How Uncertainty About Heterogeneity Impacts Technology Adoption*

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Abstract

I study an empirical anomaly about how individuals learn about new technologies. Information received from peers is often based on only a handful of experiences. By contrast, information from official sources, such as the government, is backed by rigorous testing. Yet, in my setting of agricultural technology adoption, government recommendations are no more effective at inducing adoption. I propose that this arises because returns to technology adoption are heterogeneous based on context and individuals face uncertainty about the context where government testing took place. I confirm this mechanism using a lab-in-the-field experiment with 1,600 small and marginal farmers in Odissa, India. I also demonstrate that my mechanism is consistent with both survey data and results from a broad set of recent field experiments on agricultural extension.

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1 Introduction

Adopting a new technology requires first learning about it: Is it effective? Is it reliable? Is it accessible? Because the technology is new, the answer to these questions are necessarily mired in uncertainty. One important source for this information is peers (Rogers 2003). Learning from our peers, or social learning, is an important information channel for decisions across domains, such as health (Qiao et al. 2020) or personal finance (Duflo and Saez 2002). Peers often have limited experience with a new technology: a neighbor farmer may have tried a new seed brand on only a single plot for a single season before voicing their recommendation. Despite their limited experience with a new technology, these peer recommendations can be just as effective as sources with much richer data (Krishnan and Patnam 2014).

Understanding why social learning is effective, despite peers' limited information, is important for economists, governments, and NGOs designing their own campaigns to disseminate information. In the agricultural sector, agricultural ministries spend hundreds of millions on agricultural extension services per year (Sajesh and Suresh 2016), which introduce farmers to new technologies that have been vetted by extensive research. Yet, extension services are not necessarily more effective than social learning (Krishnan and Patnam 2014; Takahashi, Mano, and Otsuka 2019), wherein recommendations are fueled by very small scale experimentation by peers.

This paper proposes one potential mechanism for why social learning is effective, which I refer to as *context uncertainty*. Context uncertainty arises from an agent's inability to predict his own expected outcome from another individual's recommendation, due to a lack of information about how their settings differ. This mechanism is rooted in two observations: (i) technologies have heterogeneous returns and (ii) individuals understand the characteristics of their peers better than those of other information providers. For example, I know a great deal about the difference in soil content between myself and my neighbor's plot. Though my neighbor's experience is limited, his recommendations carry great weight because I know how to extrapolate them to my own context.[1] By contrast, the recommendation I receive from an extension agent is based on testing in a distant location, on plot conditions I am unfamiliar with. As a result, though the extension agent's recommendation is generated by a bigger sample size, it suffers from high context uncertainty.

I test this mechanism using an experiment on a sample of 1,600 small and marginal farmers in Odisha, India. The impact of context uncertainty on how individuals learn about the returns to new agricultural technology is difficult to test in the field due to three broad issues. First, isolating

[1]This paper presents the model under the assumption that the mapping required for extrapolation is known. This is done for ease of exposition. However, the model extends to the case where an agent faces uncertainty about how to extrapolate to their own context.

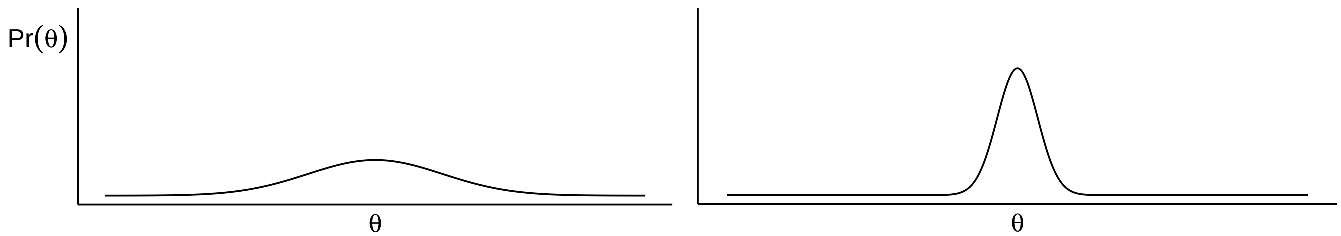
the impact of uncertainty requires first developing an accurate benchmark for risk-neutral behavior by knowing the technology's efficacy for that agent. Unfortunately, measuring the average returns to a new agricultural technology requires accounting for stochastic aggregate shocks with long-run data (Rosenzweig and Udry 2020). Accurately measuring heterogeneous returns is therefore outside the scope of a project with significant time and budget constraints. Second, understanding the impact of information provision on adoption behavior requires accounting for issues including heterogeneities in priors, opportunity costs to adoption, and confirmation bias (Fryer, Harms, and Jackson 2019). Third, examining the role of social learning requires also accounting for beliefs about others, unmonitored signal sharing, social pressures for conformity, and confounding factors in the learning process such as whether agents fully account for the correlation between signals (Enke and Zimmermann 2019).[2] I study context uncertainty in isolation by using a lab-in-the-field experiment. To demonstrate external validity, I show that my results are consistent with survey responses by farmers about their experiences with information from both extension agents and peers. My results are also consistent with Munshi (2004) who studied the impact of social learning on agricultural technology adoption using observational data from the Indian Green Revolution.

