments both because we did not run an RCT and because this was not common back in 2011. But, in looking to our original grant application we list the following two testable hypotheses: "1, cognitive ability contributes to hasten learning and stimulate adoption" and "2, social learning is more effective than individual learning among individuals with lower cognitive ability." Thus the focus on the interactive effects of cognitive ability and receptiveness to advice follow directly from our original hypotheses. The fact that 'social learning' (being receptive to advice) is not only more effective for individuals with low cognitive ability, but slows adoption for high cognitive ability individuals was discovered in the data and in the model ex-post.

more profitably without having to engage in as much low productivity experimentation. Thus, for individuals with high cognitive ability, those who are receptive to advice will delay more than those who are not.

For farmers with low cognitive ability, opposite results can hold. Low-ability individuals know that their own experimentation will yield low information content and so they rely on advice signals to decide when it is worthwhile adopting. Less receptive individuals do not believe these external signals to be very informative, so they learn very slowly about the crop and are late adopters. On the other hand, low-ability high-receptive individuals believe that they are receiving relatively precise advice signals and so incorporate information regarding the crop more quickly. For individuals with low cognitive ability, being receptive to advice may speed adoption.

Our conceptualization of 'learning from advice' differs slightly from the 'learning from others' analyzed in Foster & Rosenzweig (1995) and Bandiera & Rasul (2006). In those models, when a farmer's neighbors plant the crop, the farmer can observe his neighbors' input and output and deduce the target from that. This may be reasonable in developing countries such as India and Mozambique where farmers live nearby one another and can easily monitor their neighbors' plots, but this does not necessarily mirror how farmers in the US receive information. Farmers in the US do not directly observe the inputs and outputs of neighboring farmers. Instead they receive advice from a myriad of sources including extension agents and neighbors. Thus, we study 'learning from advice' and assume individuals receive one piece of advice from external sources at the end of each growing season.

2.1 Model Set-Up

This model follows the target-input model first laid out by Jovanovic & Nyarko (1996) and Foster & Rosenzweig (1995). Here we closely follow the formulation in Bardhan & Udry (1999) and Bandiera & Rasul (2006). A farmer must decide whether to continue to use a traditional technology or to adopt a new technology. If used correctly, the new technology is known to produce higher output than the traditional technology. But, there is one parameter of the production function of the new technology, here called the target, which is unknown. Output of farmer i in period t is higher the closer the farmer's input, k_{it}, is to the unknown target, κ_{it}, with output defined as $q_{it} = 1 - (k_{it} - \kappa_{it})^2$. After the crop is harvested, the farmer can deduce the value of κ_{it} in that period. The target is a random variable defined by $\kappa_{it} = \kappa^* + \mu_{it}$ where $\mu_{it} \sim$ i.i.d. N(0,$\sigma^2_{u_i}$). We assume, as does the rest of the literature, that while κ^* is unknown, $\sigma^2_{u_i}$ is known. We also make the simplifying assumption that the input is costless.

In period 0, before the new technology is available commercially, the farmers have beliefs about κ^* which are distributed $\mathrm{N}(\kappa_0^*, \sigma_{\kappa 0}^2)$. Once the technology is available, there are two ways in which the farmer can learn. One is 'learning by doing.' The farmer can plant the new technology himself and learn from his own experimentation. In every period in which the farmer plants the new technology and harvests output, he gains one observation of κ_{it} which has variance $\sigma_{u_i}^2$. The other way the farmer can learn is 'learning from advice.' For every period in which the seed is commercially available, the farmer receives an advice signal $\tilde{\kappa}_{it}$. The farmer subjectively believes this signal to have variance $\sigma_{v_i}^2$.

In terms of 'learning from doing,' we model individuals with high cognitive ability as having a lower $\sigma_{u_i}^2$. This means that they interpret the signals from their own experimentation with more precision. High cognitive ability individuals are better able to calculate and interpret the signal which derives from their experimentation and so their signal is more precise.

In terms of 'learning from advice,' we model individuals who are highly receptive to advice as having a lower $\sigma_{v_i}^2$. We consider it to be a fixed character trait in the same way Ambuehl & Li (2015) do; more receptive farmers perceive the signal they receive from others to be more informative. It will become clear as the exposition progresses that it would be isomorphic to instead assume that everyone receives an advice signal with the same precision but that more receptive individuals receive more of these signals. Throughout the model, the number of advice signals received is multiplied by the precision of those advice signals. So, more receptive individuals can either receive more signals, or believe the signals to be more precise, or both.

Assuming Bayesian updating, the variance of farmer i's beliefs at the beginning of period t is

$$\sigma_{\kappa_{it}}^2 = \frac{1}{\rho_0 + I_{t-1}\rho_{u_i} + S_{t-1}\rho_{v_i}}. \tag{1}$$

Here $\rho_0 = \frac{1}{\sigma_{\kappa_0}^2}$, $\rho_{u_i} = \frac{1}{\sigma_{u_i}^2}$ is the precision of the signal associated with 'learning by doing' (cognitive ability), $\rho_{v_i} = \frac{1}{\sigma_{v_i}^2}$ is the precision of the signal associated with 'learning from advice' (receptiveness to advice), I_{t-1} is the number of previous periods in which the farmer himself planted the new technology, and S_{t-1} is the number of previous periods in which the new technology was commercially available and so the farmer received an advice signal.

2.2 Expected Output

If the farmer adopts the new technology, he chooses as his input level his expectation of the target, so he chooses $k_{it} = \mathrm{E}_t(\kappa_{it})$.[4] Expected output is $\mathrm{E}_t(q_{it}) = 1 - \mathrm{E}_t[\mathrm{E}_t(\kappa_{it}) - \kappa_{it}]^2 = 1 - \sigma^2_{\kappa_{it}} - \sigma^2_{u_i}$. We can take first derivatives of expected output with respect to different quantities to gain useful insights. First we see that learning by doing increases expected output.

$$\frac{\partial \mathrm{E}_t(q_{it})}{\partial I_{t-1}} = \frac{\rho_{u_i}}{(\rho_0 + I_{t-1}\rho_{u_i} + S_{t-1}\rho_{v_i})^2} > 0 \tag{2}$$

Similarly, learning from advice also increases expected output.

$$\frac{\partial \mathrm{E}_t(q_{it})}{\partial S_{t-1}} = \frac{\rho_{v_i}}{(\rho_0 + I_{t-1}\rho_{u_i} + S_{t-1}\rho_{v_i})^2} > 0 \tag{3}$$

We can also look at the effects of two individual characteristics: cognitive ability and receptiveness to advice. We see that both individuals with higher cognitive ability and individuals who are more receptive to advice have higher expected output

$$\frac{\partial \mathrm{E}_t(q_{it})}{\partial \rho_{u_i}} = \frac{1}{(\rho_{u_i})^2} + \frac{I_{t-1}}{(\rho_0 + I_{t-1}\rho_{u_i} + S_{t-1}\rho_{v_i})^2} > 0 \tag{4}$$

$$\frac{\partial \mathrm{E}_t(q_{it})}{\partial \rho_{v_i}} = \frac{S_{t-1}}{(\rho_0 + I_{t-1}\rho_{u_i} + S_{t-1}\rho_{v_i})^2} > 0. \tag{5}$$

2.3 Farmer's Adoption Decision

Although we have shown that both cognitive ability and receptiveness to advice lead to higher expected output, it does not necessarily follow that they will speed adoption. We now evaluate the effects of these individual characteristics on timing of adoption. At the beginning of each period, the farmer faces a discrete choice to plant his farm in the new crop, in which case $a_{it} = 1$, or to plant the traditional crop, in which case $a_{it} = 0$. The traditional crop has known riskless returns $\underline{q}$. In any period t the farmer faces the following problem:

$$V_t[I_{t-1}, S_{t-1}] = \max_{a_{it}\in\{0,1\}} (1 - a_{it})\underline{q} + a_{it}\mathrm{E}_t q_t[I_{t-1}, S_{t-1}] + \delta V_{t+1}[I_t, S_t] \tag{6}$$

[4] In section 4.2, when we estimate, ρ_{v_i}, our empirical measure of receptiveness to advice, we will take advantage of the fact that with a normal distribution the expectation of the target equals a weighted sum of the farmer's posterior beliefs and the signals he receives, and the weights are functions of the precisions of the two.

Because we showed that learning by doing increases expected output, there is no disadoption. Once the farmer tries the new technology he never goes back to the traditional technology. In any period t (starting from period 1) in which the farmer has not yet adopted, the farmer will adopt if the net gains from adopting, G, are non-negative. Thus, the farmer will adopt at time t if the following inequality holds:

$$G_t \equiv \mathrm{E}_t q_t[0, S_{t-1}] - \underline{q} + \delta V_{t+1}[1, S_t] - \delta V_{t+1}[0, S_t] \geq 0 \tag{7}$$

As shown in Bardhan & Udry (1999) and Bandiera & Rasul (2006), we have:

$$V_{t+1}[1, S_t] - V_{t+1}[0, S_t] = \mathrm{E}_t \sum_{s=t+1}^{T} \delta^{s-t-1}(q[s-t, S_{s-1}] - q[s-t-1, S_{s-1}])$$

We now examine how the farmer's net gains from adopting, and thus his adoption decision, depend on his own cognitive ability (ρ_{u_i}) and his receptiveness to advice (ρ_{v_i}). The derivative of the net gains in period t with respect to ρ_{u_i} is[5]

$$\frac{\partial G}{\partial \rho_{u_i}} = \frac{1}{\rho_{u_i}^2} + \sum_{s=t+1}^{T} \delta^{s-t}\{\frac{s-t}{(\rho_0 + (s-t)\rho_{u_i} + (s-1)\rho_{v_i})^2} - \frac{s-t-1}{(\rho_0 + (s-t-1)\rho_{u_i} + (s-1)\rho_{v_i})^2}\} > 0 \tag{8}$$

The more precise the own experimentation signal is, the higher the net gains from adoption, the more likely the farmer is to adopt. Thus, individuals with higher cognitive ability adopt sooner.

When looking at the impact of receptiveness to advice (the precision of the advice signal ρ_{v_i}) on timing adoption, note that the derivative cannot be signed generally.

$$\frac{\partial G}{\partial \rho_{v_i}} = \frac{t-1}{(\rho_0 + (t-1)\rho_{v_i})^2} + \sum_{s=t+1}^{T} \delta^{s-t}\{\frac{s-1}{(\rho_0 + (s-t)\rho_{u_i} + (s-1)\rho_{v_i})^2} - \frac{s-1}{(\rho_0 + (s-t-1)\rho_{u_i} + (s-1)\rho_{v_i})^2}\} \gtreqless 0 \tag{9}$$

There are two opposing effects on the farmer's incentives to adopt as his receptiveness to

[5]To show that this derivative is always positive, note that the first term which is a variance is always positive. To see that the element within the summation sign is also always positive let us call the first term in the summation A_s and the second term in the summation B_s. The summation term equals:

$$(\delta A_{s=t+1} - \delta B_{s=t+1}) + (\delta^2 A_{s=t+2} - \delta^2 B_{s=t+2}) + ... + (\delta^{T-t} A_{s=T} - \delta^{T-t} B_{s=T}).$$

We know that $\delta B_{s=t+1} = 0$ and so this equation can be rearranged and written as:

$$(\delta A_{s=t+1} - \delta^2 B_{s=t+2}) + (\delta^2 A_{s=t+2} - \delta^3 B_{s=t+3}) + ... + (\delta^{T-t} A_{s=T}).$$

Within each set of parentheses the A and B terms have the same numerator. The second term is smaller both because it is discounted more and has a larger denominator. Thus this derivative is always positive.

advice increases. On the one hand, the more receptive he is, the higher his profitability will be in the current period which encourages him to adopt. On the other hand, the more receptive he is, the greater are his strategic incentives to delay adoption and wait to receive more advice signals. A farmer with high cognitive ability who is not receptive will not see his uncertainty regarding the correct level of the target input decrease if he delays adoption. Thus, he might as well begin to experiment with the new technology to benefit from learning by doing. In contrast, a farmer with high cognitive ability who is receptive to advice can learn more by delaying and waiting to get advice from others. This will reduce his uncertainty about the correct level of the target input, and make his adoption decision a more profitable one at a later date.

This derivative can be positive for low levels of cognitive ability (ρ_{u_i}) and negative for high levels of cognitive ability. This would imply that being receptive to advice slows adoption for high cognitive ability individuals but speeds adoption for low cognitive ability individuals.

3 The Setting, Games, and Survey

Experimental and survey data were collected in early 2012 from farmers at the Wisconsin Corn and Soybean Conferences and the Wisconsin Corn/Soy Expo. 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 Corn Growers' Association and the Wisconsin Soybean 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. Although our sample may not represent the general population of Wisconsin farmers, which includes a larger share of part-time farmers, our participants are more 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 technologies in section 3.1, the games in section 3.2, and the survey in section 3.3.

3.1 GM Corn Seed Technology

As noted in the introduction, since 1996 GM technology has had a significant impact on agricultural productivity. GM corn seed is an ideal technology to study because over the course of twenty years, adoption rates went from 0% to close to 100%. This implies that adoption was the ex-post optimal choice. Moreover, widespread adoption of GM corn was not associated with major shifts in the composition or agrarian structure on US corn farms. There was substantial heterogeneity in terms of how long different farmers took to adopt, and yet the transition from no to full adoption took place within the lifetime of farmers. GM seeds were released commercially in 1996. As measured by area planted, the US adoption rate for GM corn was 25 percent in 2000, 52 percent in 2005, and was estimated at 93 percent in 2014 (Fernandez-Cornejo 2010).

