The Role of Active Discussion in Learning about Uncertain Technologies *

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Abstract

The decision to adopt one technology versus another depends on how uncertain the decision maker views each technology. Attitudes towards risk (known probabilities) and ambiguity (unknown probabilities) have been shown to partially explain the observed sub-optimal level of adoption of agricultural technologies in developing countries. While social learning can help resolve associated information frictions and peer learning interventions are gaining increasing traction, we know little about how these interventions work: is it the information being shared, or is it the role of participating in sharing that leads to increased adoption? To fill this gap, we ran an artefactual laboratory experiment with potato farmers in Peru to elicit their beliefs about the relative riskiness and ambiguity of different technologies (specifically, strategies to deal with Late Blight). Our experiment, designed as a coordination game, allows us to understand the role of active discussion in resolving information frictions associated with these beliefs. We find that active discussion does not help subjects learn from each other about the uncertainty surrounding the technologies. Instead, such interventions solidify their private uninformed beliefs. The results suggest the need to complement active discussion with knowledge interventions to improve learning associated with technology adoption.

JEL Codes: C91, D83, O13, O33.

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1 Introduction

Developing country agriculture is characterized by high risk and uncertainty, increasing over time due to climate change (Ahmed et al., 2009; de Janvry et al., 2017). One way that producers can meet this challenge is to adopt new agricultural technologies. However, subsistence farmers are often reluctant to adopt these despite being among the most vulnerable to shocks (Jack, 2013; Carter et al., 2017; Takahashi et al., 2019; Suri and Udry, 2022). Information frictions are one of the leading causes of low adoption (Magruder, 2018; Mobarak and Saldanha, 2022). One of the channels through which information frictions may affect adoption is the uncertainty surrounding the relative riskiness of a technology (Chavas and Nauges, 2020). Social learning may help counter these frictions by getting agents to learn from each other about the relative riskiness of technologies (Raeburn et al., 2023). Interventions that leverage peer learning to improve adoption can help in such a scenario (Maertens and Barrett, 2012; Cheng, 2021). However, little is known about how such interventions would work: is it the information being shared, or is it the role of participating in sharing that leads to increased adoption?

In this paper, we study the role of active discussion in resolving information frictions in technology adoption. In particular, we focus on the information frictions related to the relative riskiness and ambiguity of different strategies to deal with Late Blight (LB) for Peruvian potato farmers. LB is a fungus perceived as Peruvian potato farmers' primary constraint to production (Perez et al., 2022). Peruvian potato production involves several thousand varieties, with some being more susceptible to LB than others (Sanabria et al., 2020).[1] There is also a large variety of technologies available to deal with LB.[2] Given the limited technical assistance to the farmers in Peru, we expect farmers to have ambiguous beliefs regarding many technologies.[3] This ambiguity, coupled with the negative effect of ambiguity aversion on adoption (Alpizar et al., 2011; Engle-Warnick et al., 2011; Ross et al., 2012) can lead to low adoption of modern technologies that could decrease the adverse effects of LB and increase yields. Do active discussions help in such a scenario by resolving the information frictions related to uncertainty surrounding different technologies?

To answer this question, we conduct an artefactual field experiment with Peruvian potato farmers.[4] We first collect information on the respondents' private beliefs regarding the relative riskiness and ambiguity of different technologies dealing with LB. Then, we randomize these respondents into two groups: participants in an active discussion

[1] According to the International Potato Center, there are more than 4,000 varieties of native potatoes in Peru, Ecuador, and Bolivia: `https://cipotato.org/potato/native-potato-varieties/`.

[2] There are several major ways to deal with LB, including, but not limited to, fungicides (agrochemicals), LB-resistant varieties, not harvesting when wet, crop rotation, and hilling.

[3] Nationally, only 5% of farmers have reported receiving technical assistance according to the 2012 Agricultural Census for Peru (INEI, 2012).

[4] Following the taxonomy of Harrison and List (2004).

and silent observers of this discussion. After the discussion, we use a coordination game to elicit respondents' common beliefs regarding the relative riskiness and ambiguity of the same technologies dealing with LB covered in the first stage.

Our results suggest that active discussions do not help subjects with ambiguous private beliefs learn about the risk distributions associated with the technologies in dealing with LB. If anything, it solidifies their private ambiguous beliefs. Additionally, more educated subjects are likely to have non-ambiguous beliefs. These results suggest that interventions only promoting active discussion for resolving information frictions may backfire. In particular, instead of getting agents to learn from each other and update their beliefs, such interventions may solidify their private, uninformed beliefs. Thus, policymakers may need to complement active discussions with knowledge interventions for improving technology adoption.

Our study makes three contributions to the existing literature. First, we contribute to the literature on understanding policies designed to transmit information effectively. Existing literature shows that the source of the information matters for the effectiveness of that information (Geana et al., 2011; Pan et al., 2021). Evidence suggests that interventions need to use existing social ties to diffuse knowledge effectively (Krishnan and Patnam, 2013; Banerjee et al., 2023; Breza et al., 2019). However, such interventions may be costly in practice (Banerjee et al., 2013; Banerjee et al., 2019; Beaman et al., 2021). Active discussion may provide a more cost-effective alternative to such interventions. However, we provide evidence similar to the *backfire effect* shown in Nyhan and Reifler (2010; 2015), where attempts to correct beliefs make individuals more entrenched in their prior beliefs. Our results indicate that, for its intended effect, active discussions may require complementary knowledge interventions, improving agents' information sets before participating in such a discussion.

We also contribute to the literature on learning for technology adoption. In this regard, we inform interventions to improve technology adoption. There is a vast literature documenting the role of learning in technology adoption (Foster and Rosenzweig, 1995; Bandiera and Rasul, 2006; Conley and Udry, 2010; Banerjee et al., 2013; Guo and Marchand, 2018; Beaman et al., 2021). A sub-section of this literature focuses on understanding the role of risk and uncertainty in that learning process (Chavas and Nauges, 2020). In this paper, we contribute to that literature by providing evidence on whether active discussion can play a role in resolving information frictions related to the relative riskiness of technologies, which can subsequently lead to improved technology adoption.

Finally, we contribute to the growing literature on the role of coordination in improving technology adoption. Recent studies focus on understanding the role played by cooperatives in improving technology adoption. The literature finds a primarily positive impact of cooperative membership on technology adoption (Abebaw and Haile, 2013; Kolade and Harpham, 2014; Abate et al., 2016; Yahaya et al., 2019; Nonvide, 2021). However, the mechanism of the underlying coordination effect still needs to be explored in the literature. This study provides evidence in this regard by exploring whether active discussion can be an explanation behind cooperative memberships increasing technology adoption.

The rest of this paper is organized as follows. Section 2 discusses the conceptual framework for our study. Section 3 presents the experimental design. Section 4 focuses on the details related to the data collection and presents the descriptive results. Section 5 presents and discusses our main results. Finally, in Section 6, we summarize our findings and make concluding remarks.

2 Conceptual Framework

Potato production remains one of the primary agricultural activities in Peru (Tobin et al., 2016; Grados et al., 2020). Potato production is subject to many production shocks, most notable being the threat of Late Blight (LB) - the fungus Phytophthora Infestans, also infamously known for causing the Great Irish Famine (Yuen, 2021). LB is the primary potato disease in Peru (Barrera et al., 2016). Many technologies are available to deal with LB, including traditional and modern technologies (Ivanov et al., 2021). Traditional technologies might have well-known yield probability distributions, while the beliefs about these distributions can be more ambiguous for modern technologies (Engle-Warnick et al., 2011). This is due to the farmers' relative unfamiliarity with the modern technologies. As a result, farmers' beliefs about the degree of uncertainty concerning their yield probabilities may vary depending on the technology they use to deal with LB. Given the several thousand varieties of potatoes produced in Peru, the need and effectiveness of different technologies for coping with LB vary substantially. Both these factors point towards the presence of information friction in adopting strategies for dealing with LB.

Information constraints are one of the most prominent barriers to learning about any technology. Over the last few decades, economic research and policy have focused extensively on investigating the nature of these frictions and the steps for resolving them in practice (Magruder, 2018). Both top-down approaches, where extension agents disseminate information, and bottom-up approaches, where the knowledge is diffused through farmers' social networks via key farmers, have been used in practice (J-PAL, 2023). Farmer-to-farmer extension services, which use farmers from the community to transmit information, are found to work better, although traditional extension services remain essential at the early stages of interventions (Takahashi et al., 2019).

