The Role of Active Discussion in Coordinating 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 adoption of agricultural technologies in developing countries. Although social learning can help resolve associated information frictions, and peer learning interventions are gaining traction, we know little about how these interventions work: is it access to information, or is it the active seeking of information that leads to effective knowledge transmission? To answer this question, we conducted an artefactual field experiment with potato farmers in Peru that focuses on their beliefs about the relative riskiness and ambiguity of different strategies of dealing with Late Blight. Our experiment allows us to understand the role of active discussion in improving coordination about common beliefs. We find that active discussion does not lead to better coordination about the common belief in our setting. Further analysis reveals the reason to be the *inertia of majority*, where a rigid majority of farmers holding structured (risky) beliefs refuse to coordinate on a belief different from their private beliefs, while the minority holding unstructured (ambiguous) beliefs lack the coherence to form an alternative bloc. These results suggest the need to complement *bottom-up* social learning interventions with *top-down* knowledge interventions to destabilize private beliefs and improve coordination.

JEL Codes: C93, D81, D83, O13, O33, Q16.

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1 Introduction

Developing country agriculture is characterized by high risk and uncertainty, which have increased over time due to climate change (Ahmed et al., 2009; de Janvry et al., 2017). One way that farmers 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 channel through which information friction can affect adoption is uncertainty about the relative riskiness of a technology (Chavas and Nauges, 2020). Social learning may help counteract these frictions by allowing agents to learn from one another 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 what determines the *effective* transmission of information from one agent to another in interventions that leverage social learning. Is access to information through social networks sufficient, or does one need to actively seek information?

In this paper, we examine the role of active discussion in facilitating coordination around common beliefs about the relative riskiness of agricultural technologies. More specifically, we focus on perceived riskiness and ambiguity about the effectiveness of various strategies to manage Late Blight (LB) among Peruvian potato farmers. LB is a fungus that is perceived as the main production constraint for Peruvian potato farmers (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 many farmers to have ambiguous beliefs

[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.

regarding several 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 potentially lead to low adoption of modern technologies that could decrease the adverse effects of LB and increase yields.

Given this context, we investigate whether participation in an active discussion about the relative riskiness of various strategies for managing LB, rather than passive learning of the same information, leads to better coordination around the common belief about the effectiveness of these strategies. This question directly focuses on whether exposure to information is sufficient or whether active discourse is required for better learning. Furthermore, we examine whether the structure of perceived uncertainty, in the form of risky (structured) or ambiguous (unstructured) private beliefs, affects agents' performance in coordinating. This question is particularly critical for farmers facing ambiguity, as they rely on social signals to form beliefs. For these farmers, it is important to determine whether social learning improves their risk assessment, which depends on their understanding of their peers' perceptions of these uncertainties.

To answer these questions, 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 the active discussion and silent observers. 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.

In response to our first question above, the results show that active discussion does not lead to better coordination regarding the relative riskiness of various LB management strategies compared to passive learning. We find that the explanation for this null result lies in the answer to our second question on belief structure. More specifically,

[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 List (2024). Others utilize the term 'lab-in-the-field' (e.g. Gangadharan et al., 2021). Specifically, we replicate the laboratory environment with a non-conventional, non-student subject pool - namely, individuals whose decision-making our study intends to model.

we identify the mechanism underlying this null result as the inertia arising from the distribution of structured versus unstructured private beliefs. We find that the majority of farmers have *risky* (structured), as opposed to *ambiguous* (unstructured) beliefs in our sample, with the *risky* majority exhibiting strong resistance to accepting the common belief to be different from their private beliefs and the *ambiguous* minority lacking the structural coherence to form an alternative bloc. Due to this feature of our sample, active discussion does not help farmers converge on a new equilibrium because they are unable to overcome the entrenched pre-existing majority view. This result suggests that active discourse alone is insufficient to improve coordination about common beliefs when the underlying distribution of private beliefs is rigid and dominated by a confident majority.

Our study makes three contributions to the existing literature. First, we contribute to the literature on whether active participation leads to better coordination than passive learning. There is a vast literature documenting that active participation and consequently "having a voice" lead to better coordination, cooperation, and learning (e.g., Mansuri and Rao, 2004; Dal Bó et al., 2010; Labonne and Chase, 2010; Gureckis and Markant, 2012; Chi and Wylie, 2014; Casey et al., 2018; Prince and Rao, 2022). We add to this literature by being the first to test whether active participation improves coordination about subjective beliefs. In our context, contrary to the expectation that active discourse improves outcomes, as drawn from the existing literature, we provide evidence that active discussion fails to improve coordination relative to passive learning.

Second, we contribute to the broader literature on social learning and technology adoption. Although there is seminal work establishing the role of social learning in technology adoption (e.g., Foster and Rosenzweig, 1995; Munshi, 2004; Bandiera and Rasul, 2006; Conley and Udry, 2010; Magruder, 2018), a separate stream of literature emphasizes that the structure of uncertainty, specifically the distinction between risk and ambiguity, determines adoption decisions (e.g., Barham et al., 2014; Chavas and Nauges, 2020). We bring these two streams of literature together by investigating the effectiveness of *active* (as opposed to *passive*) social interactions in improving group coordination about the structure of uncertainty associated with agricultural technology adoption decisions. We focus on coordination as a mechanism, as it is central to adoption within cooperatives and farmer groups (Abebaw and Haile, 2013; Abate et al., 2016; Yahaya et al., 2019). We add to this literature by documenting that a specific barrier to the coordination problem can be the inertia of the majority, where a confident majority holding a particular belief may block the updating required for coordination, even after active discourse.

Finally, we contribute to the literature on the design of information interventions to improve technology adoption. Recent work highlights the potential of networks for the cost-effective diffusion of information (e.g., Banerjee et al., 2013; Takahashi et al., 2019; BenYishay and Mobarak, 2018; Beaman et al., 2021; Chakraborty, 2023). Our results add to these findings by documenting the limitations in relying solely on interventions that exploit social exchanges. In particular, our finding on the ineffectiveness of active discourse in breaking the inertia of a rigid majority to improve coordination provides evidence for the need to complement *bottom-up* participatory interventions with *top-down* extension interventions. Put differently, when the prior distribution is rigid and dominated by a confident majority, *voice* and active discourse are unlikely to shift common beliefs on their own; some form of top-down knowledge intervention is needed to destabilize pre-existing beliefs so that subsequent social learning can operate. In practice, these findings highlight the importance of traditional extension services (or similar interventions) to destabilize rigid beliefs before social learning can be effective.

The remainder of this paper is organized as follows. Section 2 discusses the background for our study. Section 3 presents details on data collection, experimental design, and our conjectures. Section 4 presents our empirical analysis, including the results. Finally, in Section 5, we summarize our findings and make concluding remarks.

2 Background on Potato and Late Blight in Peru

Potato production remains one of the primary agricultural activities in Peru (Tobin et al., 2016; Grados et al., 2020). It is subject to various production shocks, the most notable being the threat of Late Blight (LB), caused by the fungus *Phytophthora Infestans*, which is also infamous for its role in the Great Irish Famine (Yuen, 2021). Although LB is the main potato disease in Peru (Barrera et al., 2016), the strategies available to mitigate it can vary substantially in perceived reliability. Traditional technologies may have well-known probability distributions (Knight, 1921), whereas beliefs about these distributions can be more ambiguous for modern technologies (Engle-Warnick et al., 2011; Barham et al., 2014) due to farmers' relative unfamiliarity with modern technologies.

The distinction in beliefs about different technologies is important, given the several thousand varieties of potatoes grown in Peru. As noted by Maertens and Barrett (2012), whether the subjective perception of a technology is risky or ambiguous may be more important than whether the technology is objectively risky or ambiguous in determining its adoption. This, combined with the fact that farmers facing uncertainty rely on social learning to form beliefs (Conley and Udry, 2010), makes the adoption of LB mitigation strategies a social, rather than an individual, optimization problem with information frictions.

Information constraints are one of the most prominent barriers to learning about any technology (Magruder, 2018). To resolve these frictions, policymakers use both *top-down approaches*, such as traditional extension services, and *bottom-up approaches*, including farmer-to-farmer extension services, in which knowledge is disseminated through farmers' social networks (J-PAL, 2023). Farmer-to-farmer extension services, which utilize community farmers to disseminate information, are found to be more effective, although traditional extension services remain essential in the early stages of interventions (Takahashi et al., 2019).

One of the main reasons for the success of such bottom-up approaches is that farmers are more likely to learn from each other than from unfamiliar extension agents. This phenomenon is driven by the greater usefulness of 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). A relatively inexpensive way to provide these farmer-to-farmer extension services is to use the networks within farmer cooperatives (Guinnane, 2001; Wollni and Zeller, 2007; Bernard and Spielman, 2009; Chemin, 2018), where farmers can discuss the usefulness of any technology they wish to adopt and learn 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).