While the universal adoption of GM corn seeds suggests that the technology is better than conventional seed, academic studies have analyzed how GM changes the distribution of output. Shi et al. (2013) find that GM corn yields have lower variance, higher skewness (lower downside risk), and lower kurtosis (thinner tails). Qaim (2009) reviews the literature and finds that GM seeds tend to increase yields and decrease spending on inputs (such as labor, pesticides, and fuel).

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 GM corn technologies at the time (Chen et al. 2001, Merrill et al. 2005). Adopting farmers reported that yield gains; reduced pesticide, herbicide, and labor costs; and improved pest and weed management were key motivations for adopting. Recommendations from seed dealers, consultants, neighbors, and extension agents were also cited as reasons for adopting.

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. Although there is some negative opinion towards GM among consumers, this is not the case among our sample of producers. In our survey not a single farmer disagreed somewhat or strongly with the following statement, and only 7% said they were neutral: "Agricultural biotechnology makes most farm families better off."

Of course this is what they say now, but what might be more relevant is what they thought when these technologies first became available. In his frequent newsletters, Joe Lauer, a WI extension agent and one of the premier experts on corn seed performance in the state, only discussed concerns regarding difficulties selling GM seeds in a single year. In 1999, he stated 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. Much of the corn grown in Wisconsin is used as feed for livestock, so this would be less of a worry for those farmers. In the 2001 and 2003 PATS surveys mentioned above, non-adopters were asked reasons they didn't adopt. The most common reasons 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 also mentioned by some farmers.

3.2 Games

All participating farmers attended a session consisting of two parts. First were the incentivized games, with a series of games measuring risk aversion, ambiguity aversion, cognitive ability, and receptiveness to advice. The farmers also completed a digit span exercise to provide an additional measure of cognitive ability. The games were 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 GM seed use. The session generally took less than 2 hours to complete and farmers earned an average of $51 from the choices they made in the games and were reimbursed for travel costs on top of that.

Upon arrival, 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. All farmers participated in the games at the same time and they were not allowed to communicate with one another. We also provided paper-based copies of the instructions for farmers to refer to. We did not supply pens until the surveys were handed out after the completion of the games. The games were incentivized and payoffs were determined after the completion of all of the games.

For the learning game, we built upon a game designed by psychologists Harvey & Fischer (1997).[6] We first ran an individual learning game before introducing the opinion of an advisor in order to study receptiveness to advice. The entire game protocol can be found in Appendix

[6]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 session.

A. More details follow, but the basic setup of the game is as follows. Farmers looked at circles of differing sizes and colors and had to guess the numerical outcome measure. They did this with 25 different circles and after each circle they were told the right answer so that they could learn more about the deterministic algorithm which related the circle to the outcome measure. Subsequently they played a slightly different game, involving the same algorithm, with another 25 circles. This time, after looking at the circle the farmer first stated his own perception of the outcome. Next he was told the perception of a more experienced player and was given the chance to change his answer. All answers were incentivized such that players earned more money the closer their answer was to the true outcome.

As in Harvey & Fischer (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 in our study are familiar, while also not being too close to the crop-based focus of our survey. Farmers were told that the severity of the outbreak depended on the color and size of a circle presented on the screen. The government makes an inspection to determine how many cattle will die in order to determine farmer compensation and this is what the farmers are learning to do.[7]

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 from the disease outbreak and after each round the farmer was told how many cattle actually died. In this way the farmers could learn more about how the disease worked. The true relationship was calculated using the following deterministic equation Dead Cattle = Color $* \pi r^2$ where Color=2, 1, 0.5 for red, green, and 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. All farmers saw the same series of predetermined circles which did not depend on previous responses.

Participants were not informed of the underlying algorithm but were able to improve their estimates based on the feedback they were given when told the correct answer. This was repeated for 25 rounds, which provided sufficient opportunity for figuring out the underlying algorithm. Results in Harvey & Fischer (1997) suggest that participants figure out the

[7] One might worry that if farmers take the framing seriously they may inflate their estimates so that the farmers receive higher compensation. This seems unlikely both because they know the game is fictitious and because they are incentivized such that they earn more money the closer their guess is to the correct answer. As a robustness check in our empirical analysis we do control for whether livestock are part of the farmer's enterprise.

average relationship by the third block of ten rounds. In our games, the players figure out the relationship more quickly, with improvements slowing after fifteen rounds. The faster calibration 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 computer games, and the specific circles chosen. In Harvey & Fischer (1997), after practice the participants reach an average absolute percentage error (APE - or the absolute difference between the prediction and the truth, divided by the truth) of approximately 30%. Our farmers do better, with an average APE of around 20% by the fifteenth round. Figure 1 depicts the average APE among all farmers for each round.[8] As expected, we see that the average APE decreases over time as farmers guesses improve. After approximately fourteen rounds, the error rate appears to plateau.

The game 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.[9] The farmer was told exactly how payoffs would be determined 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.

Following this individual learning game, we completed an advice-taking game that utilized the same context and the same algorithm translating the signal (circle size and color) to state (number of dead cattle) with two major differences: we no longer provided correct answers, thus ending the learning process, and we introduced a recommendation from an advisor in order to enable the measurement of receptiveness to advice.

In our advice-taking game, participants were told the following: “In this second part

[8]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. APEs for round 1 are an order of magnitude higher than for subsequent rounds. 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.

[9]We chose this scoring rule because it is always positive and it is easy to understand. Many other more common scoring rules would not have consistently yielded non-negative payoffs. For example, a quadratic scoring rule has many good properties and yields strictly non-negative payoffs when the belief being elicited is a probability which is bounded between 0 and 1. In our case, such a rule might pay the farmer \$50 minus the square of the difference between the estimate and the truth which could be negative since the number of cattle which die is not bounded from above. Our scoring rule places a heavy incentive on supplying a number which is within one of the truth, since the player earns \$50 for such answers, and payoffs quickly decline as the answer gets further from the truth. A good rule of thumb for the farmer might be to guess the mode of his beliefs.

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 game 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, individuals made an initial guess regarding how many cattle they thought died, the advisor's guess for that specific circle was offered, and individuals then made a final guess. 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 and that we could isolate a measure of receptiveness to advice.[10] 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.

Figure 1 showed that learning plateaus by Round 14, and so a participant might not expect the predictions of an advisor who received 100 rounds of training to be any better than his own predictions having received 25 rounds of training. Even so, the farmer's prediction and the advisor's prediction are two noisy signals regarding the true number of cattle which perished. An individual using Bayesian updating should incorporate both numbers when making his final guess.

We did not tell the participants any additional details about the individual whose advice we showed them. In fact, 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 game 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.

[10]Bikhchandani et al. (1998) review models of learning from choices made by peers. When an advisor receives a signal and makes a decision (as in our game), the participant will only learn from the advisor's decision if the participant does not also see the signal. In our case because the participant views the signal itself, he will not learn anything additional from the advisor's decision.

Many psychology 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 into account (see Bonaccio & Dalal (2006) for an overview).

3.3 Survey Data

After the games, 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 production. In particular, farmers were asked in what year they first adopted GM corn.[11]

Participants also performed a digit span exercise testing short-term or working 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 sign of sequential processing ability that measures how able a person is to take in and process information in an orderly fashion (Dempster 1981). It is a standard measure of cognitive ability because it is relatively easy to measure. But, it is not the main measure used in our empirical analysis below both because it cannot be directly compared to the measure of receptiveness to advice and because our measure captures how individuals take in and process new information rather than pure memorization. In section 4.3 we do, however, examine its correlation with our experimental measure of cognitive ability.

3.4 Summary Statistics

Table 1 provides summary statistics of the survey and cognitive information among the farmers in our final sample.[12] All of these farmers have planted corn and 96% of them have planted GM corn. This adoption rate (at the farmer level) is comparable to the state average

[11]The specific question was: "In what year did you first plant genetically modified (GM) corn? (Please enter a number between 1996 and 2011.)" Thus no dates were reported before 1996. Farmers often plant multiple types of corn and so this does not imply the farmer exclusively planted GM corn.

[12]One farmer cheated on the digit span, writing down the numbers on a piece of paper by his side with a pen he had brought. He is dropped in regressions when digit span is included.

(at the acreage level), which in 2011 was 86% (Fernandez-Cornejo 2010). In 2011, farmers in our sample had planted GM corn for an average of 10.9 years.

There has been almost no disadoption. Of the 127 farmers in our sample who had previously planted GM corn, there are three who planted only non-GM corn 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 operated an average of 947 acres of cropland in 2011; 15% of those surveyed report that in 2011 farming was not their principal occupation; and the average years that participants have made decisions on the farm is 26.[13] The average age of our participants is 51, there are four females, and the average household size at the time of the survey is three. A quarter of participants (26%) received a high school degree or less and went no further. The average digit span is 7.5 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).

4 Measuring Cognitive Ability and Receptiveness to Advice

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, they learn about the new technology. As noted above, there are two main avenues for learning: learning from doing, where agents use the new technology and learn from the results; and learning from advice by which they receive advice from relevant professionals and peers.

In the following subsections of section 4 we will first discuss issues of measurement: how we measure cognitive ability and receptiveness to advice. Next we will look at how cognitive ability and receptiveness to advice 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.

[13]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.

4.1 Cognitive Ability

In each round t the farmer becomes better at translating the given color severity and circle area x into a numeric determination of how many cattle died, Y. The farmer's prediction is determined by: $\hat{Y}_t = \hat{\beta}_t x_t + u_t$. With each subsequent round the farmer can better calibrate the value of the true β. In each round there is an error, u, for example because the farmer converts the signal to his belief of the outcome incorrectly. If we assume that $\hat{\beta}$ and u are uncorrelated, which seems reasonable, then: $\mathrm{var}(\hat{Y}) = x^2 \mathrm{var}(\hat{\beta}) + \mathrm{var}(u)$. As the farmer gets better at calibration, $x^2 \mathrm{var}(\hat{\beta})$ will go to 0 and so after enough periods the variance in the prediction will equal the variance of the error term ($\mathrm{var}(\hat{Y}) = \mathrm{var}(u)$). Thus, according to the model, the variance of the prediction error after the farmer has determined β would summarize farmer cognitive ability.[14] In Section 2 we modeled cognitive ability as being the precision of the individual signal, $\rho_u = 1/\sigma_u^2$ or one over the variance, and here we will proceed similarly.

We calculate our measure of cognitive ability as follows. We create the error term u_t by subtracting the true number of cattle which died from the farmers' guesses in the individual learning game. The farmer knows exactly what this error is, because at the end of each round he is told the true number of cattle which died and is reminded of his answer. We calculate the variance of this error for each farmer in the last ten rounds of the learning game, after they have determined β.[15] We then take the inverse as our measure of cognitive ability and precision, ρ_u (and multiply by 100 for scaling). As seen in Table 1, the average own precision in the last ten rounds is 0.40 and is distributed as shown in the histogram in Figure 2a where higher precision signifies higher cognitive ability.

4.2 Receptiveness to Advice

We combine the individual learning game and the advice-taking game to calculate a measure of receptiveness to advice for each individual. In the model in section 2, ρ_v is the perceived precision of advice. By comparing the farmer's initial guess in the advice-taking game, the advice he receives, and his final guess, we can calculate the Bayesian weight the farmer places on advice, which we call the farmer's *responsiveness* to advice. According to Bayesian updating with a normal distribution, this weight equals $\alpha_v = \rho_v/(\rho_v + \rho_u)$. From this it is

[14] We have explored farmer heterogeneity in the round the variance plateaus, but this measure of calibration speed is not significant in predicting technology adoption.

[15] In the first session (affecting 20 out of 132 observations) the circle for round 24 did not appear on the screen. Thus we exclude this round, and create our measure using rounds 15 to 23 and 25 for all farmers.

clear that individuals with high cognitive ability (high ρ_u) will be less responsive to advice (because their own prior is quite precise), while more *receptive* individuals (high ρ_v) will change their guess by more (because they believe the advice signal to be quite precise). Here we distinguish between *receptiveness* to advice, ρ_v, which we define as the character trait such that a person believes that the precision of advice is high; and *responsiveness* to advice, α_v, which we define as the choice the individual makes regarding by how much to change his initial guess in response to advice.

Before calculating our measures of responsiveness and receptiveness to advice, we first show that farmers would be well-served by taking the advice. We show that the APE error rate of the advice is quite low and the precision of the advice is quite high. 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. Table 1 showed that the average precision over all farmers is 0.4 with a maximum of 2.9, while the advisor's precision is 3.3.

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' initial guesses, and for the farmers' final guesses. Collectively, this provides evidence that the advisor is worth paying attention to and that individuals stand to improve their performance if they take advice.