Farmer-to-farmer extension services are widely promoted in the agriculture of developing regions due to their cost-effectiveness (Wellard et al., 2013; Franzel et al., 2018).

One of the main reasons behind the success of such bottom-up approaches is that farmers are more likely to learn from each other than from extension agents unknown to them. This phenomenon is driven by the higher usefulness of the information when coming from sources making similar choices (Munshi, 2004; Conley and Udry, 2010; Crane-Droesch, 2017; Tjernström, 2017; BenYishay and Mobarak, 2018; Chakraborty, 2023). One relatively inexpensive methodology for providing these farmer-to-farmer extension services is using the networks within farmer cooperatives (Guinnane, 2001; Wollni and Zeller, 2007; Bernard and Spielman, 2009; Chemin, 2018). In these informal settings, farmers can discuss the usefulness of any technology they wish to adopt, effectively learning from each other's experience. Evidence suggests a positive impact of these cooperative memberships on farmers' technology adoption decisions (Abebaw and Haile, 2013; Kolade and Harpham, 2014; Abate et al., 2016; Yahaya et al., 2019; Nonvide, 2021).

How does information transmit from one agent to another in these cooperatives? Do agents need to seek input from one another actively? or is it so that being a member of these cooperatives is sufficient to receive the information necessary for making a technology adoption decision? These questions draw from the cognitive science literature on active vs passive learning. According to that literature, active learning allows individuals to focus effort on useful information that they might miss while learning passively (Gureckis and Markant, 2012). We need to answer the question of whether to seek active or passive learning within the farmer cooperatives to shape the interventions for delivering extension services using these cooperatives. If being a passive member of the cooperatives is good enough to receive the necessary information, the policy should focus on incentivizing farmers to join these organizations. In addition, if cooperative members need to learn from each other actively, we need to provide incentives to spur active discussion.

This study focuses on Peruvian potato farmers to answer these questions for the adoption of different strategies for dealing with LB. In particular, we are interested in understanding whether the act of active discussion (as opposed to being a passive listener of the same discussion) helps farmers better understand the common beliefs regarding relative riskiness and ambiguity of the probabilities that the potato harvest will be affected by LB for different strategies.

This study concentrates on information frictions, downplaying other potential explanations for low adoption. One of the leading alternative explanations behind low technology adoption may be the presence of liquidity or credit constraints (Jack, 2013). But, in our context, many of the technologies available for dealing with LB are relatively cheap (e.g., agrochemicals), freely available (e.g., avoiding harvest on rainy days), or demand minor additional labor costs (e.g., crop rotation). Additionally, adoptions are observed for farmers with similar wealth, education, family labor composition, and living in the same areas as those who lag in adoption. Thus, the explanation of farmers being credit or liquidity-constrained for low technology adoption seems less plausible.

3 Experimental Design

We design an artefactual field experiment to mimic certain aspects of farmers' decision-making process under uncertainty when learning from others is possible. Taking the context of Peruvian potato production, we elicit farmers' beliefs about different technologies (strategies) available to mitigate the threat of late blight. These strategies vary in the probability that they will successfully prevent blight-related crop loss. Some of these strategies are more tried and true, with relatively known probabilities generating yield distributions. In this case, we expect farmers to assess them as being risky. Other strategies may be associated with newer technologies or practices for which farmers have little information or experience, where even the probabilities are unknown. In this case, farmers may view these as being ambiguous as opposed to risky. Because we are interested in different mechanisms to resolve information frictions, we consider the role that active – as opposed to passive – learning might have on farmers' beliefs. We thus require an instrument that allows us to elicit farmers' beliefs about whether they view a certain strategy as risky versus ambiguous.

We begin by eliciting individual beliefs, as we had no prior knowledge of which strategy farmers would consider risky or ambiguous. Following this individual belief elicitation, we introduce a social learning treatment designed to allow us to evaluate the effect of active versus passive learning. In this context, active learning allows for greater coordination in beliefs, allowing information and knowledge to become more common. In other words, active learning in a social context can increase the salience of information and act as a coordination device, affecting how well individuals can form common beliefs. Thus, our ultimate objective is how well active learning affects common beliefs.

3.1 Elicitation Instrument

We elicit beliefs about whether farmers view each of the five different strategies as risky or ambiguous. Most existing strategies to combat late blight can be categorized into five categories: do nothing, agrochemical product use, technical assistance, crop rotation, and (except in arid regions of the coast) avoiding harvesting on rainy days. Specifically, the goal is to determine whether the subjects view these technologies as risky (known probabilities) or ambiguous (unknown probabilities). Eliciting actual probabilities is difficult in most situations but may be particularly problematic for participants with potentially low numeracy skills. We thus opted for a simple design. We asked subjects to evaluate the risks of crop loss for five strategies they might use to combat LB. We constructed a multiple-choice question from each of the five strategies (see Figure 1). The first three answers involve risky scenarios (chance of losses are small, 50/50, or large), and the latter three involve ambiguous scenarios (could be small or 50/50, could be 50/50 or large, could be small or large).

3.2 Design and Conjectures

Task 1: Individual belief elicitation. Since we do not know a priori whether strategies are viewed as risky or ambiguous, we begin by eliciting individual beliefs about the relative riskiness/ambiguity of the effectiveness of each strategy. In the first stage, subjects were tasked to select only one answer that best describes their individual assessment of the risks of having their potato harvest affected by LB for each strategy they can use to control it. This provides a baseline characterization of the relative ambiguity or riskiness of different strategies.

Task 2: Active discussion treatment. The second stage of the experiment is to allow subjects to participate in a discussion to engage in social learning. We randomly selected subjects into two groups: half were to join the discussion, and the other half were to observe it. We split the session in this way to evaluate whether the act of participating is salient or whether it is simply the information shared. This is similar to the light touch interventions used in the literature (Leight et al., 2022; Shrestha and Shrestha, 2023; Miehe et al., 2023; Leight et al., 2024). Existing literature suggests that participating in a discussion group can have different effects on subsequent decisions on the discussion compared to simply observing (Raeburn et al., 2023).

Task 3: Common belief elicitation. The objective of the third stage is to elicit common beliefs about the relative riskiness and ambiguity of the probabilities that the potato harvest will be affected by LB for each of the five strategies in question. Subjects were instructed to answer the same multiple-choice questionnaire from Task 1 (Figure 1) but with one significant difference. This round was a coordination game, where subjects' earnings were determined by the number of answers that coincided with the responses from another randomly chosen. subject. As in other laboratory coordination games (e.g., Engle-Warnick et al., 2013; Laszlo et al., 2024), this mechanism allows us to evaluate common beliefs instead of private ones. This approach also builds on the literature that uses coordination games to extract common beliefs (Mehta et al., 1994; Hellwig, 2002; Schmidt et al., 2022).

The experimental design is intended to inform on whether subjects view different technologies as ambiguous or risky, whether these beliefs can be influenced by peers, and how these beliefs are related to actual field decisions about technologies. To explain technology take-up, whether subjects view technologies as risky or ambiguous maybe even more important than whether the technology is factually risky or ambiguous (Maertens and Barrett, 2012). Task 1 thus allows us to infer subjects' private beliefs. Task 3 elicits common beliefs. Task 2 provides a setting in which these common beliefs can be formed. Task 1 does not lend itself to any theoretical prediction, as we elicit private beliefs. In other words, there is no *a priori* reason to expect any of the strategies here as being more risky than ambiguous or vice-versa. The only modern technology here, which could have been a candidate for being relatively more ambiguous, is agrochemicals. However, these are widespread in the Peruvian potato industry, even among small-holder farmers. If anything, the "do nothing" strategy should be the relatively riskiest (as opposed to ambiguous). Tasks 2 and 3 do lend themselves to some degree of theoretical prediction. The discussion provides an environment where social learning can occur to establish common beliefs or social norms. As documented in Wong and Kahsay (2022), learning common beliefs can subsequently influence the respondents' private beliefs. As in Engle-Warnick et al. (2011), social exchange in an environment of decision-making under risk and uncertainty can act as a means by which peers can affect decision-making. As in their paper, there are reasons to expect subjects who participate in a discussion to respond differently than those who observe it.