However, it remains an open question as to how information is effectively transmitted from one agent to another. Is exposure to the social network sufficient (passive learning), or is active participation a requirement? The question mirrors the distinction in the cognitive science and education literature between active and passive learning (Gureckis and Markant, 2012; Chi and Wylie, 2014), with roots in the political economy of development literature (Mansuri and Rao, 2004). The literature on participatory learning and community participation suggests that outcomes improve when agents have their *voice* in the process (Mansuri and Rao, 2004; Prince and Rao, 2022). If being a passive member of a cooperative is sufficient to receive the necessary information, we should focus on incentivizing farmers to join these organizations. In contrast, if cooperative members are to learn from one another, we must also provide incentives to encourage active discourse.

In line with the above-mentioned findings in the existing literature, this study treats the resolution of ambiguity regarding LB mitigation strategies as a coordination problem. It has been argued that, in an uncertain environment, common beliefs are disproportionately more important than private beliefs in determining agents' decisions (Morris and Shin, 2002). This is because shared beliefs can reduce strategic uncertainty and establish social norms for the adoption of different practices (Young, 2015). We link these concepts by focusing on two main questions. First, we investigate whether having a *voice* in the communication process, through active discussion rather than passive learning of the same information, leads to better coordination. Second, we examine how structured perceived uncertainty (in the form of *risky* private beliefs) influences agents' ability to assess common beliefs, as opposed to unstructured perceived uncertainty (in the form of *ambiguous* private beliefs).

3 Experimental Design

We design an artefactual field experiment (Harrison and List, 2004) to mimic certain aspects of farmers' decision-making process under uncertainty when learning from others is possible (Conley and Udry, 2010). 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 their effectiveness in preventing blight-related crop loss. Some of these strategies are more tried-and-true, with relatively well-known probabilities that generate yield distributions. In this case, we expect farmers to assess them as *risky* (Knight, 1921). Other strategies may be associated with newer technologies or practices for which farmers have little information or experience, where the probabilities are unknown. In this case, in line with the literature on technology adoption, farmers may view these as *ambiguous* rather than *risky* (Barham et al., 2014; Ward and Singh, 2015). Thus, we 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 elicitation of individual beliefs, we introduce a social-learning treatment to evaluate the effects of active versus passive learning. Because we are interested in different mechanisms to resolve information frictions, we consider the role that active – rather than passive – learning might play in farmers' ability to coordinate around their common beliefs. In our setting, active learning can facilitate greater coordination around shared beliefs, as information and knowledge become more widely accessible through this approach. In other words, active learning in a social context can increase the salience of information and serve as a coordination device, influencing how well individuals can form shared beliefs. Thus, our ultimate objective is to determine the extent to which active learning influences the coordination of common beliefs.

3.1 Elicitation Instrument

"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

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, use agrochemical products, receive technical assistance, use crop rotation, and (except in arid coastal regions) avoid harvesting on rainy days. The goal is to determine whether subjects perceive these strategies as risky (with known probabilities) or ambiguous (with unknown probabilities). Eliciting actual probabilities is difficult in most situations, but may be particularly problematic for participants with potentially low numeracy skills. We therefore 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 (with a *small*, *50/50*, or *large* chance of loss), and the latter three involve ambiguous scenarios (which *could be small or 50/50*, *could be 50/50 or large*, or *could be small or large*). For our empirical analysis below, we construct dummies for each strategy, capturing whether the associated beliefs are "risky" (answers 1,2, and 3) or "ambiguous" (answers 4, 5, and 6).

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 private beliefs about the relative riskiness/ambiguity of the effectiveness of each strategy. In the first stage, subjects were asked to select one answer that best described their assessment of the risk that their potato harvest would be affected by LB for each strategy they could use to combat it. This provides a baseline characterization of the relative ambiguity or risk associated with 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 assigned subjects to two groups of equal size: active participants in a discussion and passive observers of the same discussion. This design allows us to isolate the effect of participation from the availability of information. This is because, although both groups have access to the same information, they differ in how they process this information. The design mirrors light-touch interventions used in the development economics literature (Leight et al., 2022; Shrestha and Shrestha, 2023; Leight et al., 2024; Miehe et al., 2025) and explores how the mode of engagement (i.e., active versus passive) affects subsequent decisions. This design is motivated by the findings in the existing literature that discussion affects decision-making under ambiguity (Raeburn et al., 2023) and that active participants may process information differently than passive observers (Merlo and Schotter, 2003).

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 respond to the same multiple-choice questionnaire from Task 1 (Figure 1) but with a significant difference. This stage is designed as a coordination game in which subjects' earnings were determined by the number of answers that matched those of another randomly chosen subject in their group. As in other laboratory coordination games (e.g., Engle-Warnick et al., 2013; Laszlo et al., 2025), this mechanism enables us to evaluate common beliefs rather than 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 aims to determine whether active discussion can help subjects better assess others' beliefs about the relative riskiness/ambiguity of different strategies. To explain the adoption of strategies, whether subjects view them as risky or ambiguous may be even more important than whether the strategies are factually risky or ambiguous (Maertens and Barrett, 2012). In this regard, Task 1 allows us to infer the subjects' private beliefs. Task 3 elicits common beliefs. Task 2 provides a setting in which these common beliefs can be better understood by the subjects.

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 to be more risky than ambiguous or vice-versa.[5] Tasks 2 and 3 lend themselves to some degree of theoretical prediction based on the literature on social influence, communication, and coordination. As documented in Wong and Kahsay (2022), learning common beliefs can subsequently influence the respondents' private beliefs. Furthermore, as in Engle-Warnick et al. (2011), social exchange in an environment of decision-making under risk and uncertainty can serve as a means by which peers influence decision-making.

The discussion fosters a social learning environment, facilitating the acquisition of knowledge about shared beliefs and social norms. The literature documents that pre-play communication, in the form of cheap talk, significantly improves coordination and efficiency by reducing strategic uncertainty (Cooper et al., 1992; Crawford, 1998).

[5] The only modern strategy here, which could have been a candidate for being relatively more ambiguous, is the use of agrochemicals. However, agrochemicals 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 the ambiguous one).

However, the literature does not provide a definitive answer on whether the benefit of cheap talk extends equally to observers who do not participate, as observers have been shown to learn better than participants by avoiding cognitive burden (Merlo and Schotter, 2003). Thus, the exact effect of Task 2 on the coordination in Task 3 becomes an empirical question.

To resolve this ambiguity, we draw on the literature on participatory learning and community participation (Mansuri and Rao, 2004; Labonne and Chase, 2010; Casey et al., 2018). This literature suggests that outcomes improve when agents are actively involved in the process rather than passive recipients. We also draw on the sociological literature on social influence in decision-making (Bruch and Feinberg, 2017) and recent evidence that socially exchanged information can influence decision-making when people feel they have a *voice* in that exchange (Prince and Rao, 2022; ter Mors and van Leeuwen, 2023). Furthermore, in experimental games, active participation in decision-making is found to improve cooperation relative to exogenous imposition (Dal Bó et al., 2010).

These results suggest that active participants of the discussion are more likely to learn from the discussion than passive observers of the same conversations, leading to our first conjecture:

Conjecture 1: *The subjects who participate in the discussion should better coordinate in terms of their common beliefs in Task 3 than the observers.*

Conjecture 1 focuses on the effect of the discussion. In this study, we further focus on the information structure of agents' beliefs as a potential mechanism underlying the effect. In terms of the information structure, risky beliefs are more structured with known probability distributions, whereas ambiguous beliefs are less structured and characterized by an environment of *comparative ignorance* with unknown probabilities (Gilboa and Schmeidler, 1989; Fox and Tversky, 1995). The success in Task 3 depends on the agents' ability to correctly anticipate others' actions. In this regard, we hypothesize that agents with risky private beliefs face lower *strategic uncertainty* about others' beliefs, as the technology's parameters are perceived as relatively more well-defined for them (Heinemann et al., 2009). In contrast, since ambiguity means a range of possibilities, it makes it more difficult for agents with ambiguous private beliefs to have clear expectations about how others will act and to have a *focal point* (Schelling, 1960). This leads to our next conjecture:

Conjecture 2: *Subjects with risky private beliefs (who possess a more structured information set) perform better in Task 3 compared to subjects with ambiguous private beliefs.*

3.3 Exit Survey

The final stage of the session consists of an exit survey designed to gather information about potato farming practices, including LB management, as well as individual and household demographics and characteristics. Given the focus on 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).[6] 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 simply by counting the number of risky or ambiguous choices for each instrument. The more *safe choices* subjects make in the risk instrument, the more *risk-averse* they are. 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, with a small fee applied to the known probability (always 50/50). See Appendix B for the risk and ambiguity instruments.

[6] We scaled the values of the hypothetical instrument since doing so tends to recover the revealed risk preference parameters in incentivized instruments (see Holt and Laury, 2002).

3.4 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 addition, the International Potato Centre identifies these areas as particularly 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.[7]

Figure 2: Map of Peru and Field Sites

The recruitment and obtaining of approval from community authorities were under-

[7]Obtaining a mapping of social connections was outside the scope of the study. We cannot exclude the possibility that participants knew each other. However, all decisions and surveys were private. Only their participation in the discussion was observable by others in their discussion group.

taken by our field staff, who, in addition to our field surveyors, have years of 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 farmers of potatoes (whether potatoes were their main crop or not), be of legal age (18), and possess 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 informed consent, as approved by our institution's ethics committee.