To measure responsiveness to information, we estimate the weight placed on advice using the Bayesian framework laid out in Section 2. According to Bayesian updating, the final estimate (F) should be a weighted average of the initial estimate (I) and the advice (A). The two weights should sum to 1. We estimate these weights using a regression-based approach similar to that employed by Lim & O'Connor (1995).[16] We make a 25 round panel for each participant in the advice-taking game and regress the final estimate (F) on the initial estimate (I) and the advice (A):

$$F_t = \alpha_u I_t + \alpha_v A_t + \epsilon_t$$

where t denotes rounds and α_u and α_v capture the weights on initial guesses and advice

[16] Bonaccio & Dalal (2006) also describe several papers that utilize regression-based models in similar contexts, including Phillips (1999) and Brehmer & Hagafors (1986).

respectively. We restrict α_u and α_v to sum to 1 and to each be between 0 and 1.[17]

Once we have estimates of ρ_u (from the individual learning game as discussed in the previous subsection) and α_v (from the advice-taking game as discussed above) for each farmer, we can solve for each farmer's receptiveness to advice using this equation $\alpha_v = \rho_v/(\rho_v + \rho_u)$. There are two individuals who always place 100% weight on the advice signal, making it impossible to solve for ρ_v since ρ_u is never zero. For these two individuals we set their receptiveness to advice to equal that of the farmer with the highest solvable receptiveness measure.

Table 1 summarizes the measures of responsiveness (Bayesian advice weight) and receptiveness (perceived precision) to advice. The average responsiveness is 0.62, indicating that individuals place slightly more weight on the advice than their own initial guesses. Two individuals (out of 132) place all weight on their initial guesses while two individuals place all weight on the advice, and the remaining individuals have intermediate values. The fact that only two individuals just copied the advice and two individuals stuck to their initial guess suggests that individuals were engaging with the games and putting effort into the task.

Figure 2b presents a histogram of responsiveness. In terms of specific decisions, in 4% of cases the initial guess, the advice, and the final estimate are all equal. In 8% of cases the player switches away from his (different) initial estimate to have a final estimate equal to the advice, and in 22% of cases the player sticks with his initial estimate even though the advice is different. In the remaining cases the individual either gives a final guess which is somewhere between his initial guess and the advice (63% of the time), or gives a final guess which is outside of the range of his initial guess and the advice (3% of the time). Table 1 shows that the average perceived precision of advice is 1.24, approximately three times higher than the own precision. The advice's true precision is 3.3, with most players underestimating the precision of the advice. We will show in section 6 that our experimental measure of receptiveness to advice is correlated with survey measures of receptiveness in the real-world.

To calculate the Bayesian weight and the perceived precision of advice, we use data from all 25 rounds of the advice-taking game under the assumption that the perceived precision of advice does not change over the 25 rounds. Participants never learn the correct value in this game so they cannot learn whether the advice is of good quality. Still, their perception of

[17]Gars et al. (2015) also construct a similar measure of advice utilization. They find that both farming ability and the precision of farmers' prior beliefs (what they call confidence) determine how farmers change their inputs in response to receiving recommendations resulting from soil tests.

the advice might change over the 25 rounds. We explore whether the weight the respondent puts on the advice increases or decreases over time and find that for 41% of the people the weight decreases and for 59% of the people it increases over time. When combining all individuals, the slope is slightly positive but far from significant. Thus, in our main analysis we assume that individuals' perceptions of the quality of advice does not change over time, and we focus on their average weighting of advice. We run robustness checks which exclude either earlier or later rounds or which use our measure or responsiveness (the advice weight) rather than our measure of receptiveness. For a more detailed discussion of the absence of learning in the measure of receptiveness to advice and the results of the robustness checks, see Appendix B.

The benefit of our measure of receptiveness to advice, ρ_v, is that it is directly linked with the model in section 2 and that it nets out the fact that individuals with high cognitive ability may be disinclined to follow advice since the precision of their own prior is high. On the other hand, the functional form relies on the assumption of the normality of the error term. Thus, we also run robustness checks using the measure of responsiveness to advice, α_v, which is just the weight placed on the advice when updating, and does not rely on any assumptions.

4.3 Linking Cognitive Ability and Receptiveness to Advice

We now evaluate the correlates of cognitive ability and receptiveness to advice. We start in columns (1) and (2) of Table 2 by looking at the correlation of cognitive ability as measured using own precision in the experiment with our survey based measures of education and cognitive ability. Attending college is not significantly correlated with the precision of the prior measured in the games but farmers who perform better in the digit span exercise have a more precise prior in the individual learning game, with a one standard deviation increase in the digit span leading to a 0.24 standard deviation increase in the precision of their prior. 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 experimental cognitive ability measure, nor do they detract from the significant correlation between digit span and our ability measure.[18][19]

These results suggest that our experiment does measure cognitive ability and also suggests that, at least for Wisconsin farmers, schooling is not as useful a measure of ability as more specific measures of cognitive ability. In fact, in results not shown here we 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 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 & Rosenzweig 2010), this correlation may be less strong in developed countries where farmers have higher average education levels.

In columns (4) through (6) we look at correlates of our measure of responsiveness to advice (Bayesian weight placed on advice) while in columns (7) through (9) we look at correlates of our measure of receptiveness to advice (perceived precision of advice). In columns (5) and (6), we find evidence that women are more responsive to advice, a finding which matches the literature mentioned previously (though one should remember our sample includes only four women). There is also evidence that older individuals are more responsive to advice, with an increase in age of ten years leading to a 0.28 standard deviation increase in responsiveness to advice. We see no significant correlation between acres operated (potentially a proxy for wealth) and willingness to take advice.

In column (6), we regress responsiveness to advice on own precision while including other controls. As we suspected, individuals who have a more precise prior do weight advice less heavily, with a one standard deviation increase in the precision of the farmer's prior leading to a 0.25 standard deviation decrease in the weight he places on advice. Strong learners may be disinclined to follow advice because their own prior is more precise. 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. This aligns with Schiebener et al. (2014) who find that those who perform worse on an

[18] Given the literature documenting declines in the brain's processing ability with age, the insignificant impact of age may be surprising. Note that these regressions simultaneously control for the digit span measure of cognitive ability. When that measure is excluded, the coefficient on age becomes negative and significant.

[19] Risk aversion is commonly posited as a strong determinant of technology adoption, although it only tangentially enters into our hypotheses regarding the speed of adoption. For all regressions with controls, risk aversion is included. In addition, in Appendix Table 1 we show the correlates of our measure of risk aversion. Neither cognitive ability nor receptiveness or responsiveness to advice is correlated with risk aversion. Males are significantly less risk averse.

experimental task, and those with lower levels of working memory and executive functioning, are most responsive to advice on that task.

Once we account for this by creating our measure of receptiveness, we find in column (9) that the correlation goes in the opposite direction. Those with higher cognitive ability (higher own precision) also have higher receptiveness to advice. In this case, a one standard deviation increase in the precision of the farmer's prior leads to a 0.30 standard deviation increase in his receptiveness to advice. It is also the case that those with higher cognitive ability as measured by the digit span perceive advice to be more precise. It may seem surprising when looking at columns (7) through (9) how few variables are correlated with receptiveness to advice. This mirrors findings in Buser et al. (2016) who find that receptiveness is a stable character trait, but that it is correlated with very few other variables they collected.

As a final set of experimental variables, we categorize individuals as having either high or low cognitive ability and having high or low receptiveness to advice. These categorizations are formed using the median value as the cutoff, and they will be useful below when analyzing real-world technology adoption. Summary statistics in Table 1 show that it is slightly more common for people to be high in both areas or low in both areas (67% of the population), though it is also quite common for individuals to have a high value in one field and a low value in the other (33% of the population).

5 Results: Learning and Technology Adoption

Effective technology adoption relies on learning. However, 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 cognitive ability and receptiveness advice with survey data on real-life decisions, this paper provides an important contribution.

5.1 Survival Model

We use data on the year of adoption of GM corn to estimate survival models that predict the probability that someone who has not yet adopted subsequently decides to adopt in each time period. 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. In robustness checks described later, we dispense with the survival analysis set-up.

The hazard function, $\lambda(z, t)$, measures the adoption rate at time t conditional on not having adopted before time t and conditional on a vector of covariates z. Different specifications of the hazard function have been proposed in the literature. We focus on the Weibull distribution because it is commonly used in the literature on technology adoption (Liu 2013, Saloner & Shepard 1995) but we also show that the main results hold under different distributional assumptions. The Weibull assumes $\lambda(z, t) = e^{-z\beta}k[e^{-z\beta}t]^{(k-1)}$ 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 corn. The first farmers using GM corn adopted in 1996 yet 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 climatic 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.

Our survival analysis models the probability of adopting in any year, with a higher value reflecting earlier predicted adoption. In Table 3 we show the hazard ratios (which are necessarily positive) for the different control variables and test whether these hazard ratios are significantly different from one. 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.[20]

We present several model specifications in Table 3. 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 own precision and the advice perceived

[20]This is different from other regression techniques such as ordinary least squares where tables present coefficients and tests of whether they are significantly different from zero.

precision, to capture the impact of an individual's cognitive ability and his receptiveness to advice. We re-run these estimations in column (4) adding standard covariates in adoption models such as individual demographic variables, farm size, and risk aversion.

We study the interplay between receptiveness to advice and cognitive ability in two ways. We control for the interaction of the two continuous variables in columns (5) and (6). Because of difficulties in interpreting the hazard ratio on the interaction of two continuous variables we use the categorization of individuals into four groups and control for the individuals' category (with low cognitive ability/low receptiveness to advice being the excluded category) in columns (7) and (8) (Greene 2010).

The fact that results are robust to this categorization eases concerns on two fronts. The histograms in Figure 2 show that there are some outliers with respect to the continuous measures of cognitive ability and receptiveness to advice. In addition, in column (9) of Table 2 we saw that cognitive ability is correlated (significant at the 10% level) with receptiveness to advice. This might make one worry that the interaction term could be picking up an inverted-U shaped relationship in cognitive ability. The fact that the results when including the binary categorization measures mirror the results when including the continuous measures and their interaction shows that the results are due neither to outliers nor to a non-linear impact of cognitive ability.[21]

5.2 Results

We now use the data to test the hypotheses which come from our model. First, individuals with higher cognitive ability are predicted to adopt earlier since their initial prior will be most precise. Second, being receptive to advice will slow adoption for those with high cognitive ability, since they are inclined to wait to incorporate advice in their decision making. Third, being receptive to advice will speed up adoption for low cognitive ability individuals since they will learn more about the technology in a shorter time span.

Table 3 provides evidence linking farmer characteristics to the timing of the adoption of GM corn. Individuals with higher schooling are earlier adopters. Our experimental measure of cognitive ability (own precision) also speeds adoption. There is robust evidence that cognitive ability is a determinant of the timing of GM corn adoption, while receptiveness to advice does not seem to have a significant impact on adoption when included on its own.

[21]We do also show in the next subsection that the results are robust to replacing cognitive ability and receptiveness to advice with log-like transformations to limit the impact of outliers, and are robust to the additional inclusion of quadratic terms.

Table 3 presents hazard ratios. A hazard ratio greater than one suggests the characteristic speeds adoption; a hazard ratio less than one suggests the characteristic slows adoption; and hazard ratios can not be negative.

Cognitive ability and receptiveness to advice are continuous variables whose scales are not necessarily easy to interpret. Imagine two farmers who have not yet adopted GM corn. According to the estimates in column (3) of Table 3, if one farmer's cognitive ability is one standard deviation higher than that of the other, his likelihood of adopting in a given year will be 54% higher. If one farmer's receptiveness to advice is one standard deviation higher than the other, his likelihood of adopting in a given year will be 10% lower (though this second impact is not significant).

In columns (5) and (6) we interact the two variables and show that, as hypothesized, the interaction is significant. Because it is difficult to interpret hazard ratios on interactions of continuous variables, we show the relationship graphically in Figure 3 as suggested by Greene (2010). There one can see the impact of receptiveness to advice on the hazard ratio of adopting for three different values of cognitive ability: the fifth percentile (0.06), the fiftieth percentile (0.21), and the ninety-fifth percentile (1.72). The figure shows that being receptive to advice has a steep negative impact on adoption for high cognitive ability individuals. On the other hand, being receptive to advice has almost no impact on adoption for low cognitive ability individuals.

Panel A of Appendix Table 2 shows that our results are robust to the inclusion of either a quadratic term in cognitive ability or a quadratic term in receptiveness to advice. When including both quadratic terms at the same time, the hazard ratio on the interaction of interest is no longer significantly different from one at conventional levels, with the p-value going up to 14%. But, the magnitude of the hazard ratio remains similar. Given the small sample sizes and multicollinearity we are confident that the interaction term is not simply picking up an inverted-U shaped impact of cognitive ability on adoption. Panel A of Appendix Table 2 also shows results when we replace the measures of cognitive ability and receptiveness to advice with their inverse hyperbolic sine, a transformation similar to the log transformation but which accommodates values of 0. This suggests that the results are not due to outliers.

To look at the interaction between these two variables in a simpler manner, in Columns (7) and (8) of Table 3 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 individuals with high cognitive ability who are not receptive to advice (high own / low advice perceived precision) are the earliest adopters. All low cognitive ability individuals, as well as high ability individuals who are receptive to advice are later adopters, with much smaller differences in adoption probability amongst themselves.

The bottom of the table shows p-values for the one-sided χ^2 inequality tests that, for those with high cognitive ability, those who are less receptive to advice adopt sooner; and that for those with low cognitive ability, those who are more receptive to advice adopt sooner. We can reject that highly receptive high ability individuals adopt sooner than do their low receptive counterparts. But, we can not reject that low receptive low ability individuals adopt later than do their more highly receptive counterparts.

Our main results modeled adoption timing using survival analysis and assuming a Weibull distribution for the hazard function, as is common in the literature on technology adoption. In Panel B of Appendix Table 2 we show that our results are robust to other distributional assumptions.