The analysis of the experiment and the survey data are consistent with the model: farmers prefer information from sources whose contexts they know well. Further, uncertainty from sampling error and context uncertainty are complements: the value of tighter statistical distribution is higher when the context is more certain. These results suggest that information campaigns by sources such as agricultural ministries should (i) provide information on heterogeneous returns when introducing technologies, and (ii) allocate more resources to acquiring data on heterogeneous returns instead of investing in more data from a narrow set of contexts.

An Intuition for Context Uncertainty

Context uncertainty is uncertainty arising from an agent's inability to predict her expected outcome based on information from someone else, due to a lack of information about how their settings differ. The intuition can be illustrated by comparing three cases: (i) a world with homogenous returns to a technology, (ii) a world with heterogeneous returns and perfect information, and (iii) a world with heterogeneous returns and context uncertainty. In each case, I consider an agent i learning from two signals: (i) a peer j with limited experience using the technology and (ii) an official recommendation from an extension agent k, derived from extensive experimentation.

[2]More broadly, the empirical literature has not reached a consensus about the best model to represent social learning. Recent work in this area highlights that while agents are not necessarily Bayesian (Chandrasekhar, Larreguy, and Xandri 2020), they do account for network structure when updating beliefs (Grimm and Mengel 2020) in a manner inconsistent with the DeGroot learning model, outlined in Jackson (2010).



(a) Peer's Signal (b) Extension Agent's Signal

Figure 1: Homogenous Risk

First, consider a world with homogenous types. Here, all agents are interested in learning a single value θ. Uncertainty arises only due to signal error: some individuals receive noisier signals about θ than others, as illustrated in Figure 1. Agent i's peer j has only experimented with the technology on a single plot for a single season, so their signal about θ is noisy. As a result, j's distribution in Figure 1a has a large variance. By contrast, the extension agent's signal in Figure 1b has a narrower variance, generated by more extensive testing. In this setting with homogenous types, agent i finds that the extension agent signal is more precise.

However, types may be heterogeneous. For an agricultural technology, types can represent differences in attributes like soil content, terrain, or opportunity costs for factors of production. When types are heterogeneous, returns are as well. Instead of learning about a single value θ, each agent is trying to learn about their individual return θ_j. This individual return is a mixture of the average return, θ, and an idiosyncratic component, γ_j, due to agent j's type or *context*. Agent j's return to adopting the technology is therefore