We conducted 14 sessions, each comprising 20-24 participants. 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.[8] 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 C 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 believed best reflected their beliefs. We distributed black ink pens for this task.

Once all subjects completed the first task, which generally took about 15 minutes, we collected all the black pens and redirected them to separate rooms to participate in Task 2 (the discussion). Half of the subjects were randomly assigned to participate in the discussion, while the other half was instructed to observe only. In full sessions (20-24 subjects), they were divided into two different rooms, allowing each session to be

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

associated with two separate discussions. For each discussion, one fieldworker acted as a "*moderator*", only calling out the speaker's ID number to (anonymously) identify them on the audio recording. The discussion instructions 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.[9] 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.

Figure 3: Room Configuration of Discussions

After the discussions, all subjects were regrouped and returned to their original seats. The instructions were given for Task 3, the last experimental task (i.e., the coordination game). Specifically, subjects received instructions to repeat the first task with one crucial difference: they would earn S/.5 for each answer that matched another randomly selected participant in the group in which they participated (i.e., participants

[9]Participants received very little nudging for the discussion. The moderator began the discussion by asking participants if they would like to share anything related to their experience and/or opinion regarding LB or the first task, but did not engage further with them other than to call on those who raised their hands, indicating their ID for the audio recording, and repeating whether anyone else wished to share anything.

or observers). We gave them a different-colored ink pen so that we could separately 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 Empirical Analysis

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics for the full sample of 295 subjects and for each of the three locations in the study. We excluded 10 observations because they contained missing information required for our analysis. However, the excluded observations are not systematically different from those included in our sample. Our subjects are predominantly male (79%), with 83% of the respondents aged 26-60 years. To protect the anonymity of our subjects, we report categorical age variables here and truncate the household size at 8 members. The average household size for the subjects in our sample is approximately 4.7.

Educational attainment is very heterogeneous across and within field sites. Forty-one percent of the full sample has completed at most primary school, while 15% have some post-secondary education. The district in the department of Huánuco, the poorest of the three communities, has the highest proportion of subjects with less than complete primary schooling (34%) but also the highest proportion of subjects with post-secondary education. Although this pattern is surprising, it can be explained by the demand for skilled labor, since the district produces both potato seeds and potatoes, and seed production is more skill-intensive.

Finally, the last two rows capture the subjects' risk and ambiguity preferences. On average, subjects chose the "safe" option around 2 times and paid to avoid ambiguity 2.35 times. These measures are comparable between study regions, documenting the absence of geographic variation in baseline risk and ambiguity preferences.

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 provides descriptive statistics on the farming practices in our sample. The majority of the farmers produce potatoes as their primary crop (83%). The number is close to being 100% for Huánuco and Junín, but only 57% for the Lima sample. This difference is because farmers in Lima often diversify into other crops, such as maize. On average, our sample households maintain significant crop diversity, cultivating about 3.3 potato varieties.

The table also shows that 95% of our sample has experienced Late Blight in the past, resulting in considerable harvest loss. In the full sample, 36% of farmers lost at least 50% of their harvest in their last episode of Late Blight. To mitigate these risks, farmers used, on average, 3.5 distinct strategies per household against Late Blight. Although

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

the application of agrochemical products is nearly universal for the sample (99%), the adoption of non-chemical strategies, such as planting resistant varieties, using healthy potato seeds, hilling, or avoiding harvest on rainy days, has a higher variation, with utilization rates ranging from 46% to 64%. Most notably, access to technical assistance varies substantially by region, with 83% of Lima farmers using it compared to only 26% in Huánuco (and 27% in Junín). Finally, the sample consists primarily of smallholders. Approximately 73% of farmers in our sample have less than 5 hectares of land. To protect the anonymity of our subjects, we also use categorical variables for land size.

More information on the categories can be found in the table.

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 3 summarizes the private beliefs elicited in Task 1 about the effectiveness of five different strategies against Late Blight. Columns (1) and (3) document the full distribution of responses, whereas Columns (2) and (4) aggregate these into two categories: "Risky" (known probability distributions) versus "Ambiguous (unknown probability distributions). We can see from these responses that most strategies are perceived as risky rather than ambiguous. The proportion of subjects who hold risky beliefs ranges from 76% to 89% in the full sample, depending on the strategy. The "Do Nothing" option and "Agrochemical Use" are viewed as the most structurally well-defined, with only 11% and 12% of subjects, respectively, categorizing their effects on Late Blight mitigation as ambiguous. In contrast, "Crop Rotation" and "Avoiding Harvesting on Rainy Days" generate the highest levels of ambiguity regarding Late Blight mitigation, with around one-fourth of respondents (24% and 23%, respectively) reporting that the probability distributions are ambiguous.

Table 4: 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)
Ambiguous private belief regarding the following strategies against late blight				
Do nothing	0.139	0.076	0.109	0.063*
	(0.028)	(0.022)	(0.018)	(0.036)
Apply agrochemicals	0.133	0.097	0.115	0.035
	(0.028)	(0.025)	(0.019)	(0.037)
Seek technical assistance	0.146	0.132	0.139	0.014
	(0.029)	(0.028)	(0.020)	(0.040)
Do crop rotation	0.238	0.250	0.244	-0.012
	(0.035)	(0.036)	(0.025)	(0.050)
Avoid harvesting on rainy days	0.238	0.215	0.227	0.023
	(0.035)	(0.034)	(0.024)	(0.049)
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.

It is also worth noting that active interventions are perceived as reducing the probability of crop loss compared to inaction. For the "Do Nothing" strategy, the modal belief (64%) is a "50/50" chance of infection for our sample. In contrast, for active intervention strategies such as the application of agrochemicals or receiving technical assistance, the modal belief changes to a "Small" chance of infection (65% and 63%, respectively). These patterns remain robust when we restrict the sample to potato farmers only (in Columns 3 and 4), which confirms that the results are not driven by the subjects lacking relevant agricultural knowledge.

Finally, Table 4 reports the randomization balance test for the randomization exercise conducted for Task 2, comparing the characteristics of active discussion participants (Treatment) with those of passive observers (Control). The table shows no significant differences between participants and observers across age, gender, education, land size, farming experience, etc. These results confirm that the randomization was successful in creating groups that are statistically comparable.

4.2 Main Results

4.2.1 Do farmers coordinate better if they engage in active discussion?

Let us turn to the main empirical analysis of this study, which examines whether farmers coordinate more effectively when they engage in active discussion (rather than passively observing it) in Task 2. This tests *Conjecture 1* discussed in Section 3 using the specification:

$$\text{ICS}_{idg} = \psi_0 + \psi_1 \times \text{Treatment}_{idg} + \mu_{idg}, \tag{1}$$

where $Treatment_{idg}$ captures whether the group g of subject i from department d got randomly assigned to a discussion group, ICS_{idg} is the *Individual Coordination Score (ICS)* for the same subject in Task 3, and μ_{idg} is a random error term.

To calculate *ICS*, we adapt a coordination index proposed by Mehta et al. (1994) and utilized subsequently by Bardsley et al. (2009) and Engle-Warnick et al. (2013). Mehta et al. (1994) defined coordination at the group level, measuring the probability of coordination between two randomly selected subjects. We use the individual component of this aggregate measure, and for each subject i of department d in a given group g of size N_{dg}, who selects the answer j chosen by a total of m_{jdg} subjects in their group (including themselves), we define the coordination score as:

$$\mathrm{ICS}_{idg} = \frac{m_{jdg} - 1}{(N_{dg} - 1)}. \tag{2}$$

This score represents the empirical probability that the subject i of the department d in group g coordinates with another randomly selected participant in the same group. A score of 1 in terms of this measure represents perfect coordination for the subject in terms of the answer chosen by everyone else in their group, and a score of 0 means an absolute failure to coordinate.

For the empirical analysis presented below, we use two versions of ICS_{idg}. The first version measures precise coordination with respect to the exact answers among the 6 possible answers documented in Figure 1. The other version measures structural coordination in terms of selecting an option that is *Risky*, rather than *Ambiguous*. We distinguish these outcomes because coordination about the structure of uncertainty (Risky vs Ambiguous) is conceptually different from coordination on the precise extent of uncertainty (a specific answer), and the two can respond differently to social learning in farmer groups. Recall that Task 2 divided the sessions into two treatments: participation in a discussion and silent passive observation of the same discussion. Thus, we construct the coordination scores for each subject within their respective treatment groups for each session.

The objective of regression (1) is then to understand whether the act of active discussion (treatment) leads to higher coordination scores, compared to the act of passively observing the same discussion (control). In the regression specification, ψ_0 represents the average coordination scores for the control group, while ψ_1 captures the deviation in terms of the average coordination scores for the treatment group. In terms of *Conjecture 1*, we expect ψ_1 to be significantly positive. We need to estimate ψ_1 separately for precise and structural coordination, as a null effect on structural coordination would indicate that active discourse does not shift agreement about *Risky* versus *Ambiguous* beliefs, whereas a null effect on precise coordination would indicate that active discourse does not help groups converge on a specific common belief.