The reason to expect participation to influence decision-making comes from the literature on participatory learning and community participation (Mansuri and Rao, 2004; Labonne and Chase, 2010; Casey et al., 2018). We also draw from the sociology literature on social influence in decision-making (Bruch and Feinberg, 2017). Evidence shows that socially exchanged information can influence decision-making if people feel they have a voice in that exchange (Prince and Rao, 2022; ter Mors and van Leeuwen, 2023). This leads us to our first conjecture:

Conjecture 1: *Beliefs about relative riskiness versus ambiguity should be more responsive to participating in rather than observing the discussion. In other words, this conjecture implies that the subjects who participate in the discussion should better coordinate in Task 3 than observers.*

Conjecture 1 focuses on the effect of the discussion. Let us now focus on the mechanism behind such an effect. Risky beliefs require more information than their ambiguous counterparts as they require more knowledge of the probability distributions associated with the technologies. There is extensive literature on active versus passive learning. In active learning, subjects experience some form of active instruction, such as learning with the expectation of teaching the material later or participating in some collaborative activity. On the contrary, in passive learning, subjects passively receive the material. The overwhelming result of the literature on active versus passive learning is that active instruction results in better learning, typically in test scores, than passive (e.g., Deslauriers et al., 2011 and Deslauriers et al., 2019). This result leads us to expect that active chat participants are more likely to learn from the discussion than passive observers of the same conversations. Thus, we expect better coordination for the participants compared to the observers. In other words, we expect the information to transmit better from agents with risky beliefs to agents with ambiguous beliefs if they participate in a discussion rather than observing it. This leads us to our second conjecture:

Conjecture 2: *Subjects who participate in the discussion are more likely to learn than the observers. This should make the agents with ambiguous private beliefs more likely to report risky common beliefs if they participate in the discussion instead of observing it.*

3.3 Exit Survey

The final stage of the session is comprised of an exit survey designed to gather information about potato farming practices, including LB management, as well as some individual and household demographics and characteristics. Given the focus of risk and ambiguity, we also include non-incentivized instruments to measure risk and ambiguity aversion. These were constructed using a hypothetical version of the risk and ambiguity instruments in Engle-Warnick et al. (2011).[5] Following Holt and Laury (2002), as well as Engle-Warnick and Laszlo (2017) and Engle-Warnick et al. (2011), we can approximate relative risk and ambiguity aversion by simply counting the number of risky or ambiguous choices for each instrument. The more safe choices subjects make in the risk instrument, the more they are risk averse. Similarly, the more often subjects pay to avoid the ambiguous gamble in the ambiguity instrument, the more ambiguity-averse they are. The risk instrument provides a series of binary gambles between relatively risky and relatively safe choices. Meanwhile, the ambiguity instrument provides a series of binary gambles with known versus unknown probabilities, but where a small fee applies to the known probability (always 50/50). See Appendix A for the risk and ambiguity instruments.

4 Data and Descriptives

4.1 Experimental Sessions

The sessions took place in Central Peru in three separate locations. All locations are important potato-producing areas to facilitate the recruitment of potato farmers. In

[5] We scaled up the values for the hypothetical instrument since doing so tends to recover the revealed risk preference parameters in incentivized instruments.

addition, the International Potato Centre identifies all these areas as areas especially prone to problems with Late Blight. We held sessions in three districts (one in Huánuco, one in Junín, and one in Lima). Participants from surrounding areas were invited to participate. In total, we recruited 305 farmers for the study. Figure 2 presents a map of Peru, pointing out the session locations. We sent advance recruiters to find suitable communities and locales to run the sessions (usually schools) and to begin advance recruiting participants one or two weeks ahead of the sessions.

The recruitment and obtention of approval of community authorities were undertaken by our field staff who, in addition to our field surveyors have years' experience conducting social science surveys in these or similar areas of Peru. In addition, they received specialized training for the experimental procedures specific to the study. Half of our field staff had previous experience running or assisting artefactual field experiments. Our recruitment criteria were straightforward: they had to be farming potatoes (whether potato was their main crop or not), they had to be of legal age (age 18), and have basic literacy and numeracy skills. A short test of literacy and eye-vision was additionally administered at the sign-up on the day of the experimental session as the ability to read was mandatory. We turned away very few subjects for this reason. All participants have provided appropriate informed consent according to our institution's ethics approval.

We held a total of 14 sessions, each consisting of between 20 and 24 subjects. However, of these 14, two were half-sessions of 10 to 12 subjects. Subjects received their show-up fee (S/.10) immediately upon arrival, approximately equivalent to an agricultural day laborer wage.[6] This was done to instill trust in the subject pool that the experimenters would be true to their word and that they would be paid per their earnings in the experiments (and not hypothetical). Once subjects were seated, instructions were read out loud (see the Appendix B for the English version of the instructions), and they were then given a task sheet that included the multiple-choice questionnaire eliciting beliefs about the relative riskiness and ambiguity of strategies used to combat LB (see Figure 1). Subjects were not told what they would do after completing this task. They were instructed to circle the answer they felt best corresponded to their beliefs. We distributed black ink pens for this task.

Once all subjects completed the first task, which generally took approximately 15 minutes, we collected all the black pens and redirected them to separate rooms for participating in Task 2 (the discussion). Half the subjects were randomly assigned to participate in the discussion, while we had instructed the other half only to observe. In full sessions (20-24 subjects), they were broken up into two different rooms. For each discussion, one fieldworker acted as a "moderator", only calling out the ID number of the speaker to (anonymously) identify the speaker on the audio recording. The

[6]The market exchange rate was approximately S/.2.6 per US $ in 2012.

instructions for the discussion were minimal. Subjects could discuss anything they wished related to the questionnaire from the first task as long as they were respectful towards others and did not identify themselves or each other by anything other than their randomly assigned ID numbers. Subjects assigned to the observation treatment were strictly instructed to remain quiet. The discussion area was arranged with two opposing semi-circles, one for the participants and the other for the observers (see Figure 3). The experimenters stopped the discussions after 15 minutes.

After the discussions, all subjects were regrouped and returned to their original seats. The instructions for Task 3, the last experimental task (i.e., the coordination game), were given. Specifically, subjects received instructions to repeat the first task with one crucial difference: they would earn S/.5 for each answer matching the answer of another randomly selected participant from the group they participated in (i.e., participants or observers). We gave them a different colored ink pen so that we could identify their decisions from the coordination game (Task 3) and the elicitation stage (Task 1). Similarly, this part of the experiment lasted about 10 to 15 minutes. An exit survey was administered orally with one of the surveyors before payment was made for the experiment (subjects received the payment privately).

4.2 Descriptive Statistics

Table 1 presents the descriptive statistics for the full sample and broken up across the three locations of the study. We keep only the 295 observations with complete data.[7] Around 83% of our sample is aged 26-60 years. [8] Around 80% of them are male. The average household size is just under 5 household members. Educational attainment is very heterogeneous across and within field sites. Forty-one percent of the full sample has at most completed primary school, while 15% have some post-secondary schooling. The district in the department of Huánuco, the poorest of the three communities, has the highest proportion of subjects with less than completed primary schooling (34%). It also has the highest proportion of subjects with post-secondary schooling. While this may be surprising, it can be explained by the demand for skilled labor since the district produces potato seeds as well as potatoes, and seed production is more skill-intensive. The last two rows capture the risk and ambiguity preferences of the subjects. The numbers show that the subjects are equally risk and ambiguity-averse across different study regions.

Panel A and B of Figure 4 show the histograms for measured risk and ambiguity

[7] Ten had missing data required for the analysis, though the dropped observations are not otherwise much different from the included ones.

[8] To protect the anonymity of the sample households, instead of using the actual age of the respondents, we are using categorical age variables. More information regarding the categories are in the table. We have also truncated the household size variable for the same reason. More information regarding this modification is in the footnote of the table.

preferences, respectively. These figures show a considerable amount of heterogeneity within and across samples, consistent with previous findings (in Engle-Warnick et al., 2011).