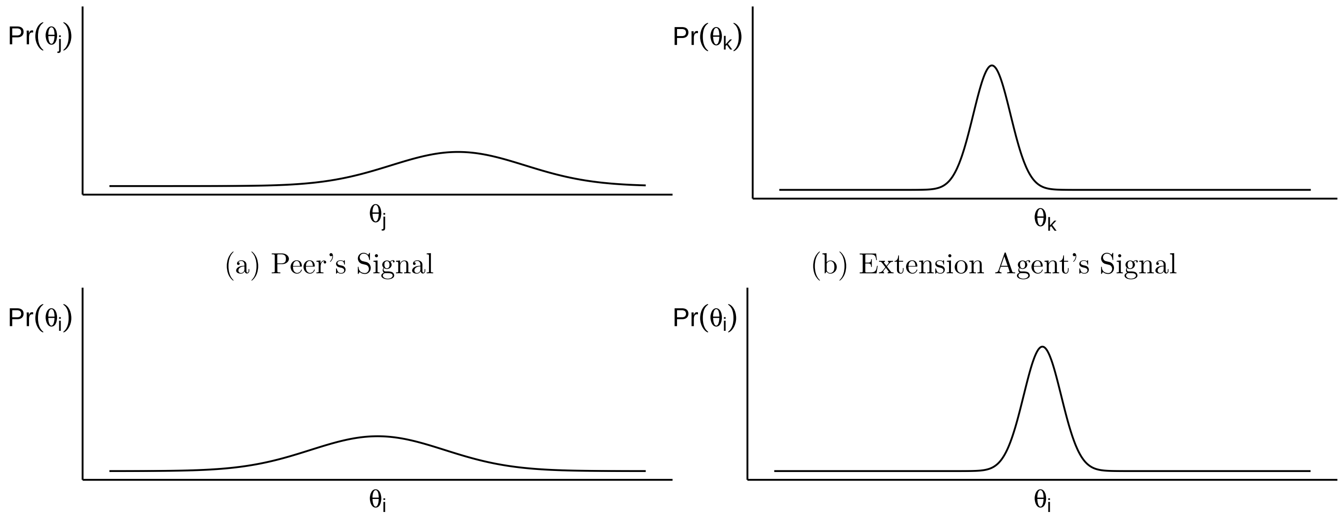
$$\underbrace{\theta_j}_{\text{Agent } j\text{'s Return}} = \underbrace{\theta}_{\text{Average Return}} + \underbrace{\gamma_j}_{\text{Agent } j\text{'s Context}} . \tag{1}$$

θ_j is not directly observed. Instead, agent j receives a noisy signal $s_j = \theta_j + \epsilon_j$ of this return, where the variance of the noise $\epsilon_j \sim \mathcal{N}(0, \sigma_j^2)$ is a function of experience.

When agent j shares s_j with an agent i, what does agent i learn about her own θ_i? Agent i knows her own return is

$$\underbrace{\theta_i}_{\text{Agent } i\text{'s Return}} = \underbrace{\theta_j}_{\text{Agent } j\text{'s Return}} - \underbrace{\gamma_j}_{\text{Agent } j\text{'s Context}} + \underbrace{\gamma_i}_{\text{Agent } i\text{'s Context}} . \tag{2}$$

If agent i knows the difference $\gamma_i - \gamma_j$ between j's context and her own, she can adapt the noisy signal s_j to $s_j^A = s_j - \gamma_j + \gamma_i$ to learn about her own returns. This adapted signal yields the same perception of risk as in the case of homogenous types. I illustrate this in Figure 2. Agent i can take the signal from peer j about θ_j, as in Figure 2a, and translate it to the signal in Figure 2c about θ_i. If agent i also knows how her context differs from the extension agent's, she can repeat this adaptation for his signal s_E, illustrated in figures 2b and 2d. Once the signals are translated, the case is analogous to the homogenous risk scenario of Figure 1. Agent i again finds the extension agent's signal to be more precise.