Table 5 presents the results of our analysis. Panel A reports the results for precise coordination scores (measuring the probability of matching on a specific answer), while Panel B presents the results for structural coordination scores (measuring the probability of matching on the broader classification of the strategy as *Risky* or *Ambiguous*).[10]

Table 5: Effect of Active Discussion on Individual-Level Coordination With Other Members of Their Groups

	Do nothing	Apply agrochemicals	Seek technical assistance	Do crop rotation	Avoid harvesting on rainy days	Avoid harvesting on rainy days (no Lima)
Panel A: For Precise Coordination						
Treatment (Active Discussion=1)	0.001	0.054	0.015	0.002	0.040	-0.014
	(0.064)	(0.046)	(0.049)	(0.046)	(0.037)	(0.027)
Constant	0.414***	0.388***	0.387***	0.317***	0.307***	0.290***
	(0.043)	(0.042)	(0.064)	(0.037)	(0.030)	(0.038)
Observations	252	252	252	252	252	192
R^2	0.000	0.007	0.001	0.000	0.005	0.001
Panel B: For Structural Coordination						
Treatment (Active Discussion=1)	-0.078	-0.043	0.054	0.032	-0.017	-0.067
	(0.073)	(0.049)	(0.057)	(0.063)	(0.054)	(0.061)
Constant	0.826***	0.803***	0.680***	0.639***	0.666***	0.656***
	(0.050)	(0.043)	(0.050)	(0.055)	(0.043)	(0.056)
Observations	252	252	252	252	252	192
R^2	0.018	0.005	0.008	0.003	0.001	0.014

Notes: * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered at the session level are in parentheses. Only potato farmers are included in the sample. The dependent variable in all regressions represents the empirical probability that the subject coordinates with another randomly selected subject in the same group on their answers. Panel A dependent variables focus on measuring precise coordination in terms of the exact answers out of the 6 possible answers documented in Figure 1. Panel B dependent variables focus on measuring structural coordination in terms of selecting an option that is *Risky*, as opposed to *Ambiguous*.

Panel A of Table 5 shows that the discussion treatment had no effect on the farmers' ability to coordinate on a precise answer. This is true for all five strategies, as the estimated $\hat{\psi}_1$ is small and statistically indistinguishable from zero. This indicates that active discussion did not help farmers coordinate more effectively in finding a specific answer than the control group. However, the estimated $\hat{\psi}_0$ is positive and highly significant, ranging from 0.290 to 0.414. This suggests that even farmers in the control group coordinated significantly better than would be expected by random chance (which would produce a coordination score of approximately 0.17). This implies the presence of pre-existing *focal points* that the act of participating in the discussion was unable to improve.

[10] In Appendix D we present the robustness of our results, controlling for several subject and session level characteristics.

Panel B of Table 5 focuses on understanding whether the act of active discussion helped farmers better coordinate with respect to the structure of uncertainty (i.e., whether the effect of the strategies is risky or ambiguous). Similarly to Panel A, we observe no significant impact of the intervention on the improvement in this coordination measure. Interestingly, control group coordination levels, captured by the estimated $\hat{\psi}_0$, are found to be quite large and highly statistically significant, ranging from 0.639 to 0.826. These values are significantly higher than the coordination score expected by chance alone for this binary classification (0.5), suggesting that the vast majority of farmers perceive the effectiveness of strategies as risky rather than ambiguous, irrespective of treatment, as highlighted earlier by our findings in Table 3.

These results suggest that, while farmers have a high degree of consensus on the structure of uncertainty (Panel B), they are less able to coordinate on the precise magnitude of the uncertainty (Panel A). However, in both cases, the discussion treatment failed to improve on these baselines, suggesting that active discussion is no more effective than passive observation of the same discussion.

4.2.2 Heterogeneity by Private Beliefs

Having documented the failure of the discussion treatment in improving coordination, we now turn to testing our *Conjecture 2*, which predicts that subjects with *risky* beliefs will coordinate better than those with *ambiguous* beliefs. For this purpose, we use the following regression specification:

$$\begin{aligned}\text{ICS}_{idg} = \alpha_0 + \sum_k \alpha_{1k} \cdot \mathbb{1}(\text{Private}_{idg} = k) + \alpha_2 \cdot \text{Treatment}_{idg} \\ + \sum_k \alpha_{3k} \cdot [\mathbb{1}(\text{Private}_{idg} = k) \times \text{Treatment}_{idg}] + \epsilon_{idg} \quad (3)\end{aligned}$$

where ICS_{idg} is the coordination score for subject i of the group g of department d, calculated using the formula in equation (2). $\mathbb{1}(\text{Private}_{idg} = k)$ represents the indicators for the six private belief categories in the analysis for precise coordination (or the two private belief categories in the analysis for structural coordination), with k representing the index for the belief categories. The specification (3) allows the intervention to differentially affect coordination depending on subjects' private beliefs. For the analysis presented in this subsection, we use this model to calculate predicted marginal means for each private-belief category, averaging across the treatment and control groups.[11]

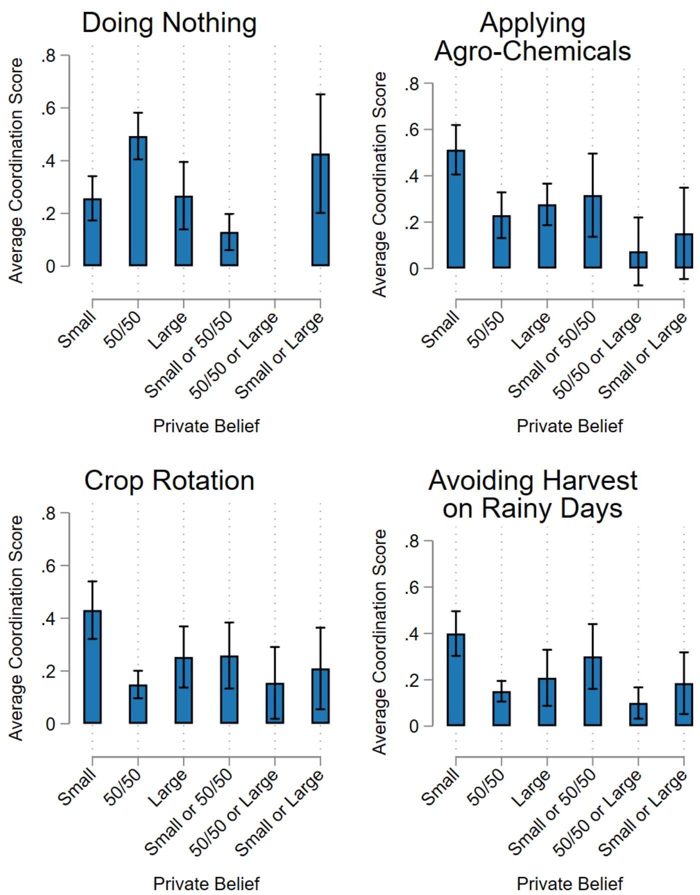


Figure 4: Heterogeneity in Precise Coordination Scores by Private Belief

Notes: Predicted marginal means of *Individual Coordination Scores* are presented for each category of private beliefs, based on the estimates from an OLS regression of the coordination score on the treatment assignment, private belief indicators, and their interactions. Standard errors are clustered at the session level. The outcome variables correspond to the five strategies: (1) Doing Nothing, (2) Applying Agro-chemicals, (3) Seeking Technical Assistance, (4) Crop Rotation, and (5) Avoiding Harvest on Rainy Days. The regression for strategy (5) excludes observations from the Lima sample. The error bars represent 95% confidence intervals. Only potato farmers are included in the sample.

Figure 4 documents the predicted marginal means from this estimation, with the average coordination performance disaggregated by subjects' private beliefs.[12] For the four active intervention strategies (namely, *Applying Agro-chemicals*, *Seeking Technical*

[11]In Appendix D we present the results for treatment and control groups separately. The results remain similar when presented by either treatment category.

[12]Note that the visualization for Figures 4 and 5 is inspired by Gangadharan et al. (2023).

Assistance, *Crop Rotation*, and *Avoiding Harvest on Rainy Days*), subjects who held the private belief "Small" performed significantly better than those who held other private beliefs. Since, as shown in Table 3, the private belief "Small" is also the dominant answer for these strategies, this suggests better coordination for subjects with the modal private belief. In line with this finding, the subjects who held the "50/50" private belief performed better for the "Doing Nothing" strategy, which is the modal private belief for that strategy.