Table 2 provides descriptive statistics on farming practices in our sample. The majority of farmers in our sample produce potatoes as their main crop (83%). This average is driven down by the Lima sample, for whom the main crop is more likely to be Maize. On average, our sample farmers grow between 3 to 4 different potato varieties. Table 2 also shows our sample's experience with Late Blight: 95% have experienced Late Blight with considerable loss to harvest. In the full sample, 36% of farmers lost at least 50% of their harvest in their last episode of Late Blight. Farmers used, on average, 3.5 different strategies against Late Blight, including the application of agrochemical products, which almost all farmers used. The sample was also split between 46% and 64% using other strategies such as the use of blight-resistant varieties, hilling, the use of healthy potato seeds, and receiving technical assistance. Around 73% of farmers in our sample hold less than 5 hectares of land.[9]

Panel A and B of Figure 5 show the histograms for the number of potato varieties and the number of strategies used by the subjects to deal with LB. As expected, there is a large variation for these variables within and across samples.

5 Empirical Analysis

5.1 What Determines Farmers' Private Beliefs?

We begin by analyzing the results of Task 1, the elicitation of private beliefs. We have no a priori hypotheses as to what should or should not predict the belief that one technology (or strategy to combat Late Blight) should be relatively more risky than ambiguous. Table 3 gives the distribution of responses to the instrument from Task 1. For each strategy, we provide the frequency of responses in columns (1) and (3) for the full sample and potato farmers only, respectively. In Columns (2) and (4), we present the aggregate risky and ambiguous answers for each strategy and each sample, respectively. We can see from these responses that most strategies are relatively more risky than ambiguous. Crop rotation and avoiding harvesting on rainy days tend to be the most relatively ambiguous than the other strategies. It is also worthwhile noticing that all strategies have lower perceived risk compared to doing nothing.

Table 4 estimates the probability that farmers view a strategy as risky relative to ambiguous as a function of observed socio-economic characteristics and measured risk and ambiguity preferences. The dependent variable for each strategy was constructed

[9]To protect the anonymity of our subjects, we are also using categorical land size variables. More information regarding the categories are in the table.

as a binary variable which takes the value 1 if the subject responded 1, 2, or 3 (relatively risky) for each of the strategies in the instrument depicted in Figure 1, and 0 if the subject responded 4, 5, or 6 (relatively ambiguous). Table 4 thus presents the marginal effect results of estimating the following Probit regression:

$$Pr(\text{Risky Private Belief}_{ij}) = X'_{ij}\beta + \Theta'_{ij}\gamma + D_j + \epsilon_{ij}, \quad (1)$$

where X'_{ij} are socio-economic and demographic characteristics, and Θ'_{ij} are the preference parameters for subject i from department j. D_j are department fixed effects, ϵ_{ij} is the random error in the regression.

Each column of Table 4 shows the results of estimating equation (1) for each one of the five strategies from the instrument in Task 1. Since it rarely rains in arid San Vicente de Cañete (Lima), we re-estimate equation (1) excluding the Lima sample in the last column. The most salient results relate to the estimated coefficients on education. More educated subjects were more likely to view the application of agrochemicals and technical assistance as risky relative to ambiguous. For the most part, the behavioral parameters (risk and ambiguity aversion) are not related to how subjects view the different strategies as risky or ambiguous except for avoiding harvesting on rainy days. However, this coefficient becomes statistically insignificant when we remove the Lima sub-sample.

5.2 Do Farmers Coordinate?

We now turn our attention to the main focus of our study: do farmers coordinate on common beliefs? Task 3 of the experiment was run as a coordination game: subjects receive a fixed amount for each answer which matches those of another, randomly selected participant. The incentive is thus for subjects to answer what they think others believe, not what they believe. Their answers thus measure common, rather than private, beliefs. This is done after the discussion, where subjects were randomly separated into two groups: those that participate in a discussion and those that observe.

Table 5 shows the randomization balance test for randomization into the active discussion (treatment). As shown in the table, there are no observable differences between the participants and observers of the discussion. We expect the subjects' common beliefs to differ depending on the group they were randomly allocated to. Additionally, we also expect these common beliefs to be somewhat reflective of the subjects' private beliefs. For our analysis, we are interested in understanding how their private beliefs interact with the discussion to affect common beliefs.

The private beliefs represent the subjects' knowledge regarding the relative riskiness of the technologies. The subjects that reported ambiguous private beliefs in Task 1 presumably know less than the ones reporting risky private beliefs. Without participating, these subjects are less likely to report risky common beliefs. This is because they won't actively get any information from other participants in their group as it was randomly assigned to observe the discussion. However, if they got assigned to a group that participated in a discussion, they may be more likely to report a risky common belief. This is because participating in the discussion should help them collect information from other subjects in their group regarding the risk associated with the technologies, and they should become more likely to report a risky common belief (conjecture 2).

To test this, we use the following Probit regression specification:

$$\begin{aligned} Pr(\text{Risky Common Belief}_{ijg}) = \psi_1 \times \text{Treatment}_{ijg} &+ \psi_2 \times \text{Ambiguous Private Belief}_{ijg} \\ &+ \psi_3 \times \text{Treatment}_{ijg} \times \text{Ambiguous Private Belief}_{ijg} \\ &+ X'_{ijg}\alpha + \Theta'_{ijg}\lambda + G'_g\delta + \mathscr{D}_j + \mu_{ijg}, \end{aligned} \tag{2}$$

where Treatment_{ijg} captures whether the group g of subject i from department j got randomly assigned to a discussion group. $\text{Ambiguous Private Belief}_{ijg}$ captures whether the same subject reported a relatively ambiguous private belief in Task 1. Our coefficient of interest is ψ_3, which represents how the subjects with ambiguous private beliefs interact with the discussion. G'_g controls for group specific characteristics. $\mathscr{D}_j$ are department fixed effects in this regression, and μ_{ijg} is the random error term.

The first column of Table 6 shows that the subjects that had an ambiguous private belief regarding doing nothing as a strategy to combat LB are 57.5% less likely to report a risky common belief after being a participant (as opposed to an observer) in Task 2. This is around a 64% reduction compared to the observers' mean common belief. This is also a 1.9 standard deviation decrease compared to the observers' standard deviation of reported common belief. The result is statistically significant at the 5% level. Similarly, the third column of the table shows that the subjects who had an ambiguous private belief regarding seeking technical assistance as a strategy to combat LB are 54.7% less likely to report a risky common belief after being a participant. This is around a 67% reduction compared to the observers' mean and a 1.4 standard deviation decrease compared to the observers' standard deviation for the dependent variable. The result is also statistically significant at the 5% level. The coefficients of the interaction term are small and statistically insignificant for the other strategies dealing with LB. We should also note that, as expected, without participating in the discussion, the subjects with ambiguous private beliefs are less likely to report a risky common belief for all strategies.

Thus, the results show that subjects with ambiguous private beliefs are less likely to report a risky common belief if they do not participate in the discussion. However, if participating in the discussion, they remain less likely to report a risky common belief. This provides evidence against our conjecture 2. This is interesting given that, in Table 3, we show that the participants are more likely to have a risky private belief. Thus, even though those reporting ambiguous private beliefs are in the minority, participating in the discussion makes them think that other subjects will coordinate with them.

To capture the coordination levels (and test conjecture 1), next, we use a coordination index proposed by Mehta et al. (1994) and utilized subsequently by Bardsley et al. (2009) and Engle-Warnick et al. (2013). Using their functional form, we can construct a session-level coordination index $\overline{C}$ for each of our 5 technologies ($q = 1, ..., 5$) as follows:

$$\overline{C}^q = \sum_j \frac{m_j(m_j - 1)}{[N(N-1)]}. \tag{3}$$

Where N is the number of subjects in the session, $j = 1, ...6$ denotes each of the $J = 6$ possible answers/choices per question, and m_j denotes the number of subjects in the session who selected the same answer/choice. This coordination index measures the probability of two randomly chosen subjects coordinating on question q. $\overline{C}^q$ is increasing in coordination. If there are exactly J subjects, then it can be easily shown that no coordination has $\overline{C}^q = 0$ and everyone coordinating has $\overline{C}^q = 1$.

Recall that Task 2 broke up the sessions into two treatments: participation in a discussion and silent and passive observation of the discussion. We thus construct the coordination index within each treatment group. There were a total of 52 groups: 26 groups of participating subjects (treatment) and 26 groups of observing subjects (control). We also construct these indices for the elicitation phase in Task 1. The idea is that the coordination indices should be greater when there was an incentive to coordinate.