As another robustness check (results shown in Appendix Table 3) instead of using survival analysis, we use linear OLS methods. To do so, we drop the 27% of individuals who either began making decisions after 1996 or who never adopted GM corn. (There are 25% of farmers who began making decisions after 1996 and 4% who never adopt, with 2% of farmers being in both groups.) We can then run a linear OLS regression in which the dependent variable is years since adopting. While the sample sizes in these regressions are quite a bit smaller, the evidence that cognitive ability speeds adoption remains strong. When treated as an interaction in columns (5) and (6) the relationship between cognitive ability and receptiveness to advice maintains the predicted sign but loses significance. When farmers are put in categories in columns (7) and (8) the fastest adopters are still those who have high cognitive ability but low receptiveness to advice.

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 67% claimed to be the primary farm operator, 30% 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 2% claimed to be a hired farm manager with no ownership interest. As can be seen in Panel A of Appendix Table 4, the qualitative results do not change if one excludes the 3% in the last two categories, or if one limits the analysis to the 67% 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.

As another robustness check (results shown in columns (1) and (2) of Appendix Table 5) we consider the full sample but look at an alternate outcome. Rather than timing of adoption, we look at the answer to the question: "In the past, have you tried new corn seeds on small plots or parcels?" Similar to results on adoption, it is those who have high cognitive ability but are not receptive to advice who are most likely to try new seeds on small plots.

A few caveats regarding the results are in order. First, one might worry about reverse causality. Our analysis uses receptiveness to advice as measured 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 receptiveness to advice. We think it is unlikely that the experience of adopting GM corn would lead farmers to change their receptiveness to advice in this experimental setting, but we cannot prove this with our current data.

Second, there is always a potential for omitted variable bias. In our main regressions we control for farm and farmer characteristics that are commonly incorporated in adoption models (education, age, sex, acres of cropland operated, farming not principal occupation, and years of experience) as well as several additional less common variables (comfort with computers and risk aversion) and our results are robust to their inclusion. In columns (7) and (8) of Panel A of Appendix Table 4 we include additional control variables, some of which may potentially be 'bad' controls due to the fact that they are endogenous. We include household size to proxy for labor availability, an indicator for whether livestock or dairy are 25% of farm income due to the fact that the game was framed around a livestock disease, acres of cropland owned which should be correlated with wealth, an indicator for whether the household purchased crop insurance as another measure of risk aversion, total household income, and the share of household income which came from farming. The results after adding those additional controls remain strong. Time preference is another variable which plays a role in the model in Section 2 but for which we do not have a measure. The best we can do is to control for variables which have found to be correlated with time preference such as income, sex, education, and age.

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 hybrid maize adoption in Kenya.) 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 cognitive ability, which suggests that this source of omitted variable bias should not impact the hazard ratios on those variables in the adoption regressions.

6 Identifying Real-World Correlates of Receptiveness to Advice

We have found that our two experimental measures are highly correlated with timing of adoption. Our experimental measure of cognitive ability was shown to be correlated with digit span in Table 2. On the other hand, in that same table our experimental measure of receptiveness to advice was not found to be correlated with any of the common demographic variables we included. Are there survey measures of receptiveness to advice which correlate with this experimental measure?

Farmers were asked to rate their confidence in 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 the number of sources in which he places confidence level 3 or 4.[22]

Columns (3) to (5) of Appendix Table 5 shows that this measure is significantly positively correlated with receptiveness to advice both when no other control variables are included and as we add subsequently more controls. Farmers with more confidence in external information sources are more responsive to advice. That said, in results not shown here, neither the survey measure itself nor the survey measure interacted with own precision is correlated with timing of adoption. Thus, while it appears possible to collect similar, simple variables in surveys to measure individuals' receptiveness to advice, experimental measures are preferable.

[22]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.

7 Conclusion

New technologies come online continually and individuals who respond most efficiently to these new advances will be more profitable than those who do not. Individuals can choose to adopt based on their own perceptions and/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 construct a model of technology adoption in which farmers differ in terms of their cognitive ability and their receptiveness to advice. This model yields three testable hypotheses. The first is unsurprising; farmers with higher cognitive ability will adopt earlier. The second and third are perhaps more interesting; being receptive to advice may slow adoption for high cognitive ability individuals, but speed adoption for low cognitive ability individuals. We combine experimental measures of cognitive ability and receptiveness to advice with survey measures of the timing of adoption of GM corn to test these hypotheses. As the model predicts, we find that the earliest adopters are those who have both high cognitive ability and also are not receptive to advice. It is the interaction of these two characteristics which is most important, compared to the isolated impact of either characteristic alone.

Maertens (2017) finds that farmers learn most from progressive farmers who adopt immediately without waiting to see what their peers do. But who are these progressive farmers who adopt without waiting to take advice or learn from others' experiences? Our results suggest they are individuals who have high cognitive ability and who have a low receptiveness to advice. This is in accord with Läpple & 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').

These results have important implications for targeting promotion efforts in a variety of contexts. In agriculture, extension agents and seed salesmen should make explicit efforts to reach out to those farmers with lower cognitive ability who are receptive to advice. Although identifying individuals with these characteristics might require repeated interactions, repeated interactions are not unlikely given the nature of the promoters' occupations. In the context of GM corn and other robust technologies, this could increase income and stimulate aggregate productivity. Therefore, it would be worthwhile for promoters to build into their relationships with local farmers ways of identifying the aforementioned traits.

Public health and conservation are two other contexts where promotion efforts could be informed by this study. In both of these realms, promoters encourage individuals to use new technologies, change common practices, or undertake additional actions aimed at improving the welfare of their families and community. Identifying individuals who would need and be likely to use the information is generally a challenge for promoters. However, it is not hard to imagine incorporating into initial screening conversations tests of receptiveness to advice. If, as both previous research and the results above suggest, an individual's receptiveness to advice has a substantive fixed' component to it, then these efforts could sharpen the efforts of health and conservation promoters to target people with lower cognitive skills and higher receptiveness.

Finally, we offer two reflections for future research. First, our game focuses on receptiveness to advice when advice is given out freely and participants have no choice but to receive it. We do not look at the relationship between receptiveness to advice and advice seeking, which may be another fruitful avenue for future research. Second, we studied GM seeds, a technology that turned out to be advantageous for all and early adopters happened to have been correct. 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 quickly and then disadopted quickly. It would be interesting to study both the adoption and disadoption decisions for a range of technologies or practices, some of which are highly attractive and others of which are less so.

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A Screen Shots from the Experiments

1. Introductory screen:

> Thank you all for taking the time to come today. Today's games will take approximately one hour. You will be compensated for your participation in the experiment, though the exact amount you receive will depend on the choices you make and on random chance (as explained later). Please pay careful attention to these instructions, as a significant amount of money is at stake. Whatever money you win will be yours to keep and take home. Although we are the ones handing you the money, the money is not our own money. It is money given to us to use for research. We do not benefit personally whether you win a lot of money or a little money.
>
> Please turn off your cellphones. If you need to use the restroom, please do so at this time.
>
> Please, if you feel confused, raise your hand. We will answer privately.

Following this screen one experiment measuring ambiguity aversion and one experiment measuring risk aversion were played.

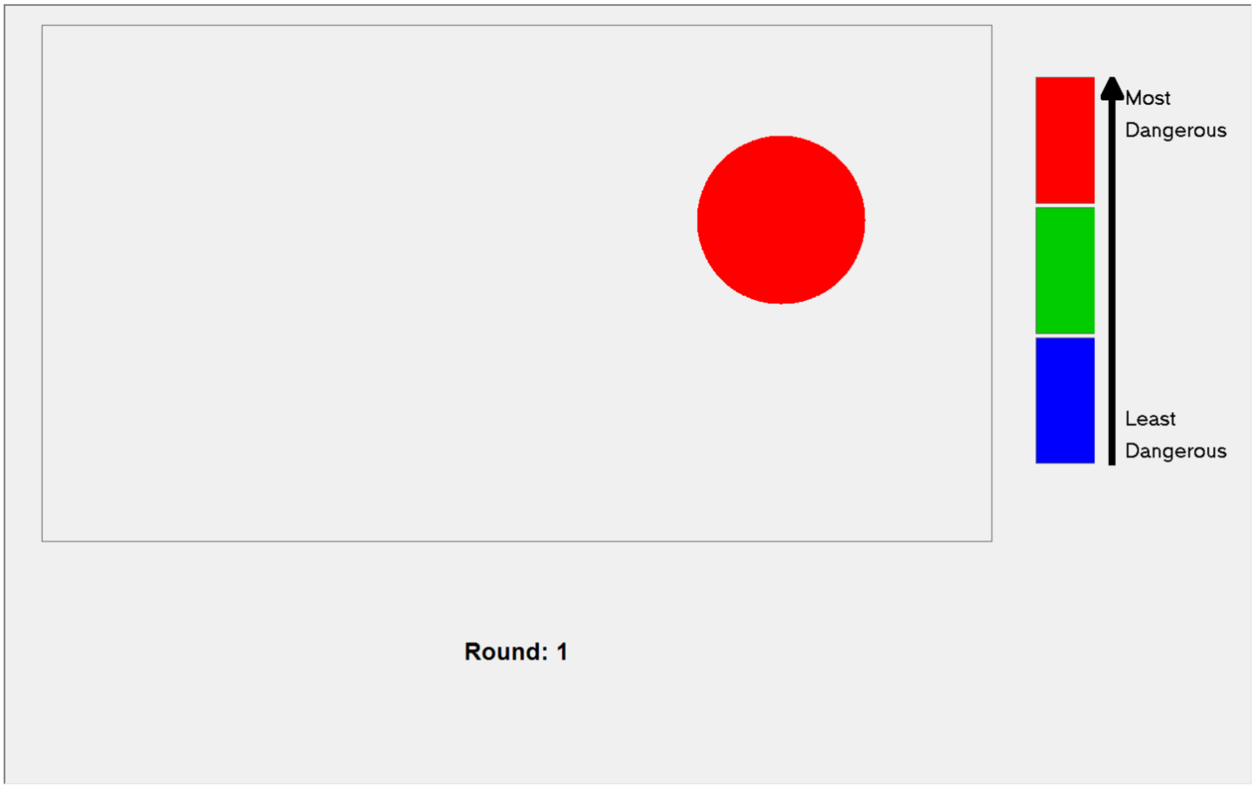
2. Screens that participants see in the individual learning game:

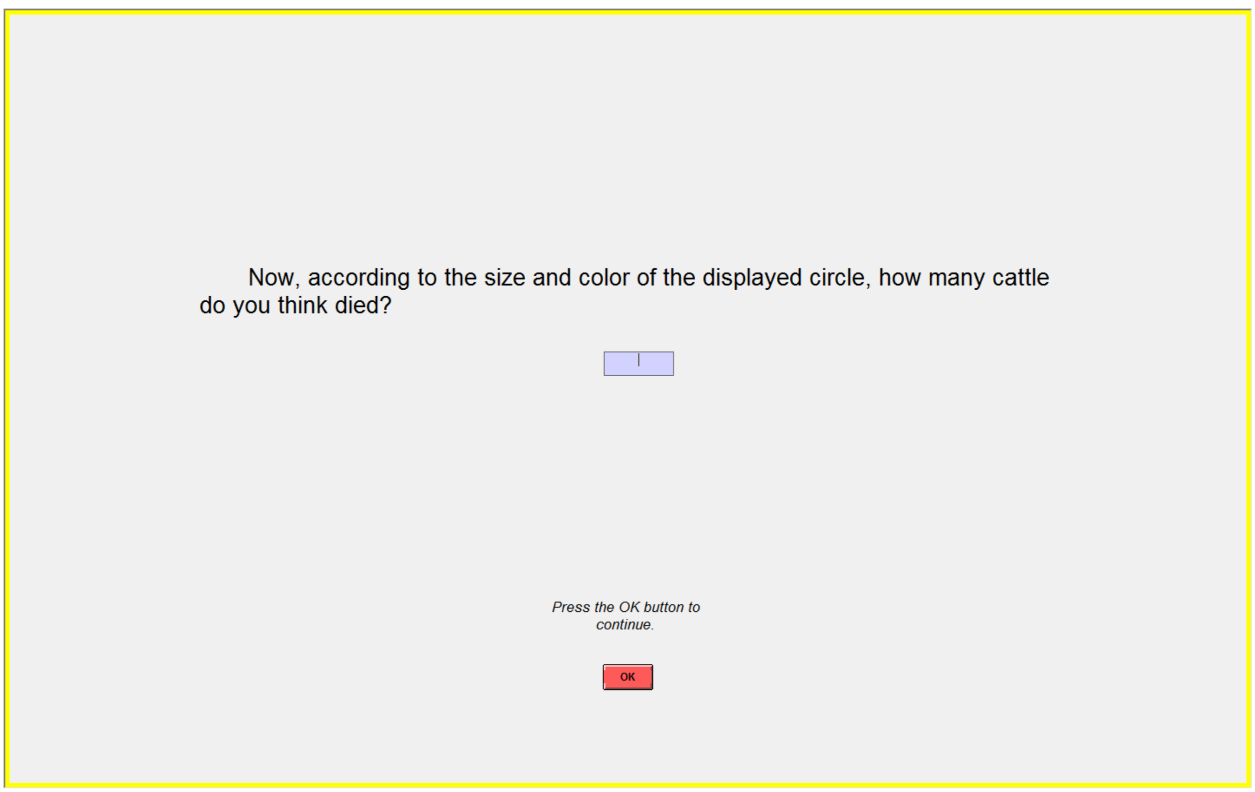
GAME 3 - Part A

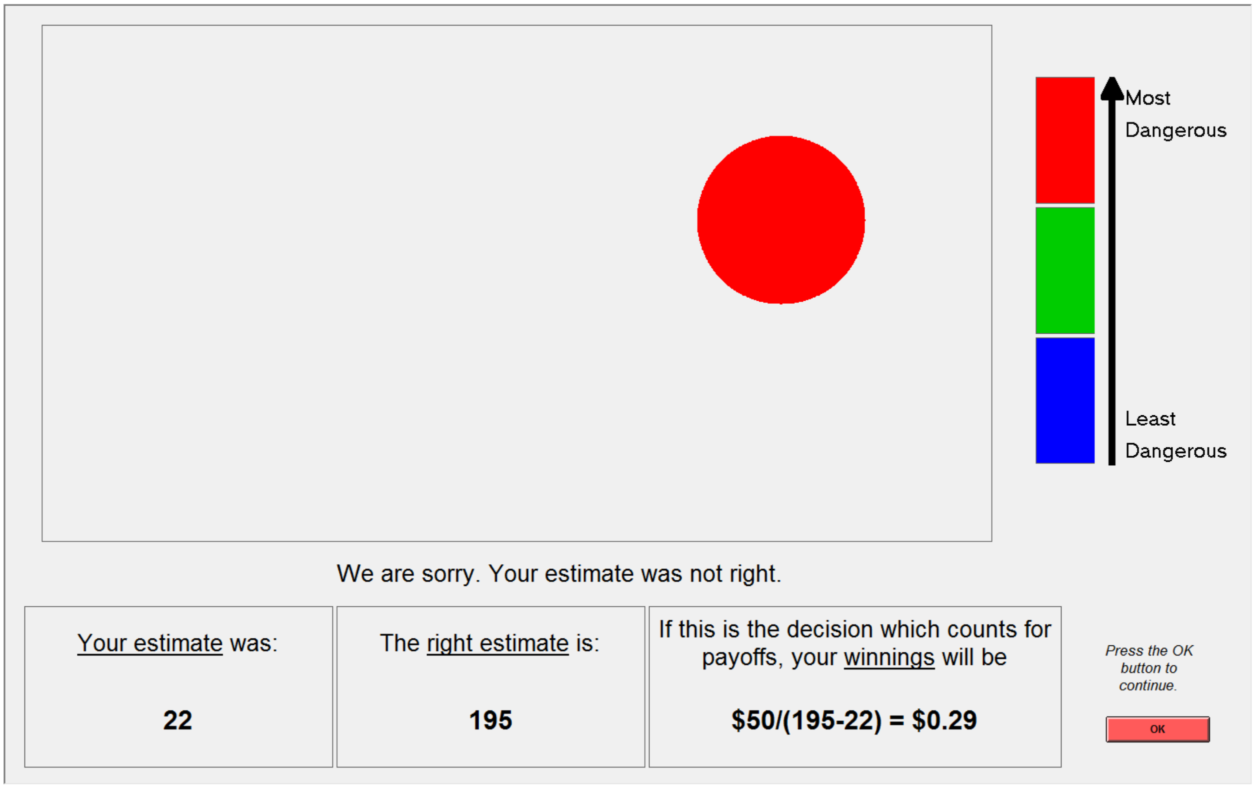
Land in a country can be infected with various different cattle viruses. More cattle die when the outbreak covers a larger amount of land and when the virus is more dangerous. When an infection is reported, the Ministry of Agriculture makes an inspection to determine how serious the situation is. This is because they have to make a forecast of how many cattle will die. These forecasts are needed because initial compensation is paid on the basis of them. This ensures that farmers have some immediate recompense rather than having to wait until the outbreak has finished before making a claim.

In the training session, you will see brief presentations of colored circles. The size of a circle reflects the amount of land that is infected. The color of the circle gives you information about how dangerous the virus is. Red signals the most dangerous virus; green the next most dangerous; and blue the least dangerous. After you have seen the circle, type in your forecast of the number of cattle that you think will die from the outbreak. After you have done this, you will be told how many actually did die according to the Ministry's historical records. You will be able to compare this with your forecast and thereby improve your future forecasts. After 25 assessments, your ability to make these judgments should have improved considerably.

We will choose one of these 25 assessments to be the basis on which you are paid. A correct estimate earns $50. An incorrect estimate receives a payoff equal to $50 divided by the absolute difference between your estimate and the truth. For example, if you estimate 90 cattle died, while the true death toll was 100, you would receive $50/(100-90) = $50/10 = $5. We will choose which one of the 25 decisions counts for your payoffs by drawing a number from 1 to 25 out of a bag at the end of this session.

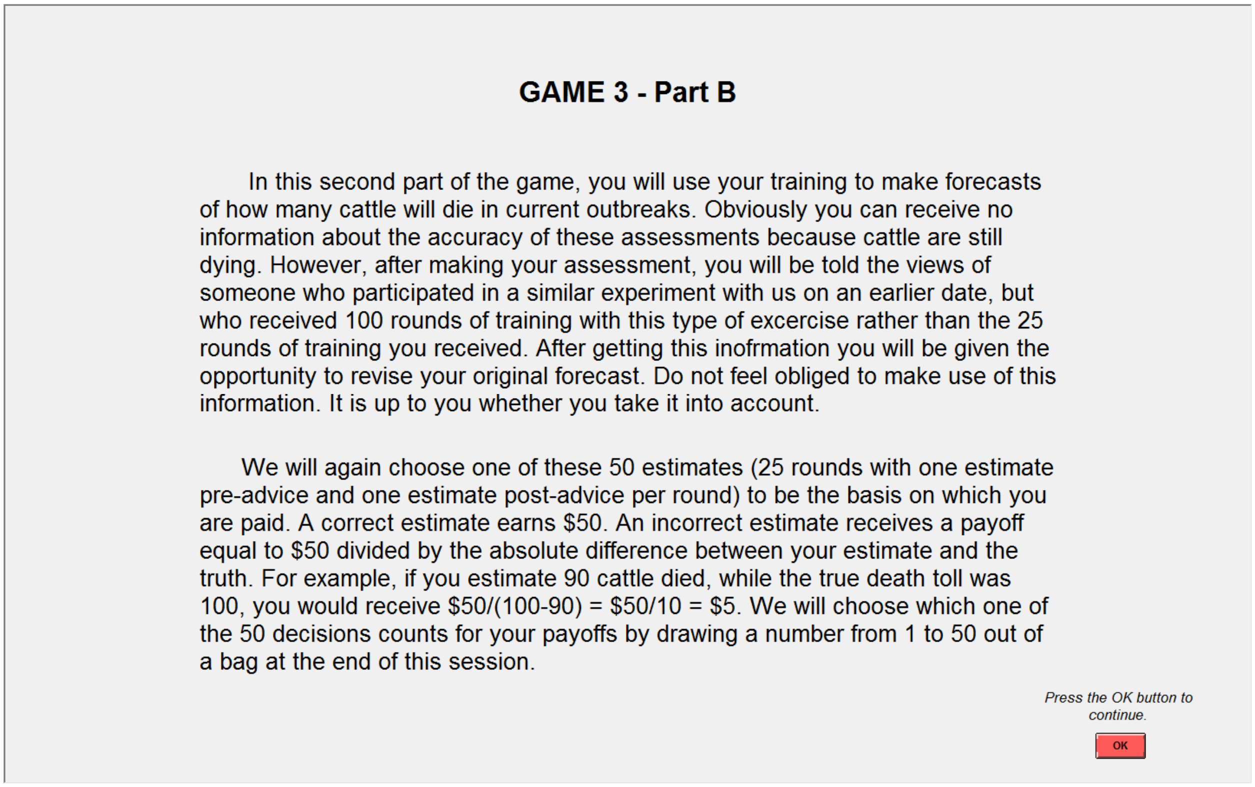

Most
Dangerous
Least
Dangerous
Round: 1


Now, according to the size and color of the displayed circle, how many cattle do you think died?
Press the OK button to continue.
OK



This was repeated for 25 rounds.

3. Screens that participants see in the advice-taking game:



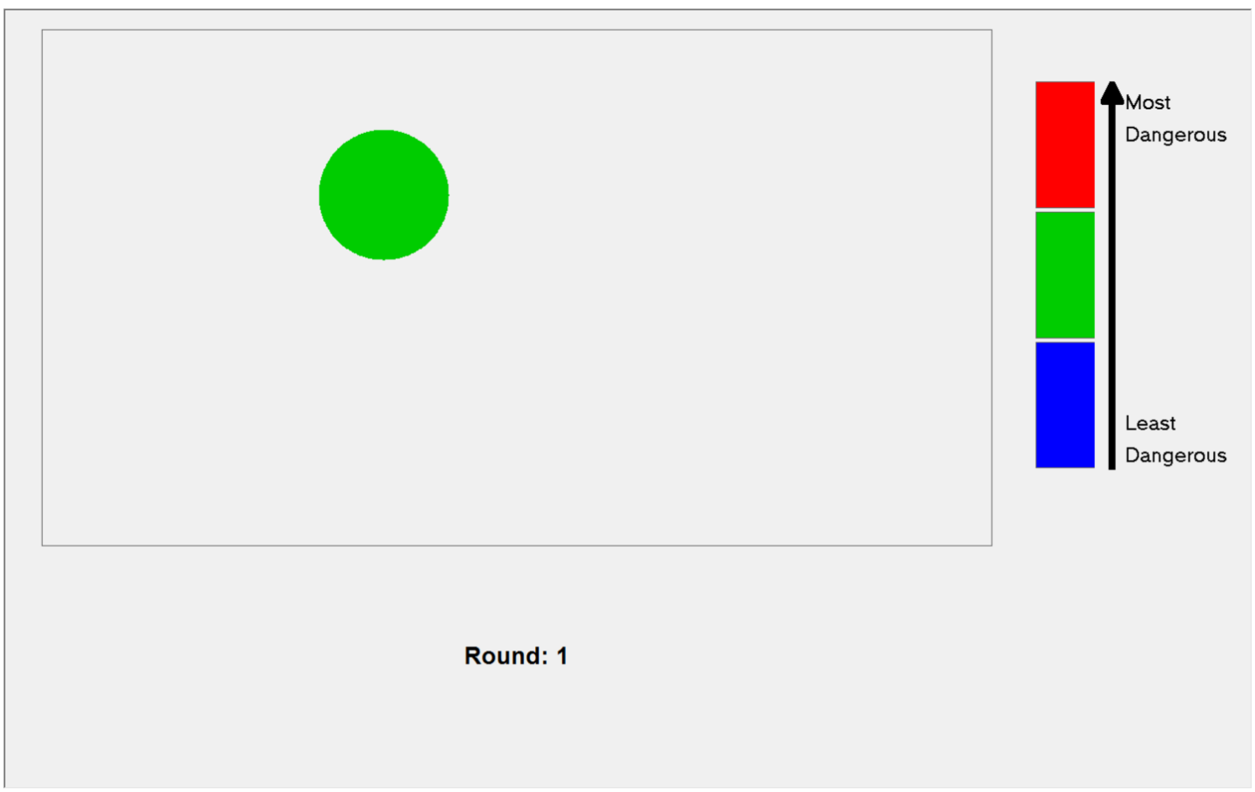
GAME 3 - Part B

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 date, but who received 100 rounds of training with this type of excercise rather than the 25 rounds of training you received. After getting this inofrmation 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.

We will again choose one of these 50 estimates (25 rounds with one estimate pre-advice and one estimate post-advice per round) to be the basis on which you are paid. A correct estimate earns $50. An incorrect estimate receives a payoff equal to $50 divided by the absolute difference between your estimate and the truth. For example, if you estimate 90 cattle died, while the true death toll was 100, you would receive $50/(100-90) = $50/10 = $5. We will choose which one of the 50 decisions counts for your payoffs by drawing a number from 1 to 50 out of a bag at the end of this session.

Press the OK button to continue.

OK



Now, according to the size and color of the displayed circle, how many cattle do you think died?

Press the OK button to continue.

OK

Your estimate was: **324 cows**	The number of trial rounds in which you trained: **25 rounds**
The advisor's estimate was: **75 cows**	The number of trial rounds in which your advisor trained: **100 rounds**

Now, you have the opportunity to revise your original estimate. How many cows do you think died?

Press the OK button to continue.

OK

This was repeated for 25 rounds.

B Learning in the Advice-Taking Game

We postulate that the advice perceived precision we measure captures an underlying personality trait which is receptiveness to advice. We use all 25 rounds of the advice-taking game to create this measure, and assume that the weight placed on the advice in each round is an independent draw, and that the player is not learning about the quality of advice over the 25 rounds. We tell the players that the advice is the estimate made by somebody who had played 100 training rounds, but we do not specify that in fact the advice comes from somebody who had played 100 training rounds and was quite good at the game. One might worry that as the 25 rounds progress, the player figures out that the advice is in fact of quite good quality and put a larger weight on it as time goes on. We think this is unlikely for several reasons.