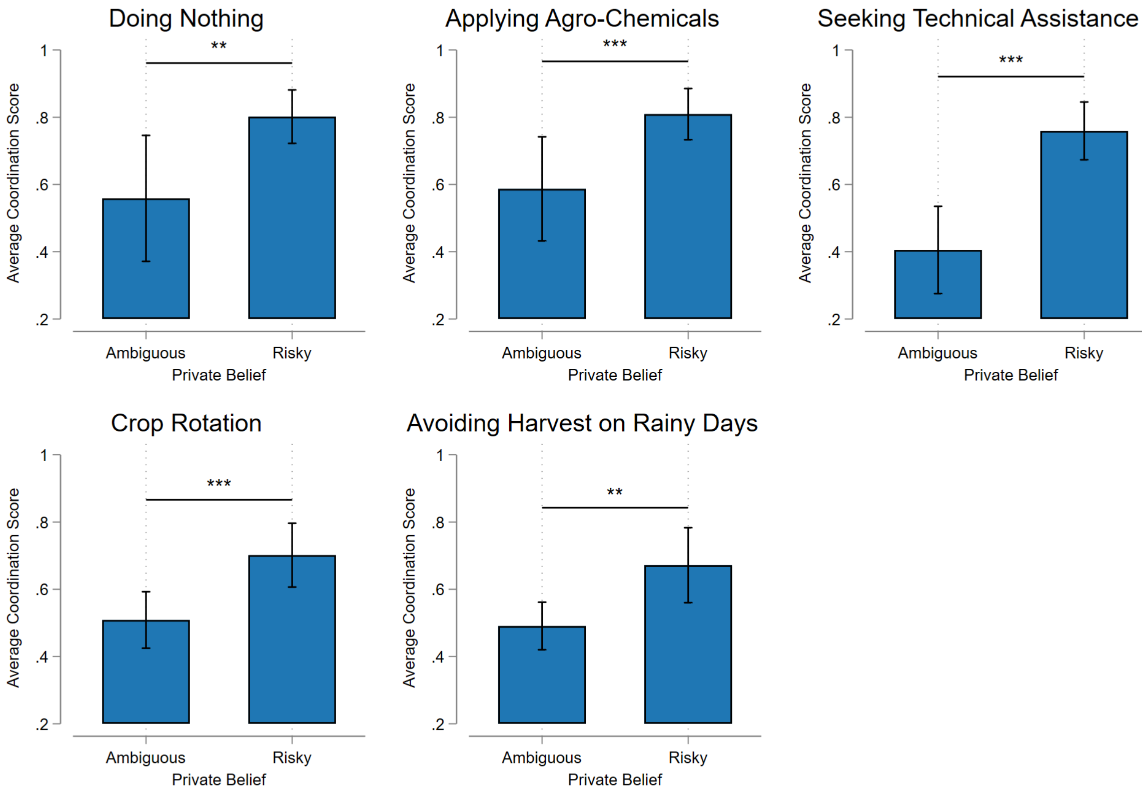


Figure 5: Heterogeneity in Structural Coordination Scores by Private Belief

Notes: Predicted marginal means of *Individual Coordination Scores* are presented for each category of private beliefs (capturing whether the belief is Risky or Ambiguous), based on the estimates from an OLS regression of the coordination score on the treatment assignment, private belief indicators, and their interactions. Standard errors are clustered at the session level. The outcome variables correspond to the five strategies: (1) Doing Nothing, (2) Applying Agro-chemicals, (3) Seeking Technical Assistance, (4) Crop Rotation, and (5) Avoiding Harvest on Rainy Days. The regression for strategy (5) excludes observations from the Lima sample. The error bars represent 95% confidence intervals. Only potato farmers are included in the sample. The brackets and asterisks indicate the statistical significance of the difference between the Risky and Ambiguous means (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

This pattern of subjects with modal beliefs performing better in Task 3, as reflected in the average coordination scores, is also apparent in structural coordination, as documented in Figure 5. The figure shows that, across all strategies, subjects with risky private beliefs perform, on average, significantly better in coordination than those with ambiguous private beliefs. Since, as documented in Table 3, subjects with risky private beliefs are also the majority for all strategies, this result is consistent with the findings for coordination on precise answers.

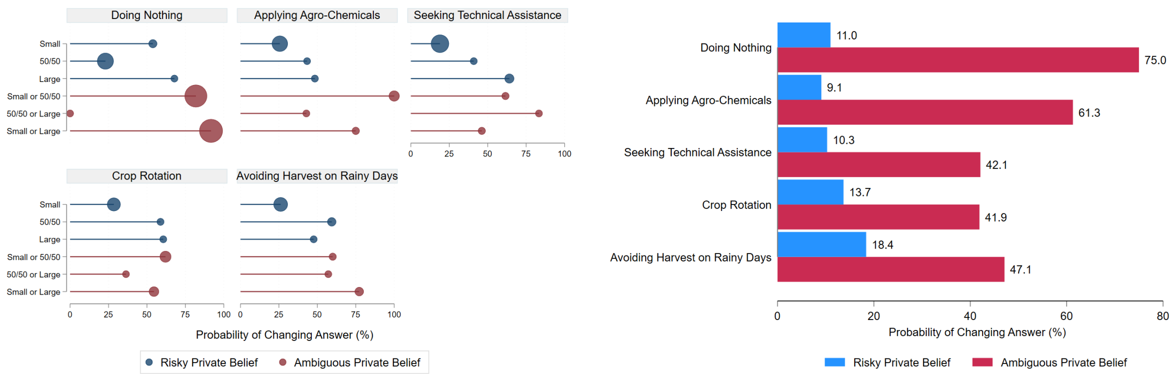
More importantly, the results of Figure 5 are also consistent with our *Conjecture 2*, which postulates better performance for subjects with risky private beliefs. In Section 3.2, we argue that the rationale behind this conjecture is that clear expectations about specific probability estimates serve as a natural *focal point* for coordination for subjects with risky private beliefs, whereas subjects with ambiguous private beliefs find it difficult to have such expectations. However, the same result can be obtained if subjects select the common belief to match their private beliefs, because they lack information about another randomly selected subject's private belief within their group (Dawes, 1989; Ross et al., 1977). If this is the case, subjects with modal private belief are expected to perform better in the coordination game, as their answers are most likely to match the answer of another randomly selected subject within their group. However, we should not observe any significant variation in the probability of selecting a common belief that differs from the private belief by the private belief category of the agents.

Figure 6 documents that the results are not driven by this incidence of all subjects selecting the common belief to match their private beliefs. Panel 6a of the figure shows that subjects with modal private belief are least likely to select a common belief different from their private beliefs.[13] For example, for strategies such as "Seeking Technical Assistance" and "Applying Agro-Chemicals," the probability of selecting a common belief different than private belief is just around 17% and 23%, respectively, for the modal private belief category "Small". However, for many categories of ambiguous private beliefs, this number exceeds 60%. This pattern is consistent across different strategies.

Furthermore, consistent with our rationale for *Conjecture 2*, Panel 6b shows that

[13] Except for the "50/50 or Large" category for the strategy "Doing Nothing". But this number is driven by only one observation.

subjects with ambiguous private beliefs are significantly more likely to select a common belief that differs from their private belief than those with risky private beliefs. The probability of choosing a common belief different from private belief ranges between 9-18% for those with risky private beliefs, while the range is 42-75% for those with ambiguous private beliefs. Combining this finding with those of Table 3 implies that not only are subjects with ambiguous private beliefs less prevalent in our data, they are also less committed to their own beliefs, creating strategic instability for subjects with ambiguous private beliefs and hindering their coordination more than subjects with risky private beliefs (who are guided by stable *focal points*).



(a) By Specific Private Belief Category (b) By Belief Structure (Risky vs. Ambiguous)

Figure 6: Probability of Selecting a Common Belief Different from the Private Belief

Notes: The figures display the probabilities of the subjects selecting a common belief different from their own private belief. Panel (a) presents this probability disaggregated by the six private belief options, with the bubble sizes being proportional to the sample size for each category. Panel (b) aggregates these probabilities by belief structure, comparing subjects who held *Risky* private priors versus those who held *Ambiguous* private beliefs, with the labels at the end of each bar indicating the percentage of subjects in that category whose selected common belief differed from their private belief. Only potato farmers are included in the sample, and the data for the "Avoiding Harvest on Rainy Days" strategy excludes observations from the Lima sample.

These results can explain the null results presented in Section 4.2.1. For active discussion to improve coordination, it must either create a new *focal point* or clarify an existing one. However, our results indicate that subjects with risky private beliefs, who are the majority in our sample, exhibited strong resistance to reporting a common belief that differs from their private belief. In contrast, the minority of agents with ambiguous private beliefs had a high likelihood of reporting a common belief that is different from their private belief. As a result, the discussion intervention failed to reach consensus, as the majority forced the group to converge on its pre-existing beliefs, while the minority lacked the structure to coordinate on an alternative answer. Thus, group consensus in our experiment was determined by the initial distribution of risky private beliefs, making active discussion redundant in this scenario.

5 Summary and Concluding Remarks

We study the role of active discussion in resolving information frictions associated with the adoption of agricultural technologies. In particular, we investigate whether active discussion helps people coordinate better than passive learning of the same information. Furthermore, we distinguish between *risky* (structured) and *ambiguous* (unstructured) beliefs and focus on understanding how these belief structures influence learning. Using data from an artefactual field experiment with Peruvian potato farmers, we document the failure of active discussion to improve coordination relative to passive learning.