(a) Peer's Signal

(b) Extension Agent's Signal

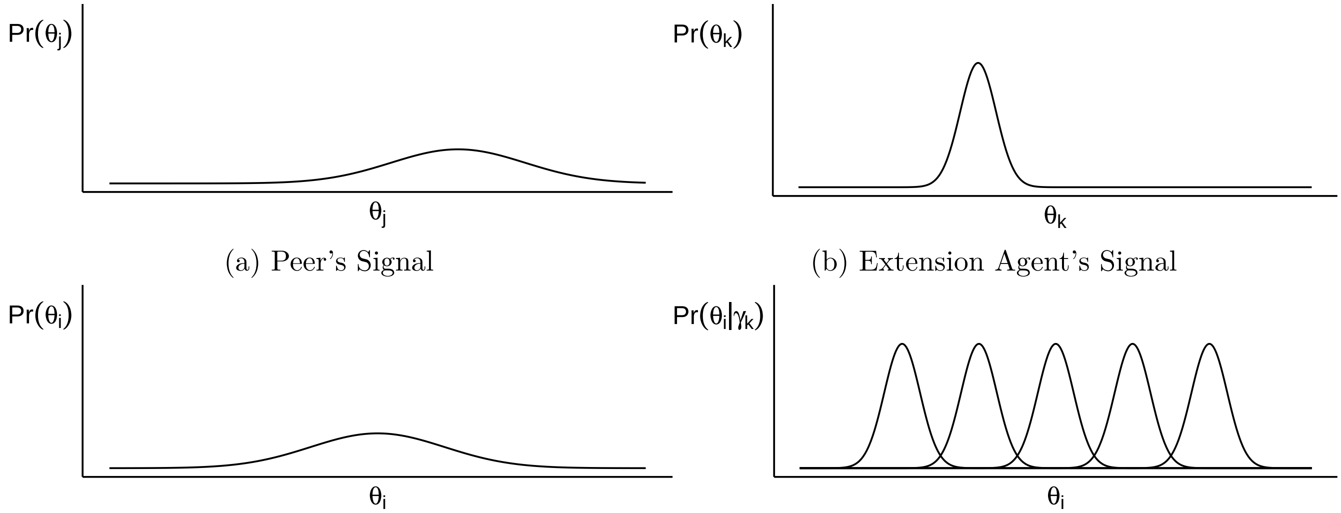
(c) Peer's Translated Signal

(d) Extension Agent's Translated Signal

Figure 2: Heterogeneous Risk without Context Uncertainty

Context uncertainty arises when agent i does not know γ_j. Without this information, agent i cannot complete the translation in Equation 2. She may, however, know a distribution of possible values for γ_j. The variance in possible values for γ_j is the *context uncertainty*. The amount of context uncertainty is a key difference between information from peers and information from extension agents. Figure 3 provides a stylized example of this. Agent i knows her peer agent j extremely well, and therefore knows γ_j exactly. Consequently, figures 3a and 3c are identical to figures 2a and 2c.

By contrast, agent i does not know the extension agent's context γ_k precisely; she is not given information about the weather patterns or soil content of test plots. However, agent i may know several possible values for γ_k and the probability of each. For example, she knows that the village on the other side of the mountain is less prone to flooding. This imperfect information about γ_k means that the extension agent's signal about θ_k, illustrated in Figure 3b, is translated into a distribution of possible distributions about θ_i. This is illustrated in Figure 3d; there are multiple distinct possible distributions for θ_i. Agent i has some belief about the probability of each distribution being true. That probability corresponds to her belief about the value of γ_k.



(a) Peer's Signal

(b) Extension Agent's Signal

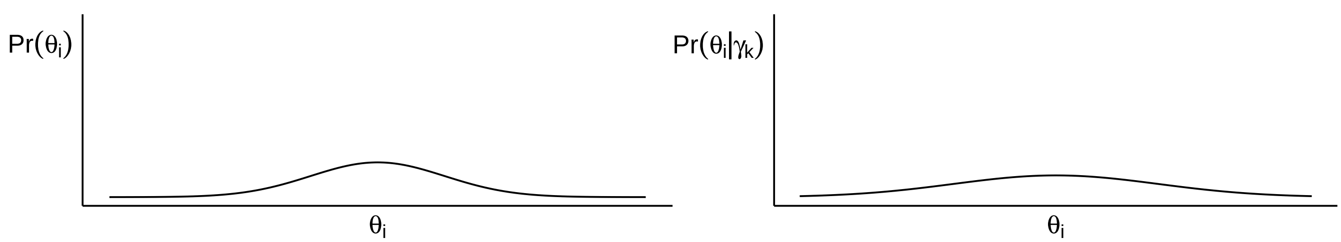
(c) Peer's Translated Signal

(d) Extension Agent's Translated Signal

Figure 3: Heterogeneous Risk with Context Uncertainty

Heterogeneity causes context uncertainty when an agent does not know enough about the differences to translate signals from another context to her own. Figures 3c and 3d show that this additional uncertainty means that agent i no longer perceives the extension agent's signal to be more precise than peer j, whose context is well known.