First, the design of the advice-taking game does not allow for learning since the players are never told the correct number of cattle which died. So, for example, the player may estimate that 60 cows died. Then, he might be told that the advisor estimated that 80 cows died. The player might then split the difference and make a final estimate that 70 cows died. But, the player then moves on to the next circle and is not told how many cattle actually died. Thus, the player does not learn whether 60 or 70 or 80 was a more accurate estimate, and so does not learn about the quality of the advice.[23]

Second, we explore whether the advice weight changes significantly over the course of the 25 rounds. Remember that the advice weight comes from a regression of the final estimate (F) on the initial estimate (I) and the advice (A). The regression is run separately for each individual, using all 25 rounds of the advice game:

$$F_t = (1 - \alpha_v)I_t + \alpha_v A_t + \epsilon_t \tag{B-1}$$

One could instead construct an advice weight for each individual in each round, $\alpha_v = (F - I)/(A - I)$, and then regress this weight on a time trend separately for each individual. We do this and find that the number of significant time trends is not much higher than one would have expected by chance. Of the 132 individuals in our sample, 2% have a time trend which is significant at the 1% level, 7% have a time trend which is significant at the 5% level, and 12% have a time trend which is significant at the 10% level. We find that 41% of the time trends are negative, and 59% are positive. Of those significant at the 5% level, three

[23]Of course if the advisor were to estimate that 6032 cattle perished, the player would learn that the advice was not good. But, within a range of reasonable estimates the player will not be able to deduce the degree of quality of the advice.

are negative and five are positive. Thus, there is no evidence that the players' perceptions of the advice is changing over time.

Third, if in fact individuals are learning over time that the advice we are giving them is quite good, we would expect decisions in the early rounds of the advice-taking game to reveal their receptiveness to advice from advisors whose quality they know little about, whereas later rounds of the advice-taking game would reveal their receptiveness to advice from an advisor they believe to be giving good advice. We can estimate equation (B-1) using play from only the first five rounds of the advice-taking game, or using only the last ten rounds of the advice-taking game to get different measures of the advice weight. Combining those with the measure of own precision, we can back out the advice perceived precision.

If there is in fact no learning, then the results using these measures should not be qualitatively different, though these measures should contain more noise than our original measure which takes advantage of all 25 rounds. Panel B of Appendix Table 4 shows the GM corn adoption regressions with varied measures of receptiveness to advice. Columns (1) and (2) use the original advice weight and replicate the results in columns (6), and (8) of Table 3. The next two columns use the perceived advice precision from the first five rounds while the subsequent two columns use the advice perceived precision from the final ten rounds. We see that the qualitative results are quite similar no what measure we use, though we sometimes lose significance.

Finally, we note that all adoption regressions simultaneously control for cognitive ability and receptiveness to advice. Thus, even if it were the case that individuals with higher cognitive ability were also better able to figure out that we were giving them good advice, we are exploring the effect of receptiveness to advice conditional on cognitive ability.

A different option we could have employed - which would have avoided the possibility that individuals learn about the quality of advice over time - would have been to have the advice be a computer-generated signal with known noise parameters. But, it would be hard to interpret the weight the farmer put on the signal as their responsiveness to advice, given that in that case the signal is not actually advice per se. In addition, it is hard to imagine that all farmers would know how to interpret this advice, and again it could be the case that higher cognitive ability individuals would be better able to understand the computer's data-generating process.

A different worry one might have about our measure of receptiveness to advice, the advice perceived precision, is that it depends heavily on the structural form of Bayesian updating under normality. We could instead look at responsiveness to advice, the advice weight itself

(α_v). We do this in the final two columns of Panel B of Appendix Table 4 and find similar results yet again.

Table 1: Summary Statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
Demographic Characteristics					
Age	132	51.31	14.46	22	83
Gender: Female	132	3.03%			
Household size in 2011	132	2.79	1.27	1	7
Household income before taxes in 2011 (Thousands)[2]	132	116.7	64.8	0	210
Share of household income from farming in 2011	132	66.6	30.4	0	100
Requested computer training	132	12.12%			
Cognitive Characteristics					
High school diploma or less	132	25.76%			
Digit span score	131	7.53	1.59	3	11
Number of risky choices made in risk game	132	5.08	2.71	0	10
Farming Characteristics					
Farming is not the principal occupation in 2011	132	15.15%			
Acres of cropland operated in 2011	132	947	1007	30	6500
Acres of cropland operated and owned in 2011	132	414	495	0	3000
Years farmer has made decisions on farm	132	26.23	14.56	2	57
Corn					
Have planted conventional but never GM corn	132	3.79%			
Have ever planted GM corn	132	96.21%			
Years planting GM corn (up through 2011)	132	10.89	4.46	0	16
Bought crop insurance for corn in 2011	132	79.55%			
Livestock/dairy yielded at least 25% of farm income in 2011	132	27.27%			
Experimentally-Measured Characteristics					
Cognitive ability (own precision, ρ_u)[1]	132	0.40	0.52	0.04	2.90
Receptiveness (advice perceived precision, ρ_v)[1]	132	1.24	2.44	0	11.58
Responsiveness (advice weight, α_v)[1]	132	0.62	0.23	0	1
High own / low advice perceived precision	132	16.7%			
Low own / high advice perceived precision	132	16.7%			
High own / high advice perceived precision	132	33.3%			
Low own / low advice perceived precision	132	33.3%			
Survey-Measured Characteristics					
# of information sources in which have confidence in 2011	132	4.31	1.36	1	6
Has ever tried new corn seeds on small plots	132	76.5%			

1 In this and all other tables the precisions are mulitplied by 100 for scaling.

2 Income is approximated as the midpoint of the chosen income category.

Table 2: Cognitive Ability, Receptiveness to Advice, and Responsiveness to Advice

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Cognitive ability (own precision, ρ_u)			Responsiveness (advice weight, α_v)			Receptiveness (advice perceived precision, ρ_v)		
Cognitive ability (own precision, ρ_u)						-11.00***			0.92*
						[4.07]			[0.51]
High school diploma or less	0.02		0.12	2.57	3.01	4.32	0.93	1.02	0.91
	[0.12]		[0.12]	[5.26]	[5.77]	[5.86]	[0.61]	[0.65]	[0.61]
Digit span		0.08**	0.07*	-1.28	-0.68	0.09	0.18**	0.25***	0.19*
		[0.03]	[0.04]	[1.25]	[1.35]	[1.35]	[0.08]	[0.09]	[0.10]
Age			0.00		0.63**	0.65**		0.05	0.05
			[0.01]		[0.30]	[0.30]		[0.04]	[0.04]
Female			0.00		26.05***	26.05***		2.36	2.36
			[0.14]		[7.87]	[7.58]		[1.73]	[1.68]
Acres operated (1000's)			-0.02		0.65	0.42		-0.01	0.01
			[0.04]		[1.97]	[2.07]		[0.21]	[0.19]
Farming not principal occupation			-0.01		5.19	5.09		0.64	0.65
			[0.16]		[5.73]	[5.31]		[0.77]	[0.79]
Years making decisions on farm			-0.01		-0.37	-0.46		-0.00	0.00
			[0.01]		[0.33]	[0.34]		[0.04]	[0.04]
Received computer refresher			0.05		-0.84	-0.29		-1.21	-1.25*
			[0.17]		[8.87]	[8.81]		[0.78]	[0.75]
Number of risky choices			0.01		-0.08	0.07		0.03	0.01
			[0.02]		[0.76]	[0.74]		[0.09]	[0.08]
Constant	0.39***	-0.19	-0.11	70.75***	41.93**	40.78**	-0.38	-3.66*	-3.57*
	[0.05]	[0.24]	[0.45]	[10.22]	[16.81]	[16.21]	[0.59]	[1.94]	[2.00]
Observations	132	131	131	131	131	131	131	131	131
R-squared	0.000	0.056	0.090	0.012	0.080	0.137	0.033	0.119	0.155

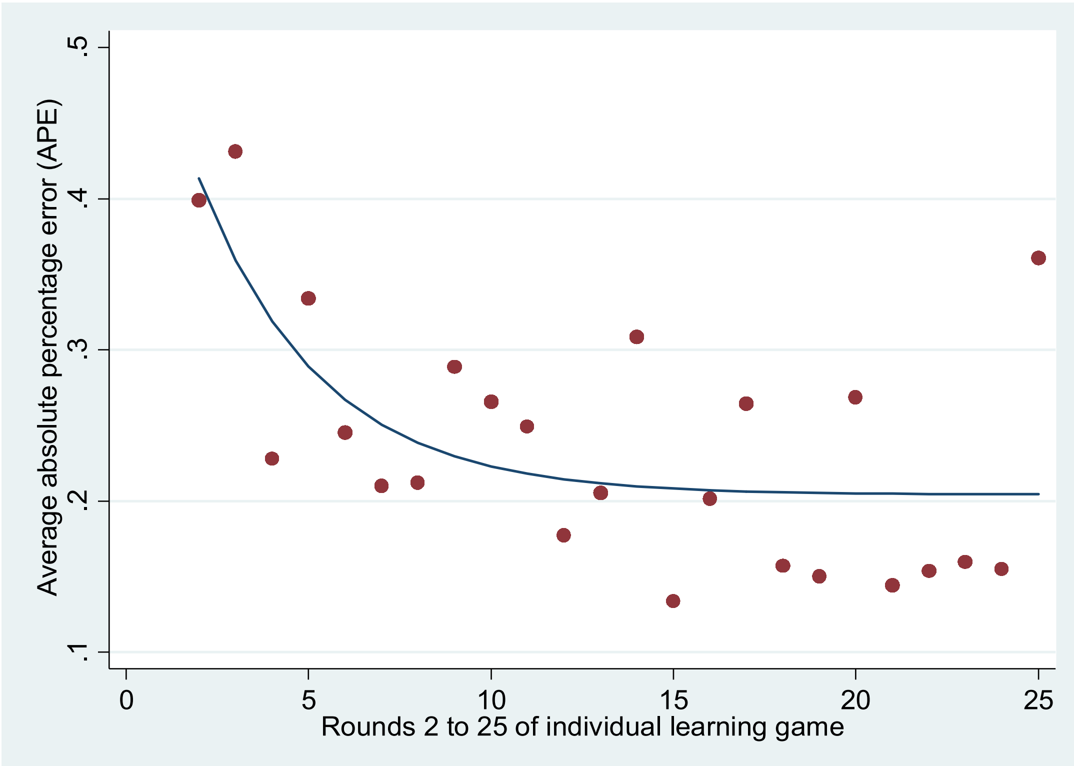
Coefficients in OLS regressions. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10. The precisions and advice weight are multiplied by 100 for scaling.

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

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High school diploma or less	0.686*			0.781		0.807		0.836
	[0.155]			[0.208]		[0.214]		[0.237]
Digit span		1.092		0.963		0.944		1.034
		[0.066]		[0.066]		[0.064]		[0.075]
Cognitive ability (own precision, ρ_u)			2.171***	2.351***	2.894***	3.185***		
			[0.369]	[0.432]	[0.662]	[0.759]		
Receptiveness (advice perceived precision, ρ_v)			0.947	0.961	0.997	1.014		
			[0.038]	[0.048]	[0.037]	[0.045]		
Cognitive ability x Receptiveness					0.922***	0.917***		
					[0.025]	[0.029]		
High ability / Low receptiveness (HL)							1.866***	1.729**
							[0.433]	[0.461]
Low ability / High receptiveness (LH)							0.760	1.162
							[0.281]	[0.384]
High ability / High receptiveness (HH)							1.250	1.162
							[0.296]	[0.293]
Age				0.998		0.997		0.996
				[0.019]		[0.018]		[0.020]
Female				0.838		0.822		0.919
				[0.229]		[0.213]		[0.287]
Acres operated (1000's)				1.415***		1.407***		1.359***
				[0.145]		[0.147]		[0.136]
Farming not principal occupation				0.563		0.539		0.594
				[0.214]		[0.204]		[0.219]
Years making decisions on farm				0.984		0.987		0.982
				[0.020]		[0.019]		[0.020]
Received computer refresher				1.036		0.899		1.322
				[0.431]		[0.387]		[0.550]
Number of risky choices				0.952		0.959		0.959
				[0.034]		[0.035]		[0.033]
k	1.356***	1.377***	1.412***	1.685***	1.442***	1.708***	1.378***	1.625***
	[0.136]	[0.136]	[0.132]	[0.157]	[0.139]	[0.162]	[0.136]	[0.152]
Number of farmers	132	131	132	131	132	131	132	131
χ^2 Inequality Tests								
HL-HH>0							0.039**	0.088*
LH>0							0.771	0.324

Hazard ratios for survival models. We test whether they are significantly different from 1 (not 0) at * – 10%, ** – 5%, and *** – 1% levels. A hazard ratio below 1 implies that the variable makes adoption less likely. Robust standard errors in brackets. All regressions assume a Weibull survival distribution and include year and crop-reporting district fixed effects. In Columns 7 and 8, "Low ability / Low receptiveness" is the excluded category. The precisions are multiplied by 100 for scaling. The χ^2 inequality tests show the *p* -values for one-sided tests of the hypothesis that the coefficient on High ability / Low receptiveness is greater than or equal to that on High ability / High receptiveness, and the hypothesis that the coefficient on Low ability / High receptiveness is greater than or equal to 0 (i.e., testing that the hazard ratio is greater than or equal to 1).

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 an exponential fit line.