Further investigation reveals that the mechanism behind this failure is the *inertia of the majority*. More specifically, we find that subjects with *risky* private beliefs, who constitute the majority of our sample, exhibit strong resistance to selecting a common belief that differs from their private beliefs, forcing coordination on their private beliefs. In contrast, subjects with *ambiguous* private beliefs, the minority in our sample, exhibit a high likelihood of selecting a common belief that differs from their private beliefs, and their private beliefs are too unstructured to help them unite into a cohesive alternative bloc. As a result, active discussion does not facilitate convergence to a new equilibrium because it cannot overcome the firm entrenchment of the majority's beliefs.

These findings have implications for policy design, particularly for participatory interventions that aim to give farmers a *voice*. We show that active discourse alone is insufficient to improve coordination when the underlying prior distribution is rigid and dominated by a confident majority. Thus, participatory interventions are more likely to be effective after beliefs have been destabilized, for example, by traditional extension services or other top-down knowledge interventions that relax the inertia of the majority. In such a scenario, bottom-up development policies, such as social learning, must be complemented by top-down knowledge interventions to destabilize incorrect priors before social learning can be more effective.

Our study is subject to several limitations that point towards avenues for future research. First, to understand the impact of active discussion, we rely on a single 15-minute discussion. Although this helps us to understand the immediate effect of the discussion on coordination, real-world social interactions are usually more iterative. As overcoming established behaviors requires repeated social reinforcement rather than a single exposure (Centola, 2010), future investigation should focus on understanding whether repeated interactions over a longer horizon help agents holding the minority unstructured belief eventually destabilize those with the majority structured belief. Second, our findings are conditional on the presence of a strong modal belief (the majority having *risky* beliefs in this case). This feature of our sample limits our ability to generalize the results to settings where beliefs are initially fragmented and lack a *focal point*. Finally, we focus on coordination as an outcome, which serves as a proxy for the formation of social norms rather than the formation of an *accurate* consensus. If the majority has beliefs that are factually incorrect, our results indicate that the discussion will not reach an *accurate* consensus, leading the groups to form information cascades (Bikhchandani et al., 1992). A natural next step is therefore to test specific bundles of external information shocks (such as top-down knowledge interventions that destabilize incorrect priors) and participatory interventions (such as active discussions) to shift common beliefs toward accuracy rather than shared focal points. We leave that for future research.

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Online Appendices

The Role of Active Discussion in Coordinating about Uncertain Technologies*

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This online appendix is organized as follows. Appendix A contains findings on the correlation between the subjects' private beliefs and their demographics. Appendix B documents risk and ambiguity instruments, and Appendix C documents the instructions used for the experiment. Finally, Appendix D documents the robustness tests for our empirical analysis results.

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A What Determines the Subjects' Private Beliefs?

In this section, we analyze the results of Task 1, which involved eliciting private beliefs. We have no a priori hypotheses about what should or should not predict the belief that one strategy to combat Late Blight is relatively more risky than ambiguous. Table A.1 estimates the probability that subjects 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 as a binary variable that 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 A.1 thus presents the marginal effect results of estimating the following Probit regression:

$$Pr(\text{Risky Private Belief}_{ij}) = X'_{ij}\beta + \Theta'_{ij}\gamma + D_j + \epsilon_{ij}, \tag{4}$$

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.

Table A.1: 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.

Each column of Table A.1 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.

B 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 B.1: Risk and Ambiguity Instrument