The distinctive distribution in Figure 3d arises from agent i's discrete beliefs about γ_k, and chosen to convey the impact of heterogeneity. In Section 2, agent i's beliefs about γ_k form a normal distribution, amounting to an extra Gaussian noise term. Consequently, the extension agent's translated signal will also be Gaussian, but with a large variance parameter. Figure 4 illustrates one example of this.



(a) Peer's Translated Signal

(b) Extension Agent's Translated Signal

Figure 4: Translated Signals With Gaussian Context Uncertainty

Related Literature

This paper touches on multiple literatures. My model, where risk averse agents collect data before deciding whether to adopt a technology, is motivated by several related theoretical literatures about agents facing uncertainty. My empirical focus is related to a broad literature on the causes of low agricultural technology adoption in various low- and middle-income countries. It is also relevant to a sub-literature of randomized controlled trials evaluating the impact of changes to agricultural extension programs. Finally, my paper has implications for a broad empirical literature studying information interventions, in both developed and developing contexts.

The first portion of my model, discussed in Section 2, studies how an agent learns from different sources about a technology with heterogeneous returns. Though I present the agent as Bayesian, the model is consistent with a frequentist agent learning about his return using maximum likelihood estimation with the data provided to him. A burgeoning literature in economic theory studies agents who are statistical learners under a diversity of learning procedures. Examples include Liang (2020), Montiel Olea et al. (2022), and Salant and Cherry (2020).

Social learning in particular is studied by a significant number of papers. The model presented here most closely resembles those in Sethi and Yildiz (2016) and Dasaratha, Golub, and Hak (2021). However, these papers focus on aggregate behaviors of the network, rather than individual decision makers. Sethi and Yildiz (2016) studies the setting closest to my own, but seeks to understand endogenous network formation when perspectives, rather than objective characteristics, are heterogeneous.

Heterogeneous learning is also studied by several papers, including Mailath and Samuelson (2020), Berardi (2007), and Haltiwanger and Waldman (1985). However, as with Sethi and Yildiz (2016), this line of work typically focuses on heterogeneity in agents' priors or learning rules, rather than in the underlying parameter of interest. One notable exception, Manski (2004), studies heterogeneous preferences by agents who received imperfect data from peers in the sense of not observing counterfactual outcomes. While my mechanism can be generalized to the case of heterogeneous preferences, I assume that agents conduct small experiments, so uncertainty only arises due to sampling error and context uncertainty.

Section 3 then studies how an agent uses what he has learned to choose his optimal level of investment in the new technology. At its core, the agent is solving the classic single-period mean-variance portfolio optimization problem, originally posed by Markowitz (1952).[3] Prior work has also stud-

[3] Gollier (2001) provides an excellent overview of the portfolio problem, its extensions, and the economics of risk more broadly.

ied agricultural technology adoption as a portfolio problem, including Feder (1980), Roosen and Hennessy (2003), and Liu and Huang (2013). I derive my results using the modern toolkit of monotone comparative statics Shannon (1995). Unlike the standard problem, I study behavior under two different and independent sources of variance: sampling error and context uncertainty. Gollier (2011) also studies the portfolio problem under multiple possible probability distributions. However, he uses the smooth ambiguity framework of Klibanoff, Marinacci, and Mukerji (2005) to study the case of decision making under ambiguity aversion. Although my results can be analogously obtained under the case of context uncertainty causing ambiguity in the smooth ambiguity model, my model makes no use of ambiguity. Instead, I model context uncertainty as one of multiple sources of risk.

My experimental design, described in Section 4, focuses on the agricultural technology adoption decisions of small and marginal farmers in rural India. The frictions behind agricultural technology adoption in developing countries is a longstanding focus of the development literature Foster and Rosenzweig (2010). This work is closely related by multiple strains of this literature.

Suri (2011) is one closely related paper. Her paper focuses on a related empirical puzzle: technology adoption is low despite high average returns. She explains this phenomenon by documenting that returns for Kenyan farmers are heterogeneous, as my model assumes, and that cross-sectional differences in adoption can be explained by this heterogeneity. However, because I focus on information, my model focuses on how heterogeneity causes uncertainty, and the impact of this interaction on risk averse farmers.