Table 7 shows the coordination indices constructed within the treatment/control group before and after the discussion. Except for strategy (1) (do nothing), we find that participating groups tended to increase coordination after the discussion while the observing groups tended to decrease their coordination. However, these differences are generally not statistically significantly different from zero. The only statistically significant difference is for the question on applying agrochemicals. Here, it is the control group that sees a lowering of their coordination index after the discussion.

6 Conclusion

We study the role of active discussion in resolving information frictions associated with technology adoption. In particular, we focus on the information friction regarding the uncertainty associated with the technology. To study this topic, we use data from an artefactual field experiment that we conducted with Peruvian potato farmers. Our results show that active discussion makes our subjects more likely to be entrenched in their private beliefs. We also do not find any evidence of the subjects learning from each other due to participation in the active discussion.

The results suggest that interventions that use active discussion to improve coordination and learning may not work well in the absence of additional knowledge interventions. Knowledge interventions are needed to improve the initial information set before this information can diffuse to others via social learning (e.g., in Beaman et al., 2021 and BenYishay and Mobarak, 2018). Further investigation is needed to understand how to best combine these knowledge interventions with active discussion to improve technology adoption, which is beyond the scope of this paper.

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Tables

Table 1: Descriptive Statistics: Sample Demographics

Variable	Full sample	Huánuco	Junín	Lima
Age between 18 and 20	0.01	0.03	0.01	0.00
Age between 21 and 25	0.06	0.14	0.05	0.01
Age between 26 and 30	0.10	0.12	0.15	0.04
Age between 31 and 35	0.12	0.14	0.14	0.07
Age between 36 and 40	0.12	0.12	0.15	0.08
Age between 41 and 45	0.12	0.11	0.11	0.14
Age between 46 and 50	0.10	0.09	0.10	0.11
Age between 51 and 55	0.12	0.10	0.07	0.17
Age between 56 and 60	0.15	0.09	0.09	0.25
Age between 61 and 65	0.05	0.03	0.06	0.05
Age 66 or more	0.05	0.03	0.04	0.08
Gender (Female =1)	0.21	0.17	0.25	0.21
Household Size	4.66	5.00	4.28	4.73
	(1.65)	(1.66)	(1.59)	(1.65)
Incomplete primary	0.22	0.34	0.16	0.16
Complete primary	0.19	0.17	0.29	0.11
Incomplete secondary	0.19	0.17	0.20	0.20
Complete secondary	0.25	0.10	0.29	0.35
Post-secondary, non-university	0.08	0.09	0.04	0.11
University	0.07	0.13	0.02	0.07
No. of safe choices	2.07	1.93	1.92	2.34
	(1.37)	(1.44)	(1.24)	(1.39)
No. of times paid to avoid ambiguity	2.35	2.36	2.23	2.44
	(1.96)	(2.03)	(1.96)	(1.89)
No. of Observations	295	92	97	106

Notes: The *household size* variable is truncated such that households with 8 or more members are considered to all have 8 members.

Table 2: Descriptive Statistics: Sample Farming Practices

Variable	Full sample	Huánuco	Junín	Lima
Potato is main crop	0.83	0.98	0.99	0.57
No. of potato varieties	3.31	3.92	3.56	2.55
	(1.52)	(1.66)	(1.42)	(1.11)
Experienced late blight in past	0.95	0.99	0.97	0.89
Proportion of crop lost to blight				
None	0.07	0.02	0.03	0.16
A little	0.57	0.54	0.55	0.60
Half	0.24	0.28	0.27	0.18
A lot	0.09	0.09	0.12	0.06
All of it	0.03	0.07	0.03	0.00
Use the following strategies against late blight				
Use more resistant varieties	0.46	0.39	0.53	0.46
Use healthy potato seeds	0.64	0.48	0.77	0.67
Hilling	0.52	0.39	0.48	0.66
Avoid harvesting on rainy days	0.46	0.45	0.56	0.39
Technical assistance	0.47	0.26	0.27	0.83
Use agrochemical products	0.99	0.98	0.99	1.00
No. of strategies	3.54	2.95	3.60	4.01
	(1.68)	(1.78)	(1.57)	(1.53)
Less than 1 hectare of land	0.15	0.20	0.21	0.06
Between 1 and 2 hectares of land	0.20	0.24	0.25	0.11
Between 2 and 3 hectares of land	0.14	0.13	0.19	0.11
Between 3 and 4 hectares of land	0.13	0.09	0.10	0.19
Between 4 and 5 hectares of land	0.11	0.05	0.07	0.19
Between 5 and 6 hectares of land	0.06	0.12	0.02	0.05
Between 6 and 7 hectares of land	0.04	0.00	0.00	0.11
Between 7 and 8 hectares of land	0.04	0.03	0.05	0.05
More than 8 hectares of land	0.13	0.14	0.11	0.13
No. of Observations	295	92	97	106

Table 3: Private Beliefs for the Chances of Late Blight Affecting Crop Production

	Full Sample N=295		Potato farmers N=246	
	(1)	(2)	(3)	(4)
If I do nothing the chances are...				
Small	14%		15%	
50/50	64%	89%	64%	90%
Large	11%		11%	
Not sure: could be small or 50/50	5%		4%	
Not sure: could be 50/50 or large	1%	11%	0%	10%
Not sure: could be small or large	5%		5%	
If I apply agrochemicals the chances are...				
Small	65%		64%	
50/50	11%	88%	12%	88%
Large	13%		12%	
Not sure: could be small or 50/50	6%		7%	
Not sure: could be 50/50 or large	2%	12%	2%	12%
Not sure: could be small or large	3%		3%	
If I receive technical assistance the chances are...				
Small	63%		62%	
50/50	8%	86%	9%	85%
Large	15%		15%	
Not sure: could be small or 50/50	5%		5%	
Not sure: could be 50/50 or large	4%	14%	5%	15%
Not sure: could be small or large	5%		5%	
If I do crop rotation the chances are...				
Small	51%		49%	
50/50	11%	76%	13%	75%
Large	14%		13%	
Not sure: could be small or 50/50	11%		12%	
Not sure: could be 50/50 or large	4%	24%	4%	25%
Not sure: could be small or large	9%		9%	
If I avoid harvesting on rainy days, the chances are...				
Small	54%		52%	
50/50	14%	77%	14%	75%
Large	9%		9%	
Not sure: could be small or 50/50	7%		8%	
Not sure: could be 50/50 or large	5%	23%	6%	25%
Not sure: could be small or large	10%		11%	

Table 4: Private Beliefs reported to be non-Ambiguous

	Do nothing	Apply agrochemicals	Seek technical assistance	Do crop rotation	Avoid harvesting on rainy days	Avoid harvesting on rainy days (no Lima)
Age above median	0.062	-0.023	0.014	0.109*	0.053	0.100
	(0.041)	(0.037)	(0.037)	(0.064)	(0.091)	(0.112)
Gender (Female=1)	-0.005	0.025	0.042	0.030	0.072*	0.070
	(0.052)	(0.060)	(0.035)	(0.102)	(0.041)	(0.054)
Some secondary education	-0.023	0.099***	0.083**	-0.057	-0.032	-0.017
	(0.038)	(0.031)	(0.040)	(0.067)	(0.073)	(0.084)
Some post-secondary education	0.016	0.105***	0.098*	0.031	-0.131	-0.151
	(0.035)	(0.031)	(0.055)	(0.087)	(0.121)	(0.146)
No. of safe choices	0.004	0.002	-0.021	-0.019	-0.019	-0.010
	(0.014)	(0.010)	(0.013)	(0.021)	(0.021)	(0.026)
No. of times paid to avoid ambiguity	-0.011	-0.007	-0.008	0.003	0.025**	0.020
	(0.011)	(0.011)	(0.009)	(0.016)	(0.012)	(0.013)
Land size above median	-0.005	-0.021	0.008	-0.070**	-0.040	-0.006
	(0.035)	(0.039)	(0.038)	(0.034)	(0.049)	(0.060)
Observations	238	238	238	238	238	182
Wald χ^2	28.877***	52.885***	58.388***	41.537***	70.490***	-
Pseudo R^2	0.039	0.107	0.066	0.034	0.038	0.030

Notes: * p<0.10, ** p<0.05, *** p<0.01. Probit marginal effects. Robust standard errors clustered at the session level are in parentheses. Only potato farmers who experienced late blight are included in the sample. For age, education, and land size, the omitted categories are *Age below median*, *At most primary education completed*, and *Land size below median*, respectively. The median age is 44 years, and the median land size is 3.28 hectares. All regressions include department-fixed effects.