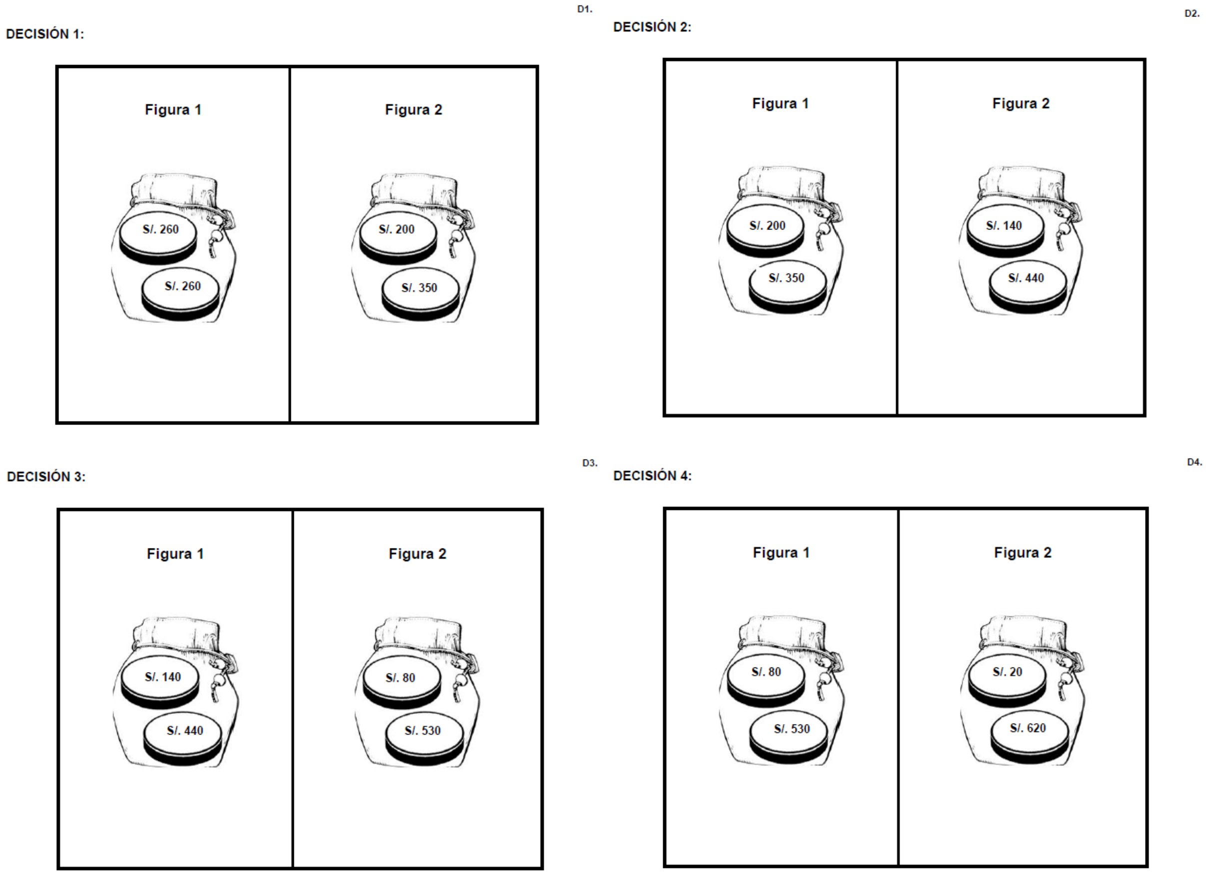

Figure B.2: Risk Instrument Flash-cards

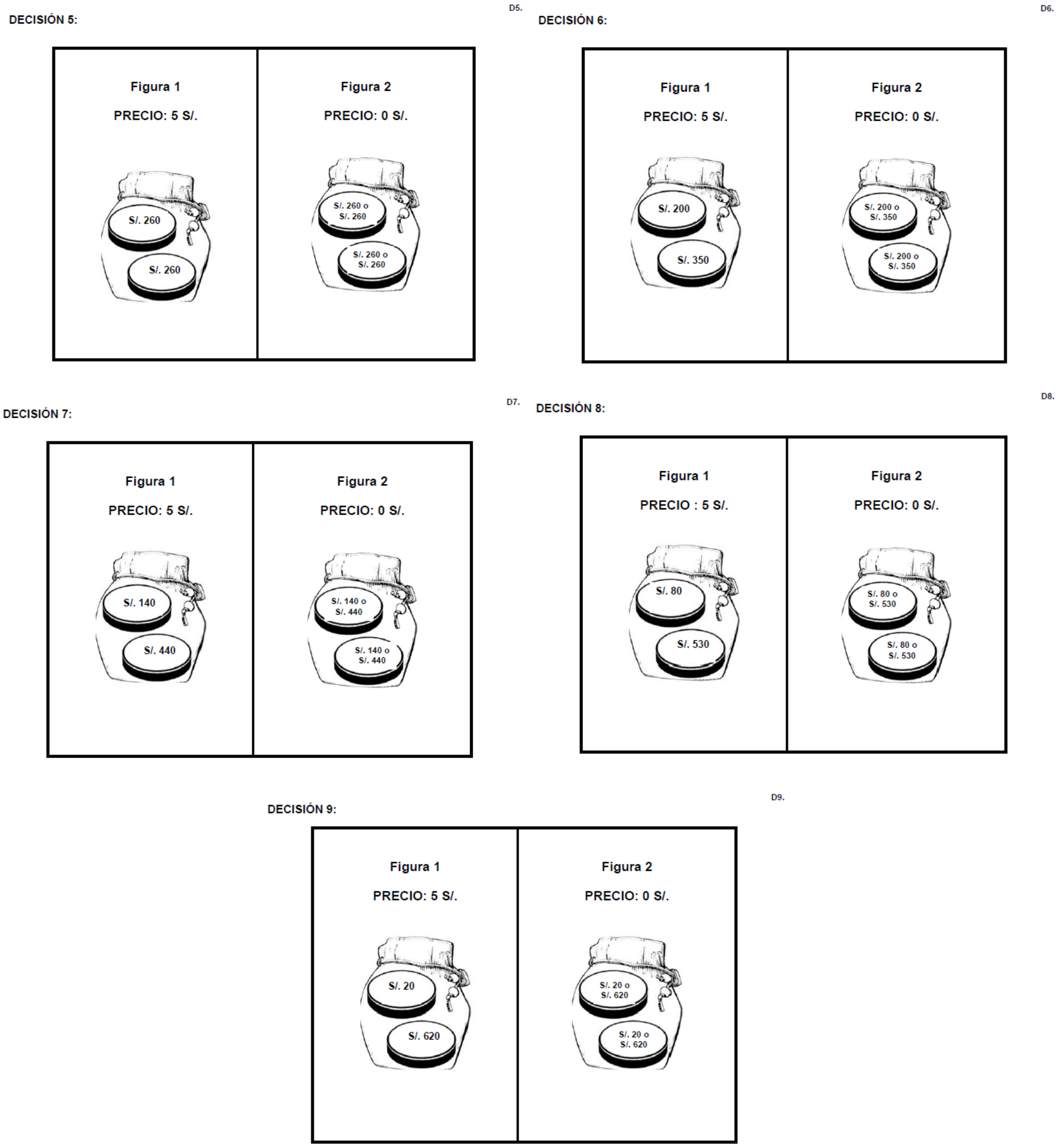

Figure B.3: Ambiguity Instrument Flash-cards

C 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?

D Robustness Checks

Table D.1: Effect of Active Discussion on Individual-Level Coordination (controlling for other characteristics)

	Do nothing	Apply agrochemicals	Seek technical assistance	Do crop rotation	Avoid harvesting on rainy days	Avoid harvesting on rainy days (no Lima)
Panel A: For Precise Coordination						
Treatment	0.036	-0.005	0.003	0.011	0.018	0.082
(Active Discussion=1)	(0.068)	(0.110)	(0.091)	(0.059)	(0.090)	(0.073)
Constant	0.114	0.043	-0.082	-0.039	0.009	0.165
	(0.082)	(0.126)	(0.091)	(0.106)	(0.122)	(0.101)
Observations	252	252	252	252	252	192
R^2	0.260	0.177	0.272	0.166	0.179	0.144
Panel B: For Structural Coordination						
Treatment	-0.097	-0.121*	-0.087	0.081	-0.032	-0.139
(Active Discussion=1)	(0.088)	(0.068)	(0.062)	(0.071)	(0.081)	(0.106)
Constant	0.520***	0.446**	0.109	0.322**	0.287***	0.400***
	(0.120)	(0.161)	(0.120)	(0.107)	(0.088)	(0.112)
Observations	252	252	252	252	252	192
R^2	0.168	0.182	0.333	0.153	0.151	0.124

Notes: * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered at the session level are in parentheses. Only potato farmers are included in the sample. The dependent variable in all regressions represents the empirical probability that the subject coordinates with another randomly selected participant in the same group on their answers. Panel A dependent variables focus on measuring precise coordination in terms of the exact answers out of the 6 possible answers documented in Figure 1. Panel B dependent variables focus on measuring structural coordination in terms of selecting an option that is *Risky*, as opposed to *Ambiguous*. All regressions include individual and group characteristics, as well as department-fixed effects. Individual characteristics include the individual's age category dummy, gender, education level (as education dummies), and whether they experienced late blight in the past. Group characteristics include the total number of lines spoken by the group and the total number of lines spoken by the individual in the group (both can be positive only if the individual was randomly selected to participate in a discussion group).

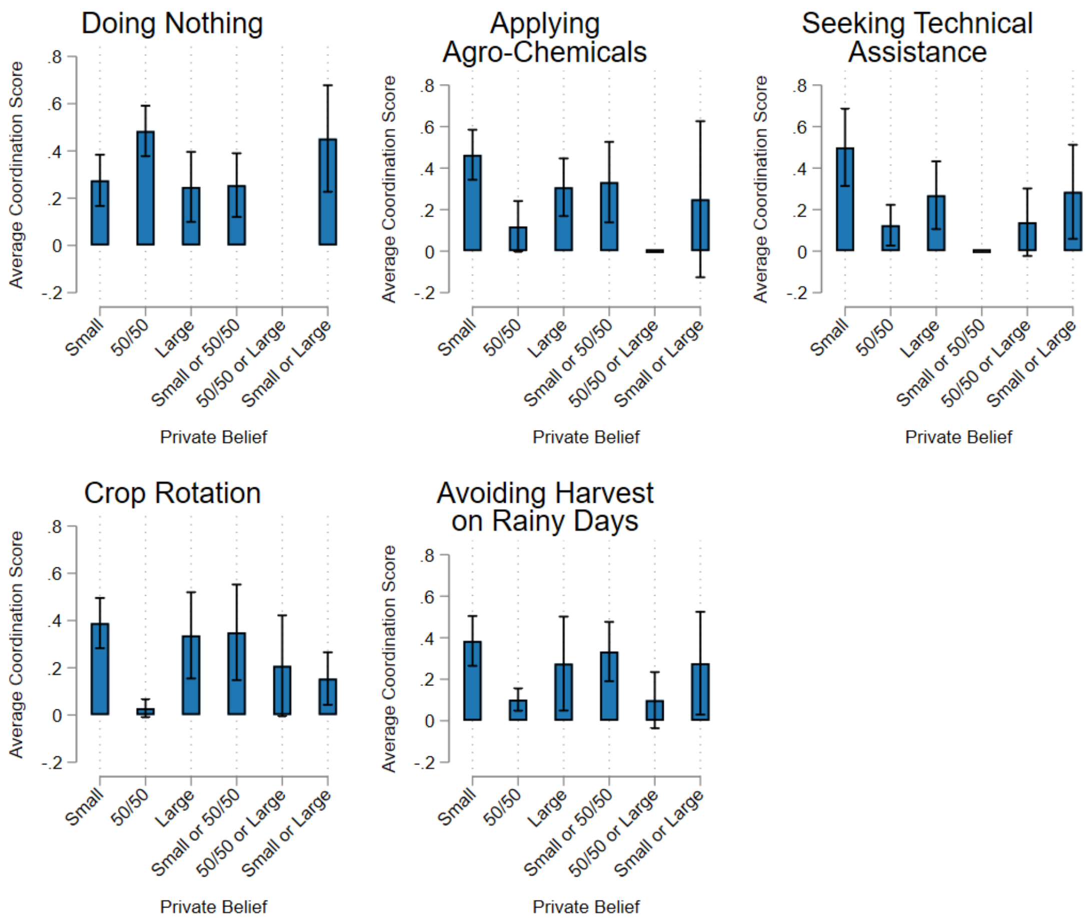

Figure D.1: Control Group Heterogeneity in Precise Coordination Scores by Private Belief

Notes: Predicted marginal means of *Individual Coordination Scores* are presented for each category of private beliefs, based on the estimates from an OLS regression of the coordination score on the treatment assignment, private belief indicators, and their interactions. Standard errors are clustered at the session level. The outcome variables correspond to the five strategies: (1) Doing Nothing, (2) Applying Agro-chemicals, (3) Seeking Technical Assistance, (4) Crop Rotation, and (5) Avoiding Harvest on Rainy Days. The regression for strategy (5) excludes observations from the Lima sample. The error bars represent 95% confidence intervals. Only potato farmers are included in the sample.

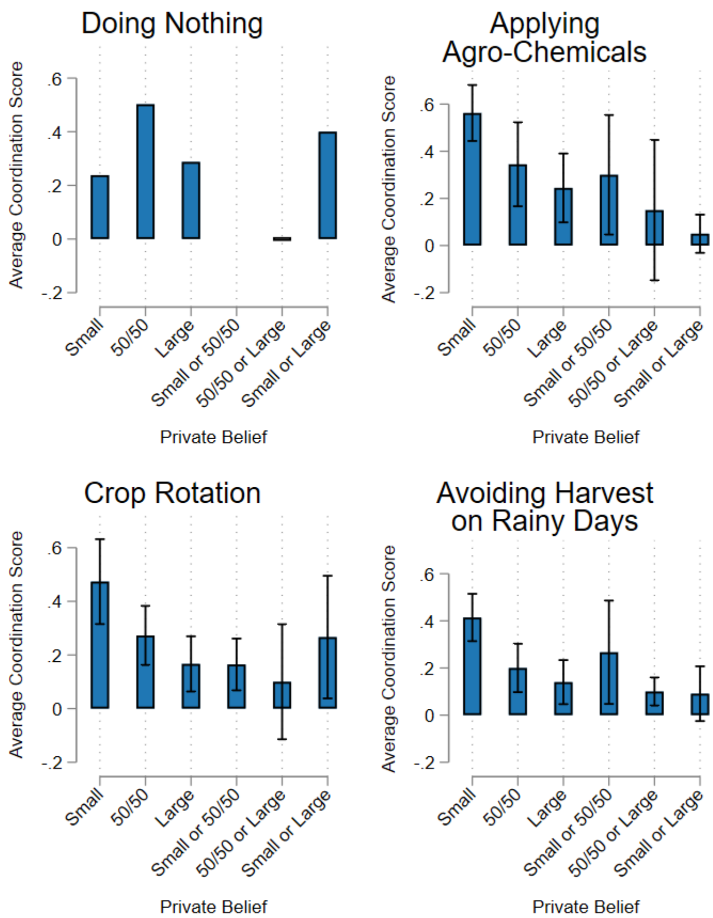

Figure D.2: Treatment Group Heterogeneity in Precise Coordination Scores by Private Belief