Figure 2a: Cognitive Ability (Own Precision, ρ_u)

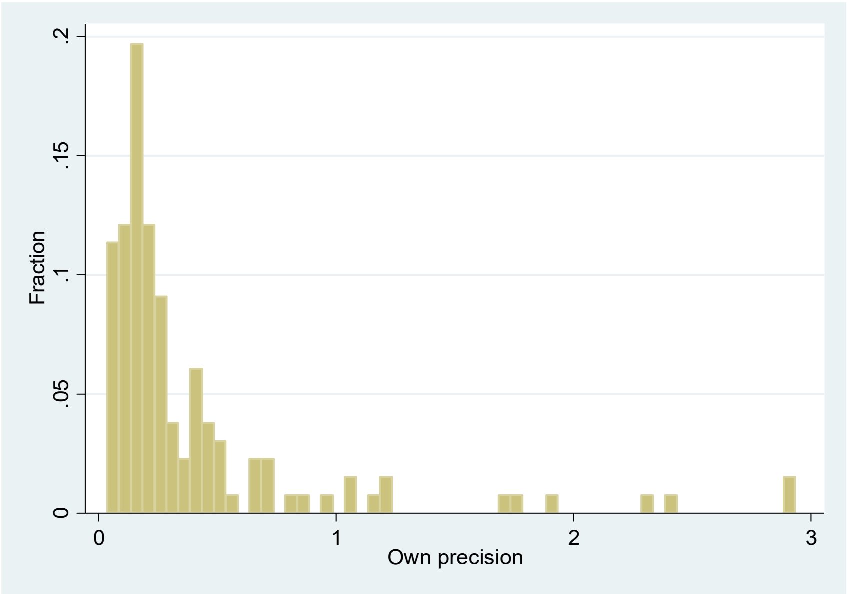


Figure 2c: Receptiveness (Advice Perceived Precision, ρ_v)

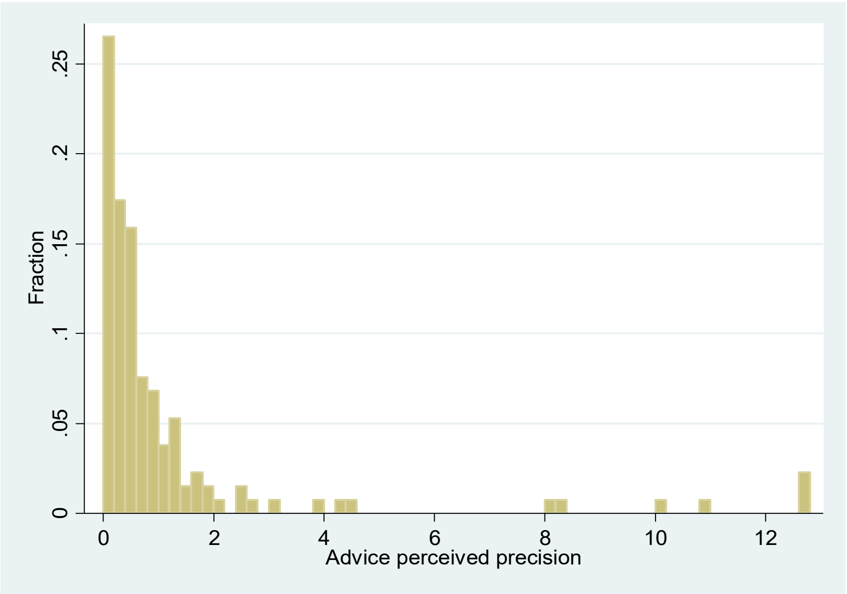


Figure 2b: Responsiveness (Advice Weight, α_v)

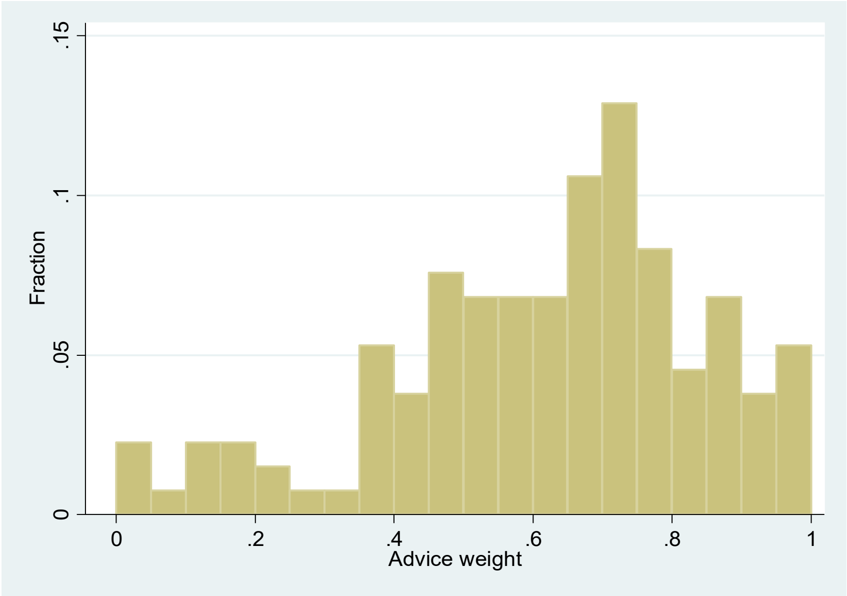
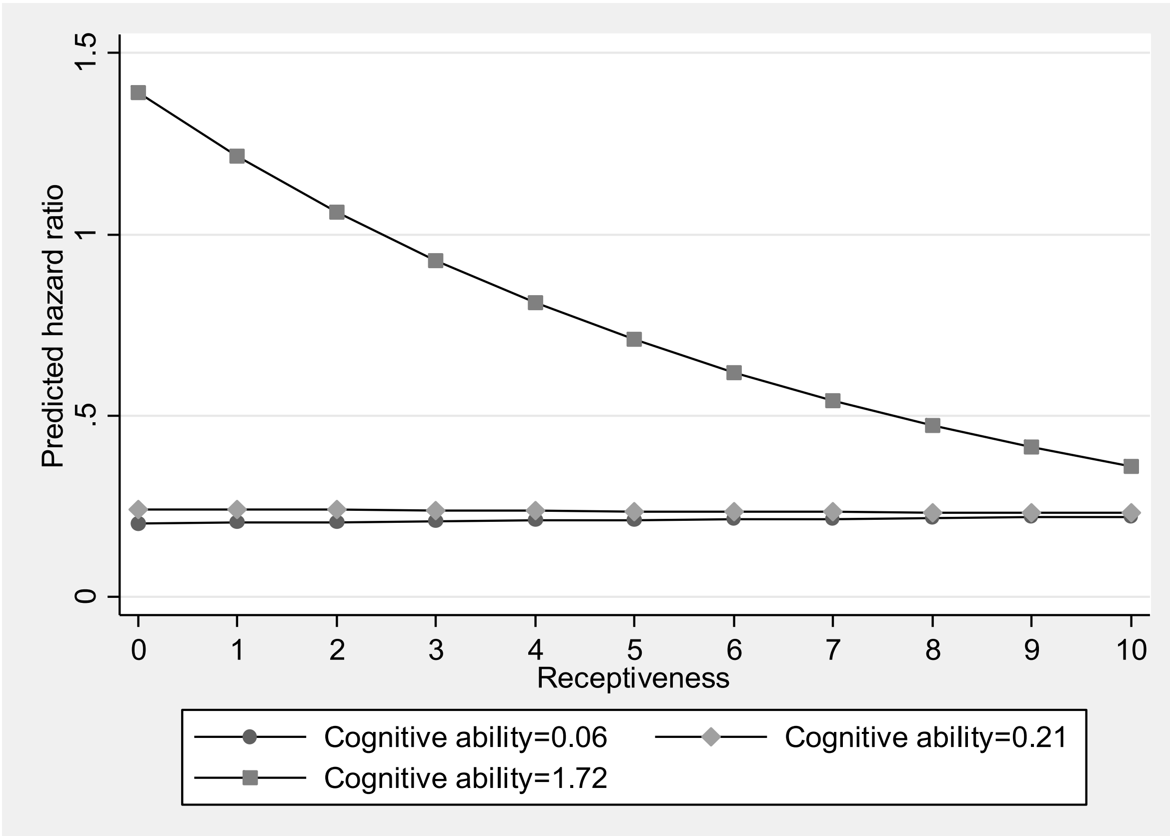


Figure 3: Corn Adoption



Predicted hazard ratios from the survival analysis in Table 3 column (6) at the 5th, 50th, and 95th percentile cognitive ability.

Appendix Table 1: Risk Aversion Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES				Number of risky decisions			
Cognitive ability (own precision, ρ_u)	0.51					0.36	0.38
	[0.43]					[0.48]	[0.49]
Receptiveness (advice perceived precision, ρ_v)		0.05				0.02	
		[0.10]				[0.11]	
Responsiveness (advice weight, α_v)			-0.34				0.10
			[1.07]				[1.09]
High school diploma or less				1.09*	1.02	0.96	0.97
				[0.59]	[0.66]	[0.66]	[0.65]
Digit span				0.26*	0.26*	0.23	0.23
				[0.14]	[0.15]	[0.16]	[0.16]
Age					0.02	0.02	0.02
					[0.04]	[0.04]	[0.04]
Female					-2.39***	-2.41***	-2.40***
					[0.71]	[0.70]	[0.72]
Acres operated (1000's)					0.28	0.29	0.29
					[0.24]	[0.24]	[0.24]
Farming not principal occupation					0.75	0.74	0.75
					[0.73]	[0.71]	[0.72]
Years making decisions on farm					-0.01	-0.00	-0.00
					[0.04]	[0.04]	[0.04]
Received computer refresher					0.32	0.33	0.30
					[0.82]	[0.84]	[0.82]
Constant	4.88***	5.02***	5.29***	2.86**	1.79	1.88	1.78
	[0.31]	[0.27	[0.71]	[1.10]	[1.67]	[1.66]	[1.80]
Observations	132	132	132	131	131	131	131
R-squared	0.010	0.002	0.001	0.041	0.083	0.088	0.088

Coefficients in OLS regressions. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10. The precisions are multiplied by 100 for scaling.

Appendix Table 2: Survival Model Adoption Robustness Checks - Distributional Assumptions

	(1)	(2)	(3)	(4)	(5)	
Panel A: Quadratic and IHS Predictors			Quadratic		IHS	
Cognitive ability (own precision, ρ_u)	3.185***	3.306**	3.541***	5.185**	6.646***	
	[0.759]	[1.972]	[0.848]	[3.436]	[2.736]	
Receptiveness (advice perceived precision, ρ_v)	1.014	1.013	0.760	0.729	0.990	
	[0.045]	[0.045]	[0.151]	[0.151]	[0.182]	
Cognitive ability x Receptiveness	0.917***	0.919**	0.923***	0.943	0.672**	
	[0.029]	[0.037]	[0.025]	[0.038]	[0.136]	
(Cognitive ability)^2		0.982		0.834		
		[0.245]		[0.239]		
(Receptiveness)^2			1.026	1.029*		
			[0.017]	[0.017]		
Number of farmers	131	131	131	131		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Different Distributions	Weibull distribution		Exponential distribution		Gompertz distribution	
Cognitive ability (own precision, ρ_u)	3.185***		2.348***		2.472***	
	[0.759]		[0.427]		[0.489]	
Receptiveness (advice perceived precision, ρ_v)	1.014		0.990		1.009	
	[0.045]		[0.034]		[0.037]	
Cognitive ability x Receptiveness	0.917***		0.939**		0.935**	
	[0.029]		[0.024]		[0.025]	
High ability / Low receptiveness (HL)		1.729**		1.445*		1.566*
		[0.461]		[0.296]		[0.362]
Low ability / High receptiveness (LH)		1.162		0.936		1.027
		[0.384]		[0.248]		[0.299]
High ability / High receptiveness (HH)		1.162		1.099		1.131
		[0.293]		[0.231]		[0.255]
Number of farmers	131	131	131	131	131	131
χ^2 Inequality Tests						
HL-HH>0		0.088*		0.095*		0.090*
LH>0		0.324		0.599		0.464

Hazard ratios for survival models. We test whether they are significantly different from 1 (not 0) at * – 10%, ** – 5%, and *** – 1% levels. A hazard ratio below 1 implies that the variable makes adoption less likely. Robust standard errors in brackets. All regressions include year and crop-reporting district fixed effects. Other control variables in all regressions include: high school diploma or less, digit span, age, female, acres operated, farming not principal occupation, years making decisions on farm, received computer refresher, and number of risky choices.The precisions and advice weight are all mulitplied by 100. Panel A: In all columns a Weibull survival function is assumed. Columns (2) through (4) show the addition of quadratics in cognitive ability and receptiveness. Column (5) show the results with the inverse hyperbolic sine (IHS) transformation for both variables (and the interaction of the two transformed variables). Panel B: In Columns 2, 4, and 6 "Low ability / Low receptiveness" is the excluded category. In columns (1) and (2) a Weibull, in columns (3) and (4) an exponential, and in columns (5) and (6) a Gompertz survival function is assumed. The χ^2 inequality tests show the *p* -values for one-sided tests of the hypothesis that the coefficient on High ability/ Low receptiveness is greater than or equal to that on High ability /High receptiveness, and the hypothesis that the coefficient on Low ability / High receptiveness is greater than or equal to 0 (i.e., testing that the hazard ratio is greater than or equal to 1).