Heterogeneity's impact on farmer risk also appears in a line of work studying barriers to farmer adoption of micro-insurance services. This literature uses the term *basis risk* to describe the difference between the actuarial probability distribution used to price an insurance product and the actual risk distribution faced by a farmer. For example, for rainfall insurance, a rain gauge may be placed in the center of a district but conditions such as distance or heterogeneous terrain cause farmers to experience a different amount of rainfall on their own plots. Giné, Townsend, and Vickery (2008) document that insurance take-up is correlated with a decrease in rainfall basis risk and show that this is consistent with survey evidence among non-purchasers. This result is extensively corroborated by other work theoretical and empirical work on micro-insurance, such as Karlan et al. (2014), Clarke (2016), and Mobarak and Rosenzweig (2012).

My paper is directly relevant to, and consistent with, the findings of multiple empirical papers on the role of information on agricultural technology adoption. Section 6 reviews a variety of experiments on agricultural extension design specifically. There, I demonstrate external validity by illustrating that context uncertainty explains the efficacy of a broad swath of designs, in contrast to several alternative mechanisms. My results are also consistent with Munshi (2004), who analyses adoption data from India's Green Revolution. Munshi finds that social learning plays a larger role in more homogenous settings. My work generalizes his results by considering information more broadly and formalizing the conditions under which heterogeneity impacts learning.

By utilizing a lab-in-the-field design, I am able to study my mechanism in isolation, which prior literature relying on field data is unable to do. Properly identifying a mechanism adds value not only for basic research (Falk and Heckman 2009), but also for policy: understanding why certain designs are more effective enables program designers to more rapidly innovate and converge to the best interventions Levitt and List (2007). Other work in development has also used lab-in-the-field experiments to study behavior that is difficult to isolate using field experiments Neggers (2018), and the external validity of qualitative results from lab experiments is demonstrated in a variety of settings Kessler and Vesterlund (2015).

Finally, this project informs not only the literature on agricultural extension design, but also a broader literature on designing information provision. Haaland, Roth, and Wohlfart (Forthcoming) provide an extensive overview of this literature. My mechanism, context uncertainty, speaks to this literature by emphasizing the importance of specificity of information. I show that whenever aggregated information is provided, agents have reason to discount the recommendation if they believe themselves to have characteristics varying from the mean of the distribution. While some of these interventions are certainly effective, a counter-factual intervention with personalized data could have greater impact. It is also important to provide contextual data to those who would consequently reduce adoption. If a source provides an individual with information suggesting better results than what the individual subsequently experiences, this can reduce an individual's trust in future information from that source.

Overview

The paper is organized as follows. The next section provides a highly stylized model of learning in the presence of context uncertainty. Section 3 shows the implications of this model for technology adoption. Section 4 provides a detailed description of the lab-in-the-field experimental design. The results of the experiment are evaluated in Section 5. Section 6 shows that these findings are consistent with a variety of empirical results from field settings. Section 8 concludes.

2 A Model of Learning from Heterogeneous Sources

An agent A is trying to learn about a new technology. She is interested in identifying her personal marginal return to adopting the technology, relative to the status quo technology already being commonly used. This marginal return is unobservable and denoted by $\theta_A \in \mathbb{R}$. As described in Equation 1, her marginal return is a function of the average marginal return $\theta \in \mathbb{R}$ and her context $\gamma_A \in \mathbb{R}$. Agent A knows the value of her own context γ_A. However, the average marginal return $\theta \in \mathbb{R}$ is also not observable.

2.1 The Information Environment

Agent A does not experiment with the new technology, so she receives no private signals about its efficacy. She does, however, receive private signals from a set of peers $N = \{1, \ldots, n\}$. She also receives a signal from an extension agent E. To avoid focusing on issues of social learning patterns, we assume the peers do not share information with each other or the extension agent, and that the extension agent also only shares information with agent i. Equivalently, the village is a social network G whose topology is a directed star graph S_{n+1}, as illustrated in Figure 5.