Table 5: Randomization Balance Test

	Control	Treatment	Combined	Differences
Age below median	0.464	0.542	0.502	-0.078
	(0.041)	(0.042)	(0.029)	(0.058)
Age above median	0.536	0.458	0.498	0.078
	(0.041)	(0.042)	(0.029)	(0.058)
Gender	0.219	0.201	0.210	0.017
(Female=1)	(0.034)	(0.034)	(0.024)	(0.048)
At most primary education completed	0.371	0.444	0.407	-0.074
	(0.039)	(0.042)	(0.029)	(0.057)
Some secondary education	0.477	0.403	0.441	0.074
	(0.041)	(0.041)	(0.029)	(0.058)
Some post-secondary education	0.152	0.153	0.153	-0.000
	(0.029)	(0.030)	(0.021)	(0.042)
Land size below median	0.464	0.535	0.498	-0.071
	(0.041)	(0.042)	(0.029)	(0.058)
Land size above median	0.536	0.465	0.502	0.071
	(0.041)	(0.042)	(0.029)	(0.058)
Potato is main crop	0.828	0.840	0.834	-0.012
	(0.031)	(0.031)	(0.022)	(0.043)
Experienced Late Blight in past	0.934	0.958	0.946	-0.025
	(0.020)	(0.017)	(0.013)	(0.026)
Observations	151	144	295	-

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Standard errors are in parentheses. The median age is 44 years, and the median land size is 3.28 hectares.

Table 6: Effects on the probability of non-Ambiguous Common Beliefs

	Do nothing	Apply agrochemicals	Seek technical assistance	Do crop rotation	Avoid harvesting on rainy days	Avoid harvesting on rainy days (no Lima)
Treatment	-0.015	-0.100*	-0.053	0.082	-0.022	-0.050
(Active Discussion=1)	(0.057)	(0.057)	(0.050)	(0.057)	(0.083)	(0.111)
Private Belief	-0.026	-0.286*	-0.185	-0.444***	-0.255***	-0.282***
(Ambiguous=1)	(0.075)	(0.150)	(0.115)	(0.114)	(0.086)	(0.085)
Treatment $\times$ Private Belief	-0.575**	0.056	-0.547**	-0.047	-0.103	-0.111
	(0.235)	(0.034)	(0.223)	(0.153)	(0.136)	(0.167)
Control Mean	0.894	0.886	0.813	0.756	0.780	0.747
(SD)	(0.309)	(0.319)	(0.391)	(0.431)	(0.416)	(0.437)
Observations	244	244	244	244	244	188
Wald χ^2	340.545***	1172.273***	5667.882***	2576.700***	1114.293***	-
pseudo R^2	0.151	0.153	0.317	0.205	0.150	0.119

Notes: * p<0.10, ** p<0.05, *** p<0.01. Probit marginal effects. Robust standard errors clustered at the session level are in parentheses. Only potato farmers who had some prior experience with LB are included in the sample. All regressions include individual characteristics, group characteristics, and department-fixed effects. Individual characteristics include the individual's age category dummy, gender, education level (as education dummies), and land size category dummy. Group characteristics include the total number of lines spoken in the group and the total number of lines spoken by the individual in the group (both can be positive if and only if the individual was randomly selected to participate in a discussion group).

Table 7: Differences in Coordination Indices by Treatment Status

		CI(Group)		
		Pre-chat	Post-chat	Difference
If I do nothing...	Participated	0.464	0.454	-0.010
		(0.050)	(0.054)	(0.062)
	Observed	0.483	0.448	-0.036
		(0.055)	(0.047)	(0.041)
	Difference	-0.019	0.006	0.026
		(0.074)	(0.072)	(0.074)
If I apply agrochemicals...	Participated	0.454	0.471	0.017
		(0.047)	(0.059)	(0.045)
	Observed	0.506	0.406	-0.100**
		(0.053)	(0.044)	(0.045)
	Difference	-0.052	0.065	0.117*
		(0.071)	(0.074)	(0.064)
If I receive technical assistance...	Participated	0.426	0.436	0.010
		(0.049)	(0.046)	(0.044)
	Observed	0.425	0.439	0.014
		(0.046)	(0.055)	(0.044)
	Difference	0.000	-0.003	-0.004
		(0.068)	(0.072)	(0.062)
If I do crop rotation...	Participated	0.299	0.361	0.062
		(0.044)	(0.056)	(0.049)
	Observed	0.381	0.336	-0.046
		(0.049)	(0.040)	(0.047)
	Difference	-0.083	0.025	0.108
		(0.066)	(0.069)	(0.068)
If I avoid harvesting on rainy days...	Participated	0.361	0.369	0.008
		(0.044)	(0.049)	(0.042)
	Observed	0.348	0.307	-0.041
		(0.036)	(0.033)	(0.039)
	Difference	0.012	0.062	0.050
		(0.057)	(0.059)	(0.058)

Notes: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are in parentheses. Coordination indices capture the probability of two randomly chosen subjects coordinating on a question. They are calculated at the group level. Group identity varies by treatment status at the session level. The calculation uses 26 groups that participated in the discussion and 26 groups that observed the discussions.

Figures

"What are the chances your potato production will be affected by Late Blight if you...:"

- Strategy 1: Do nothing
- Strategy 2: Apply agrochemical products
- Strategy 3: Receive technical assistance
- Strategy 4: Practice crop rotation
- Strategy 5: Avoid harvesting on rainy days

Possible answers:

1. Small
2. 50/50
3. Large
4. Not sure: Could be small or 50/50
5. Not sure: Could be 50/50 or large
6. Not sure: Could be small or large

Figure 1: Instrument for Eliciting Risk and Ambiguity Perception

Figure 2: Map of Peru and Field Sites

Figure 3: Room Configuration of Discussions

Panel A: Risk Aversion

Panel B: Ambiguity Aversion

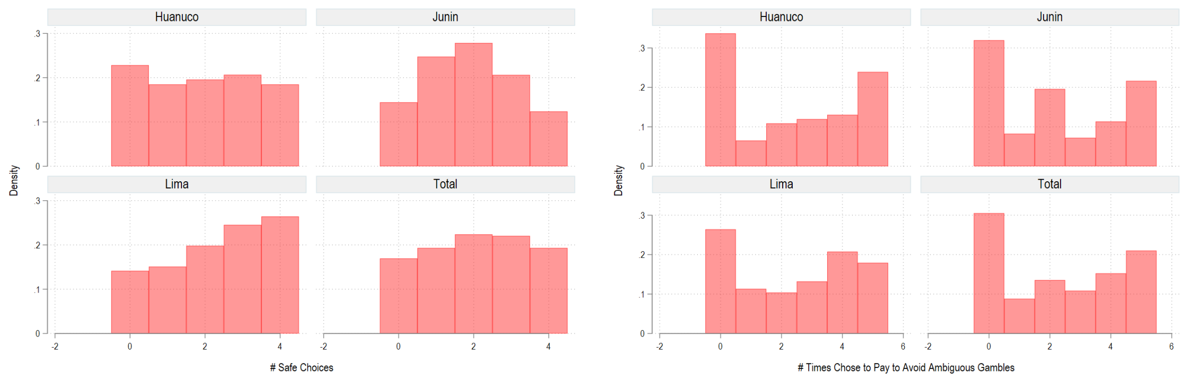

Figure 4: Distribution of Risk and Ambiguity Preferences of the Subjects

Panel A: Potato Varieties

Panel B: Strategies dealing with LB

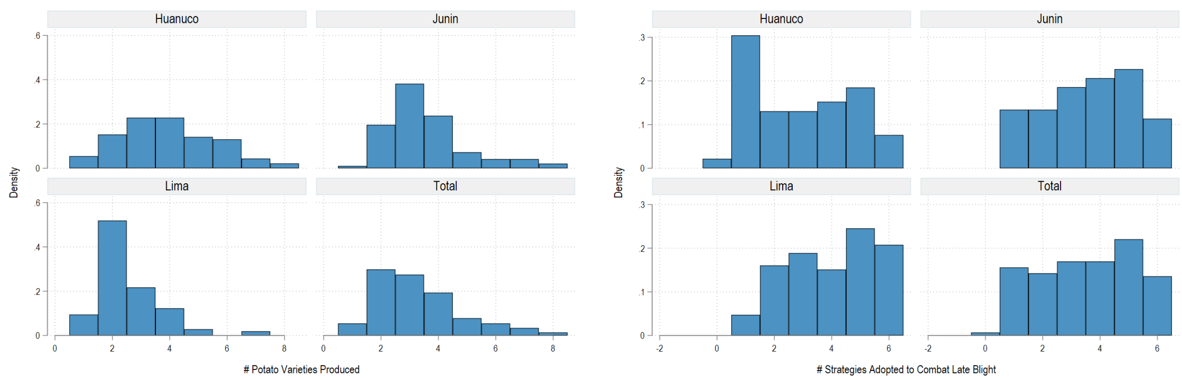

Figure 5: Distribution of Potato Varieties produced and Strategies adopted to combat LB