Notes: Predicted marginal means of *Individual Coordination Scores* are presented for each category of private beliefs, based on the estimates from an OLS regression of the coordination score on the treatment assignment, private belief indicators, and their interactions. Standard errors are clustered at the session level. The outcome variables correspond to the five strategies: (1) Doing Nothing, (2) Applying Agro-chemicals, (3) Seeking Technical Assistance, (4) Crop Rotation, and (5) Avoiding Harvest on Rainy Days. The regression for strategy (5) excludes observations from the Lima sample. The error bars represent 95% confidence intervals. Only potato farmers are included in the sample.

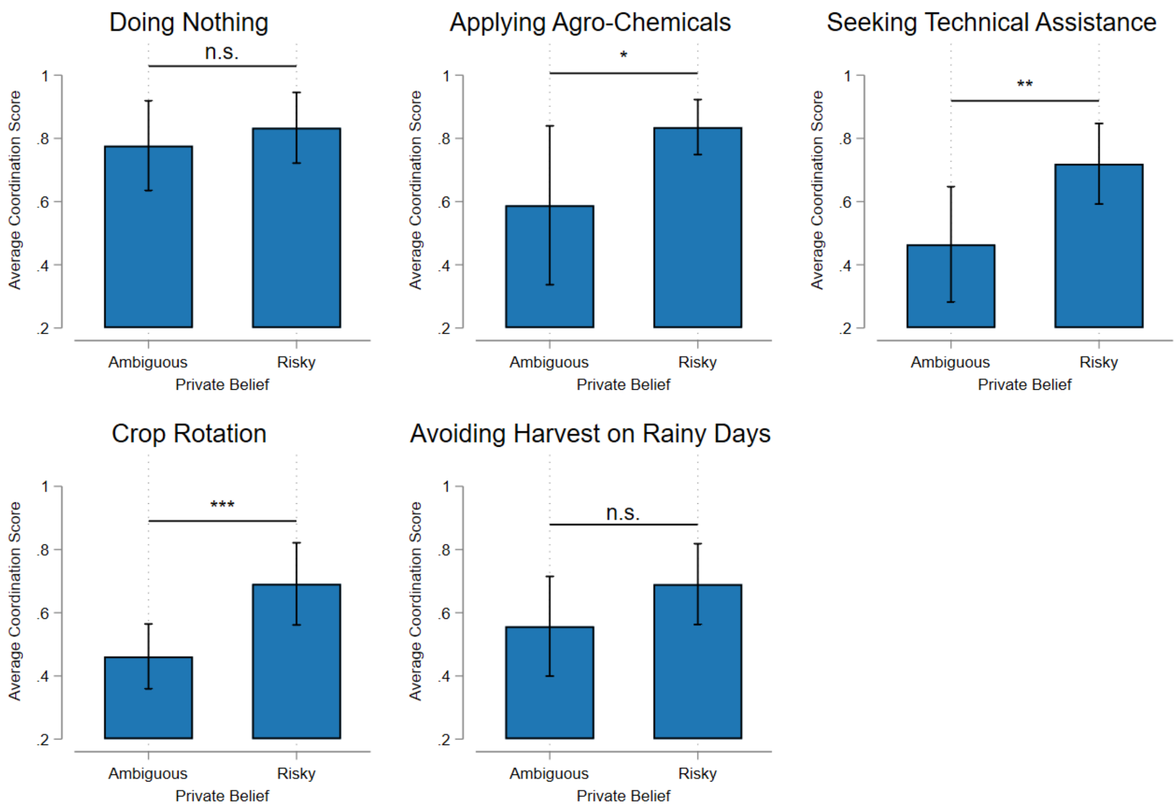

Figure D.3: Control Group Heterogeneity in Structural Coordination Scores by Private Belief

Notes: Predicted marginal means of *Individual Coordination Scores* are presented for each category of private beliefs (capturing whether the belief is Risky or Ambiguous), based on the estimates from an OLS regression of the coordination score on the treatment assignment, private belief indicators, and their interactions. Standard errors are clustered at the session level. The outcome variables correspond to the five strategies: (1) Doing Nothing, (2) Applying Agro-chemicals, (3) Seeking Technical Assistance, (4) Crop Rotation, and (5) Avoiding Harvest on Rainy Days. The regression for strategy (5) excludes observations from the Lima sample. The error bars represent 95% confidence intervals. Only potato farmers are included in the sample. The brackets and asterisks indicate the statistical significance of the difference between the Risky and Ambiguous means (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

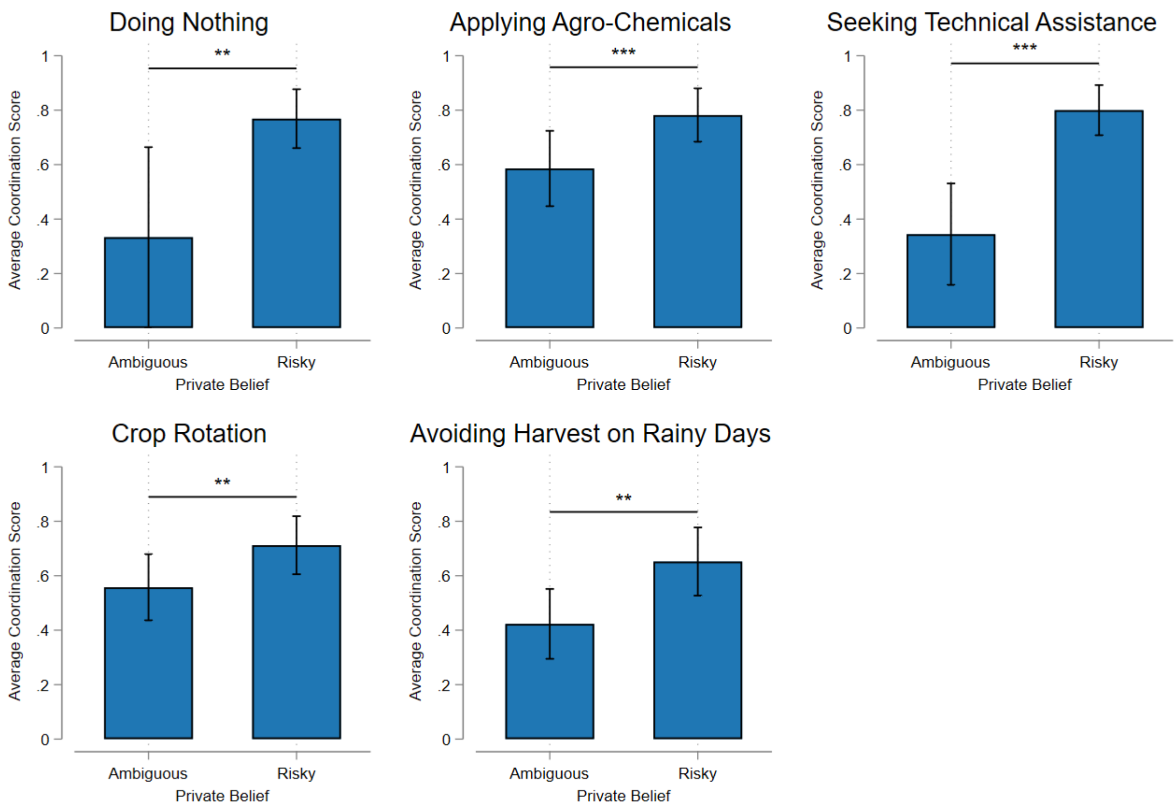

Figure D.4: Treatment Group Heterogeneity in Structural Coordination Scores by Private Belief

Notes: Predicted marginal means of *Individual Coordination Scores* are presented for each category of private beliefs (capturing whether the belief is Risky or Ambiguous), based on the estimates from an OLS regression of the coordination score on the treatment assignment, private belief indicators, and their interactions. Standard errors are clustered at the session level. The outcome variables correspond to the five strategies: (1) Doing Nothing, (2) Applying Agro-chemicals, (3) Seeking Technical Assistance, (4) Crop Rotation, and (5) Avoiding Harvest on Rainy Days. The regression for strategy (5) excludes observations from the Lima sample. The error bars represent 95% confidence intervals. Only potato farmers are included in the sample. The brackets and asterisks indicate the statistical significance of the difference between the Risky and Ambiguous means (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).