Appendix Table 3: OLS years since GM Corn Adoption

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High school diploma or less	-0.906			-0.980		-0.947		-0.651
	[0.768]			[0.747]		[0.754]		[0.761]
Digit span		-0.051		-0.208		-0.221		-0.097
		[0.197]		[0.201]		[0.202]		[0.216]
Cognitive ability (own precision, ρ_u)			1.568***	2.101***	2.085**	2.651***		
			[0.553]	[0.562]	[0.792]	[0.732]		
Receptiveness (advice perceived precision, ρ_v)			-0.075	-0.057	-0.028	-0.007		
			[0.120]	[0.091]	[0.138]	[0.100]		
Cognitive ability x Receptiveness					-0.119	-0.128		
					[0.090]	[0.083]		
High ability / Low receptiveness (HL)							1.482**	1.242*
							[0.708]	[0.716]
Low ability / High receptiveness (LH)							-0.544	-0.507
							[1.150]	[1.082]
High ability / High receptiveness (HH)							-0.048	0.110
							[0.828]	[0.962]
Age				-0.008		-0.009		-0.018
				[0.079]		[0.080]		[0.084]
Female				-0.133		-0.117		0.206
				[0.818]		[0.802]		[0.989]
Acres operated (1000's)				0.657**		0.644**		0.564*
				[0.273]		[0.275]		[0.299]
Farming not principal occupation				-2.014		-2.128		-1.860
				[1.468]		[1.484]		[1.590]
Years making decisions on farm				0.027		0.028		0.025
				[0.074]		[0.074]		[0.077]
Received computer refresher				-0.863		-0.935		-0.718
				[1.206]		[1.231]		[1.214]
Number of risky choices				-0.173		-0.162		-0.165
				[0.123]		[0.124]		[0.128]
Observations	97	97	97	97	97	97	97	97
R-squared	0.131	0.117	0.156	0.302	0.161	0.307	0.150	0.260
χ^2 Inequality Tests								
HL-HH>0							0.016**	0.085*
LH>0							0.682	0.680

Coefficients in OLS regressions. All regressions include crop-reporting district fixed effects. Regressions drop farmers who started farming after 1996 or who never adopted GM corn. In Columns 7 and 8, "Low ability / Low receptiveness" is the excluded category. The precisions are multiplied by 100 for scaling. Robust standard errors in brackets. Significantly different from 1 at * – 10%, ** – 5%, and *** – 1% levels. The χ^2 inequality tests show the *p* -values for one-sided tests of the hypothesis that the coefficient on High ability / Low receptiveness is greater than or equal to that on High ability / High receptiveness, and the hypothesis that the coefficient on Low ability / High receptiveness is greater than or equal to 0 (i.e., testing that the hazard ratio is greater than or equal to 1).

Appendix Table 4: Survival Model Adoption Robustness - Different Samples, Controls, and Advice Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Different Samples/Controls	All respondents		Sole and joint proprietors		Sole proprietors		Additional controls	
Cognitive ability (own precision, ρ_u)	3.185***		3.040***		6.422***		3.172***	
	[0.759]		[0.745]		[2.637]		[0.832]	
Receptiveness (advice perceived precision, ρ_v)	1.014		1.017		1.005		1.011	
	[0.045]		[0.045]		[0.048]		[0.047]	
Cognitive ability x Receptiveness	0.917***		0.915**		0.891***		0.911***	
	[0.029]		[0.032]		[0.035]		[0.033]	
High ability / Low receptiveness (HL)		1.729**		1.839**		1.672		2.047**
		[0.461]		[0.506]		[0.535]		[0.611]
Low ability / High receptiveness (LH)		1.162		1.483		1.141		1.326
		[0.384]		[0.504]		[0.495]		[0.528]
High ability / High receptiveness (HH)		1.162		1.132		1.016		1.232
		[0.293]		[0.292]		[0.351]		[0.355]
Number of farmers	131	131	127	127	88	88	131	131
χ^2 Inequality Tests								
HL-HH>0		0.088*		0.056*		0.092*		0.046**
LH>0		0.324		0.124		0.380		0.240

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B: Different Advice Measures	Receptiveness - Original		Receptiveness - First 5		Receptiveness - Last 10		Responsiveness	
Cognitive ability (own precision, ρ_u)	3.185***		2.406***		3.222***		4.580***	
	[0.759]		[0.569]		[0.758]		[2.038]	
Advice receptiveness (ρ_v) or responsiveness (α_v)	1.014		1.045		1.018		1.000	
	[0.045]		[0.066]		[0.018]		[0.006]	
Cognitive ability x Advice measure	0.917***		0.935		0.932***		0.986**	
	[0.029]		[0.091]		[0.025]		[0.007]	
High ability / Low advice measure (HL)		1.729**		1.281		1.297		2.095**
		[0.461]		[0.429]		[0.356]		[0.662]
Low ability / High advice measure (LH)		1.162		1.039		0.867		1.426
		[0.384]		[0.375]		[0.275]		[0.473]
High ability / High advice measure (HH)		1.162		1.280		1.162		1.070
		[0.293]		[0.342]		[0.301]		[0.327]
Number of farmers	131	131	131	131	131	131	131	131
χ^2 Inequality Tests								
HL-HH>0		0.088*		0.499		0.360		0.022**
LH>0		0.324		0.458		0.673		0.142

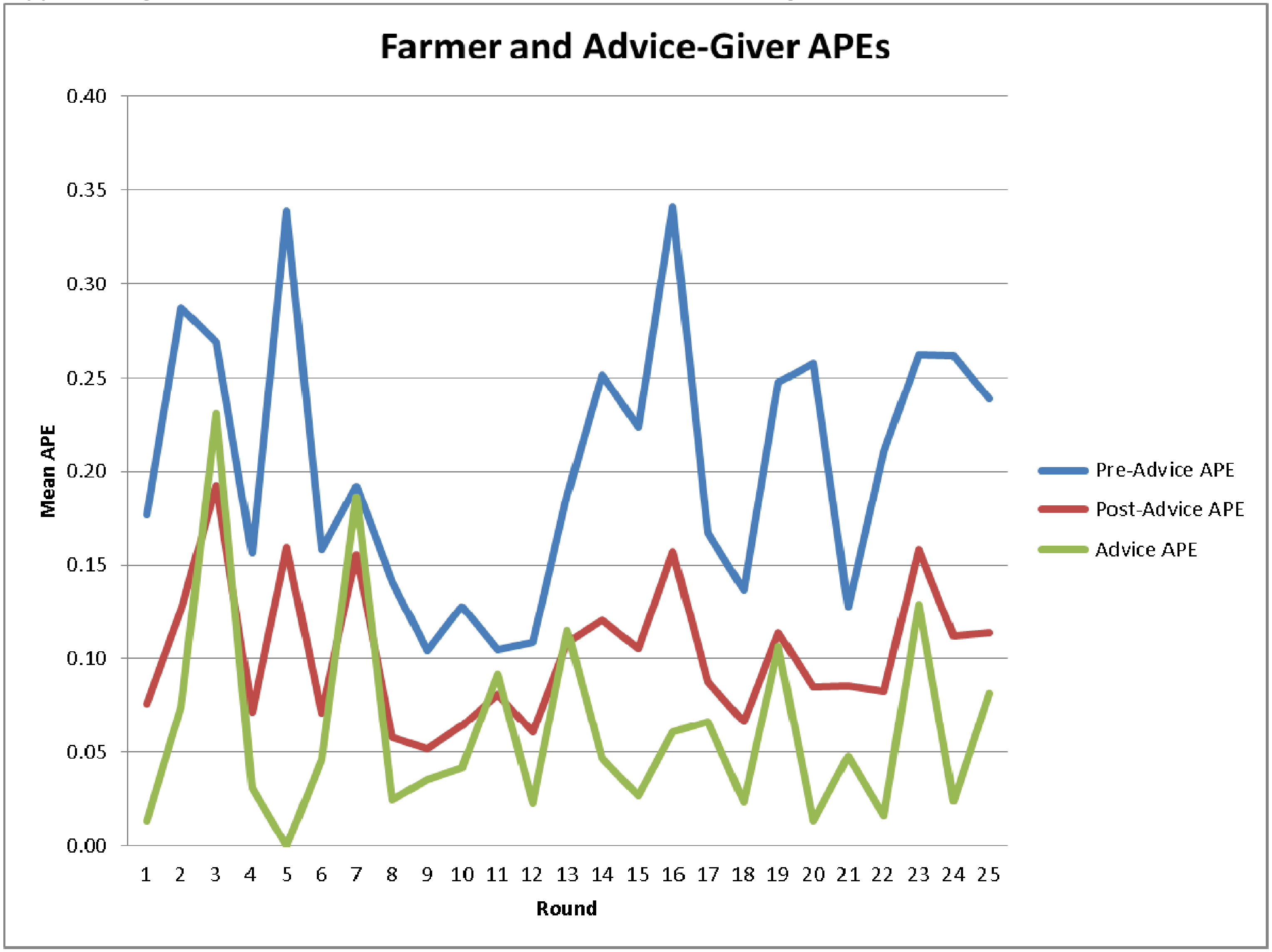
Hazard ratios for survival models. We test whether they are significantly different from 1 (not 0) at * – 10%, ** – 5%, and *** – 1% levels. A hazard ratic below 1 implies that the variable makes adoption less likely. Robust standard errors in brackets. All regressions assume a Weibull survival distribution and include year and crop-reporting district fixed effects. In Columns 2, 4, 6, and 8, "Low ability / Low advice measure" is the excluded category. Other control variables in all regressions include: high school diploma or less, digit span, age, female, acres operated, farming not principal occupation, years making decisions on farm, received computer refresher, and number of risky choices.The precisions and advice weight are all mulitplied by 100. Panel A: In columns (1) and (2) the sample is the full sample, in columns (3) and (4) the sample includes sole and joint proprietors only, and in columns (5) and (6) the sample includes sole proprietors only. Columns (7) and (8) contain all controls listed in note above in addition to household size, livestock/dairy are 25% of farm income, acres owned, purchased crop insurance, total household income, and share of household income from farming. Panel B: In columns (1) and (2) the advice measure is the original receptiveness, using the weight from all 25 rounds of the advice game. In columns (3) and (4) it is receptiveness using only the first 5 rounds of the advice game while in columns (5) and (6) it is the receptiveness using only the last 10 rounds of the advice game. In columns (7) and (8) it is responsiveness, rather than receptiveness. The χ^2 inequality tests show the *p* -values for one-sided tests of the hypothesis that the coefficient on High ability / Low advice is greater than or equal to that on High ability / High advice, and the hypothesis that the coefficient on Low ability / High advice is greater than or equal to 0 (i.e., testing that the hazard ratio is greater than or equal to 1).

Appendix Table 5: Alternate Outcomes and Comparing Experimental Results and Survey Questions

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Test corn		Receptiveness, (advice perceived precision, ρ_v)		
# of sources in which have confidence			0.241*	0.322**	0.365***
			[0.133]	[0.138]	[0.136]
High school diploma or less		-0.135		1.224*	1.129*
		[0.090]		[0.658]	[0.611]
Digit span		0.052**		0.286***	0.219**
		[0.021]		[0.104]	[0.107]
Cognitive ability (own precision, ρ_u)					1.026**
					[0.458]
High ability / Low receptiveness (HL)	0.182*	0.166*			
	[0.103]	[0.091]			
Low ability / High receptiveness (LH)	0.091	0.148			
	[0.115]	[0.103]			
High ability / High receptiveness (HH)	0.114	0.150			
	[0.094]	[0.092]			
Age		-0.005		0.046	0.043
		[0.006]		[0.042]	[0.043]
Female		-0.148		2.411	2.417
		[0.229]		[1.813]	[1.757]
Acres operated (1000's)		0.091***		-0.025	-0.006
		[0.026]		[0.201]	[0.180]
Farming not principal occupation		-0.207*		0.632	0.640
		[0.123]		[0.755]	[0.766]
Years making decisions on farm		0.006		0.002	0.011
		[0.005]		[0.039]	[0.040]
Received computer refresher		0.122		-1.342*	-1.410*
		[0.139]		[0.780]	[0.748]
Number of risky choices		-0.025*		0.015	-0.001
		[0.014]		[0.084]	[0.079]
Constant	0.682***	0.483	0.200	-5.063**	-5.142**
	[0.071]	[0.299]	[0.490]	[2.195]	[2.237]
Observations	132	131	132	131	131
R-squared	0.024	0.197	0.018	0.150	0.193
χ^2 Inequality Tests					
HL-HH>0	0.240	0.438			
LH>0	0.215	0.077			

Coefficients in OLS regressions. "Test corn" is the answer to: "In the past, have you tried new corn seeds on small plots or parcels?" In Columns 1-2, "Low advice / low receptiveness" is the excluded category. The "# of sources in which have confidence" is the number out of six in which they have confidence levels 3 or 4. The precisions are multiplied by 100 for scaling. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10. The χ^2 inequality tests show the *p* -values for one-sided tests of the hypothesis that the coefficient on High ability / Low receptiveness is greater than or equal to that on High ability /High receptiveness, and the hypothesis that the coefficient on Low ability / High receptiveness is greater than or equal to 0 (i.e., testing that the hazard ratio is greater than or equal to 1).

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



Absolute percentage error (APE) from the 25 circles in the advice-taking game. This is the absolute difference between the prediction and the truth, divided by the truth. Pre-advice and post-advice APE are from the farmers and advice APE is from the advice giver.