Appendices

A Risk and Ambiguity Instruments

	Ya casi terminamos con la entrevista. El último grupo de preguntas es completamente diferente de lo que hemos hecho hasta ahora. Este es un ejercicio divertido en el que se le muestra una serie de fichas con distintas situaciones imaginarias y le pedimos que decida la opción que usted prefiera. Le voy a explicar cómo funciona esto.
D.1.	*(Muestre la Tarjeta D1)*. **Quiero que me diga cual de las siguientes alternativas prefería: (1) jugar cara o sello para ganar 260 soles si sale cara y 260 soles si sale sello** *(Muestre la figura 1)* **o (2) jugar cara o sello para ganar 200 soles si sale cara y 350 soles si sale sello** *(Muestre la figura 1)*. *Apunte la seleccion (Figura 1 o Figura 2) con un* ✓ **DECISIÓN 1:** FIGURA 1 ☐1 FIGURA 2 ☐2
D.2.	*(Muestre la Tarjeta D2)*. **Quiero que me diga cual de las siguientes alternativas prefería: (1) jugar cara o sello para ganar 200 soles si sale cara y 350 soles si sale sello** *(Muestre la figura 1)* **o (2) jugar cara o sello para ganar 140 soles si sale cara y 440 soles si sale sello** *(Muestre la figura 1)*. *Apunte la seleccion (Figura 1 o Figura 2) con un* ✓ **DECISIÓN 2:** FIGURA 1 ☐1 FIGURA 2 ☐2
D.3.	*(Muestre la Tarjeta D3)*. **Quiero que me diga cual de las siguientes alternativas prefería: (1) jugar cara o sello para ganar 140 soles si sale cara y 440 soles si sale sello** *(Muestre la figura 1)* **o (2) jugar cara o sello para ganar 80 soles si sale cara y 530 soles si sale sello** *(Muestre la figura 1)*. *Apunte la seleccion (Figura 1 o Figura 2) con un* ✓ **DECISIÓN 3:** FIGURA 1 ☐1 FIGURA 2 ☐2
D.4.	*(Muestre la Tarjeta D4)*. **Quiero que me diga cual de las siguientes alternativas prefería: (1) jugar cara o sello para ganar 80 soles si sale cara y 530 soles si sale sello** *(Muestre la figura 1)* **o (2) jugar cara o sello para ganar 20 soles si sale cara y 620 soles si sale sello (Muestre la figura 1).** *Apunte la seleccion (Figura 1 o Figura 2) con un* ✓ **DECISIÓN 4:** FIGURA 1 ☐1 FIGURA 2 ☐2
D.5.	*(Muestre la Tarjeta D5)*. **¿Si usted tuviera la oportunidad de jugar y ganar uno de dos premios 260 soles o 260 soles, pero no sabe las chances o probabilidades** *(muestre la figura 2)*, **pagaria 5 soles para conocer las chances o probabilidades antes de jugar** *(muestre la figura 1)*? *Apunte la seleccion (Figura 1 o Figura 2) con un* ✓ **DECISIÓN 5:** FIGURA 1 ☐1 FIGURA 2 ☐2
D.6.	*(Muestre la Tarjeta D6)*. **¿Si usted tuviera la oportunidad de jugar y ganar uno de dos premios 200 soles o 350 soles, pero no sabe las chances o probabilidades** *(muestre la figura 2)*, **pagaria 5 soles para conocer las chances o probabilidades antes de jugar** *(muestre la figura 1)*? *Apunte la seleccion (Figura 1 o Figura 2) con un* ✓ **DECISIÓN 6:** FIGURA 1 ☐1 FIGURA 2 ☐2
D.7.	*(Muestre la Tarjeta D7)*. **¿Si usted tuviera la oportunidad de jugar y ganar uno de dos premios 140 soles o 440 soles, pero no sabe las chances o probabilidades** *(muestre la figura 2)*, **pagaria 5 soles para conocer las chances o probabilidades antes de jugar** *(muestre la figura 1)*? *Apunte la seleccion (Figura 1 o Figura 2) con un* ✓ **DECISIÓN 7:** FIGURA 1 ☐1 FIGURA 2 ☐2
D.8.	*(Muestre la Tarjeta D8)*. **¿Si usted tuviera la oportunidad de jugar y ganar uno de dos premios 80 soles o 530 soles, pero no sabe las chances o probabilidades (muestre la figura 2), pagaria 5 soles para conocer las chances o probabilidades antes de jugar (muestre la figura 1)?** *Apunte la seleccion (Figura 1 o Figura 2) con un* ✓ **DECISIÓN 8:** FIGURA 1 ☐1 FIGURA 2 ☐2
D.9.	*(Muestre la Tarjeta D9)*. **¿Si usted tuviera la oportunidad de jugar y ganar uno de dos premios 20 soles o 620 soles, pero no sabe las chances o probabilidades (muestre la figura 2), pagaria 5 soles para conocer las chances o probabilidades antes de jugar (muestre la figura 1)?** *Apunte la seleccion (Figura 1 o Figura 2) con un* ✓ **DECISIÓN 9:** FIGURA 1 ☐1 FIGURA 2 ☐2

Figure 6: Risk and Ambiguity Instrument

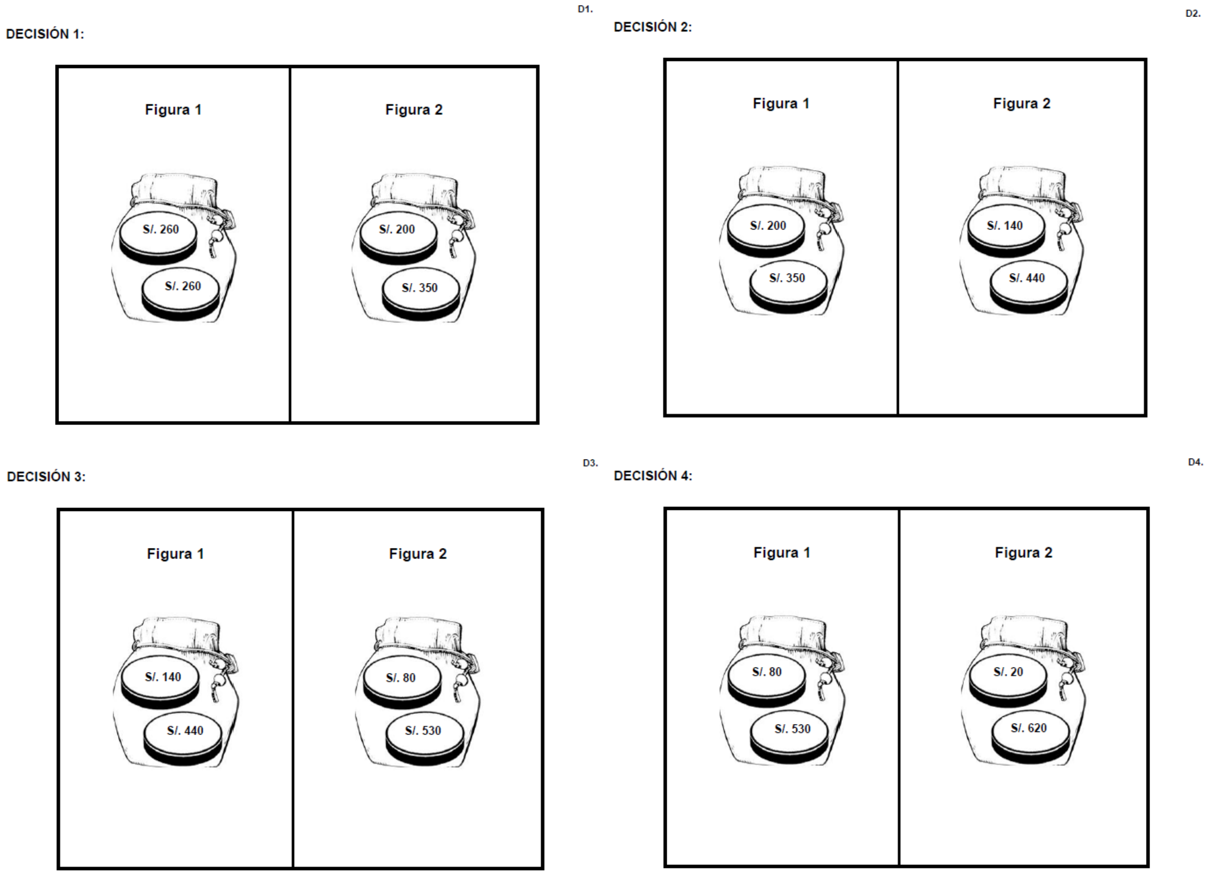

Figure 7: Risk Instrument Flash-cards

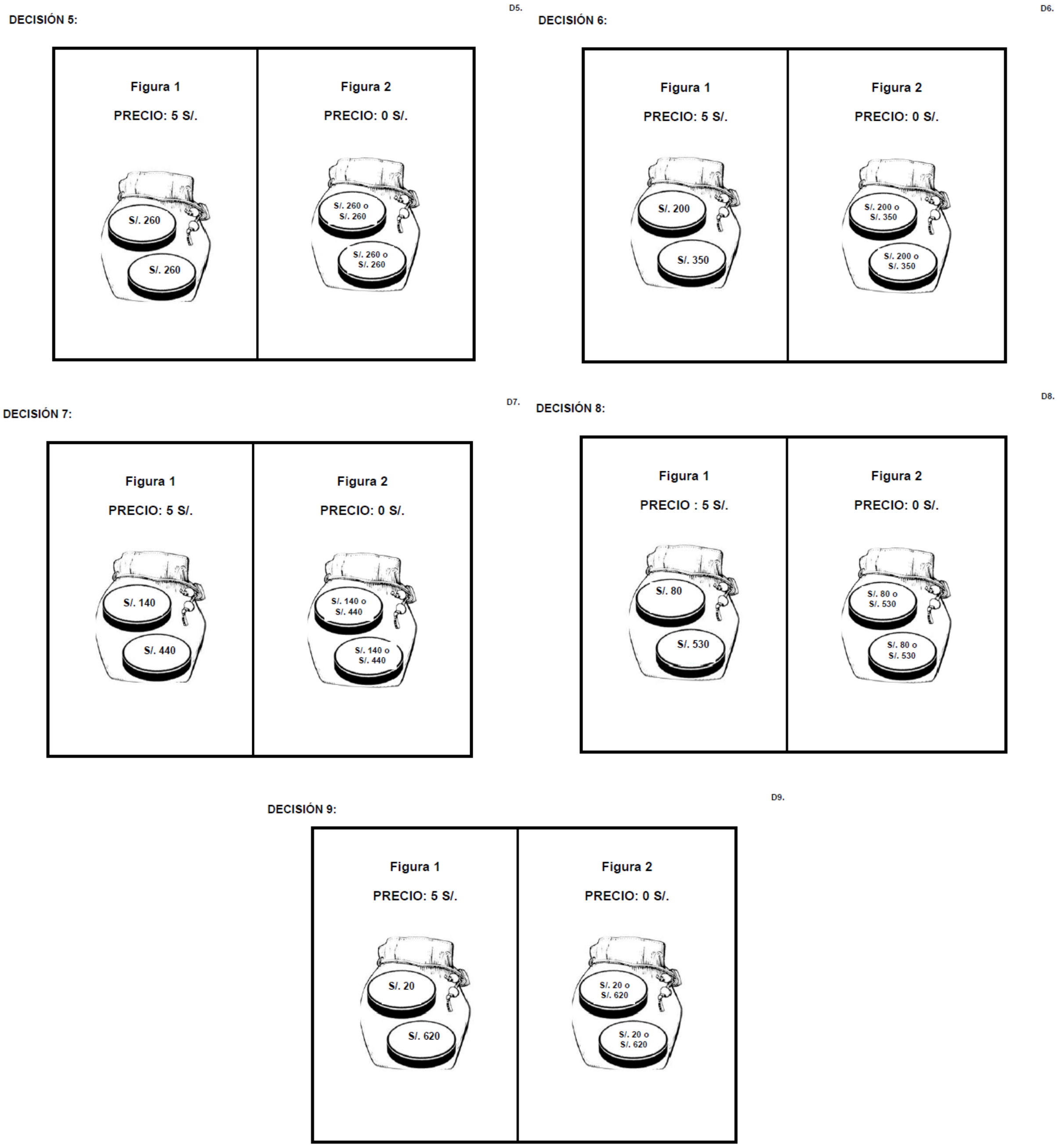

Figure 8: Ambiguity Instrument Flash-cards

B Instructions for the Experiment

Welcome to our experiment

Welcome to our decision-making experiment. We are very grateful for your participation. We will go over the instructions together, and then you will make some decisions. You will be paid for your participation. If you need anything during the session, please let us know.

You will wear an id number for the session. This is so that we can know what you do without knowing who you are. Everything you do and say today is anonymous. No one will ever know what decisions you make.

Please answer five questions

On your sheet of paper, you answer five questions. Look at your sheet now. Let's work the first question together. The first question says:

If I do nothing to control blight, my chances of receiving blight:

And then there are six possible answers. Always choose the answer you think is closest to the correct answer, even if the correct answer is not a choice.

If you think you know the chances of receiving blight if you do nothing to control for it, you choose answer 1, 2, or 3. These answers are:

1. my chances are small

2. my chances are 50/50

3. my chances are large

If you think you are not sure about the chances of receiving blight, if you do nothing to control for it, you choose answer 4, 5, or 6.

You choose answer 4, 5, or 6 if you are not sure about the chances of receiving blight, if you do nothing to control it. These answers are:

4. my chances could be small or 50/50

5. my chances could be large or 50/50

6. my chances could be small or large

You might think that the correct answer is not one of your choices. That is ok. Always choose the answer that is the closest to what you think the correct answer is.

Go ahead and make your choice for the first question by circling 1, 2, 3, 4, 5, or 6. Do not tell anyone what you chose. Raise your hand if you have any questions.

You may continue and finish the other four questions when you are ready.

Discussion

What you will be doing

You will now participate in a discussion. Half of the participants will be randomly chosen to discuss, and the other half will watch the discussion.

If you are chosen for the discussion, you may say anything you like, as long as you respect the other participants. The discussion group will sit together.

If you are chosen to view the discussion, you will sit quietly and not participate in the discussion. The viewing group will sit together.

How it works

The way the discussion works is like this:

If you wish to say something, raise your hand. The facilitator will record your identification number, and call on you to speak when it is your turn.

The discussion will be recorded, and later written down. Only your identification number will be recorded. You will not be identified by anything you say.

The discussion will last about 15 minutes.

What to discuss

You should discuss the questions on the sheet that you just answered. You will be asked more questions about the same thing after the discussion.

What you learn in the discussion may help you with the exercise you perform after the discussion.

What you will be doing

You will now answer the same five questions on your sheet again, with the new pen we handed you.

There is a big difference now in how you answer your questions:

Every answer you give that is exactly the same as the answer of another participant in the group you were sitting with earns you X. Every answer that is different earns you 0.

After you have finished answering your questions, you will go to the payment table. There, you will close your eyes and choose the answer sheet of another participant in the group you were sitting with.

The experimenter will match your answers with the answers on the sheet you chose, and show you how many answers match.

If you match every question, you earn X. If you match 2 questions, you earn X. If you match 0 questions, you earn 0.

You always earn X for participating, no matter how many of your questions match.

You will never know who your answers were matched with. Only you will know how much money you earn.

The more your answers match the other participant's, the more money you will earn.

Do you have any questions?