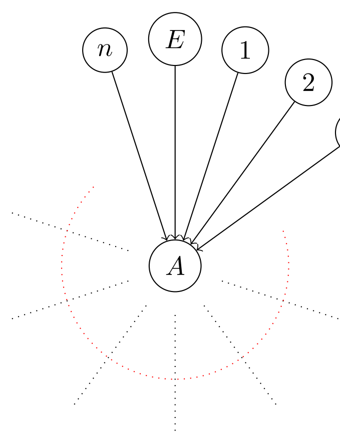


Figure 5: Signal Sharing Network S_{n+1}

Each individual $j \in \{1, \ldots, n, E\}$ receives a single private signal s_j about their own marginal return to the technology, $\theta_j \in \mathbb{R}$. This noisy signal can be decomposed as

$$s_j = \theta + \gamma_j + \epsilon_j. \tag{3}$$

where $\epsilon_j \sim \mathcal{N}(0, \sigma_j)$ are independent normally distributed random variables. We refer to ϵ_j as agent j's *sampling error* and σ_j as their *sampling uncertainty*. Further, we will refer to any independent

Gaussian random variables with mean zero and finite variance, including ϵ_j, as *Gaussian white noise*. Comparing Equation 1 with Equation 3 clarifies that a signal is a noisy observation of θ_j, where noise arises from limited experience testing the technology.

Each of these peers and the extension agent subsequently shares their signal with agent A. They also share their values σ_j by communicating the sample size behind their recommendation.[4] However, agent A does not know the context for other individuals equally well. Her belief about each context is normally distributed

$$\gamma_j \sim_A \mathcal{N}(\mu_j^\gamma, \sigma_j^\gamma)$$

where mean μ_j is the *expected context* and σ_j^γ is the *context uncertainty* A has about j. Because the focus of this paper is on context uncertainty parameter σ_j^γ, we assume that agent A's estimate of μ_j is known to be unbiased so that $\mu_j^\gamma = \gamma_j$ and is believed with certainty.[56]

2.2 Signal Translation

In order to use the information from her peers, agent A first must translate their signals to her context in order to learn about her own marginal return, θ_A. Recall that, for each agent, she observes their signal s_j and sampling error σ_j and also has beliefs over their context parameterized by μ_j^γ and σ_j^γ. She uses this information to create a modified signal

$$s_j^A = \underbrace{\theta + \epsilon_j + \gamma_j}_{\text{Original Signal}} + \underbrace{(\gamma_i - \mu_j)}_{\text{Context Adjustment}} \tag{4}$$

composed of the original signal she received from an individual j and adjusting it using her own γ_i and her belief μ_j. This amounts to agent A receiving a signal with the structure

$$s_j^A = \theta + \epsilon_j + \bar{\gamma}_j + \gamma_i \tag{5}$$

where $\bar{\gamma}_j \sim_A \mathcal{N}(0, \sigma_j^\gamma)$ is a random variable denoting agent A's uncertainty over the difference between agent j's realized context and her own γ_i. Under this translation, agent A interprets $\bar{\gamma}_j$

[4]This can be generalized to also sharing other attributes behind sampling error, such as the care placed into their experimentation.

[5]A possible extension of this model is introducing additional uncertainty from agent A's estimation μ_j^γ.

[6]An alternative specification can assume that the context for each individual is drawn from a personal distribution $\mathcal{N}(0, \sigma_j^\gamma)$. In this setting, we assume that agent A knows the distribution for each agent, but does not know their realization. This specification implies that agent A will not need to subtract a mean belief to evaluate her translated signal in Equation 4 of Section 2.2. Instead, she can allow $s_j^A = s_j + \gamma_i$, where her own context γ_i is a known scalar and her beliefs over γ_j act as another centered Gaussian noise parameter, as with ϵ_j. This amounts to skipping directly to Equation 5.

as a Gaussian white noise parameter.

Note that equations 4 and 5 imply that s_j^A is the sum of two scalars, θ and γ_i, and two Gaussian random variables, $\epsilon_j \sim \mathcal{N}(0, \sigma_j^2)$ and $\bar{\gamma}_j \sim_A \mathcal{N}(0, (\sigma_j^\gamma)^2)$. The arithmetic for Gaussian random variables implies that

$$s_j^A \sim_A \mathcal{N}(\theta + \gamma_i, \sigma_j^2 + (\sigma_j^\gamma)^2). \tag{6}$$

The Gaussian structure of each translated signal s_j^A, with common mean $\theta + \gamma_i$, allows agent A to cleanly aggregate signals from various sources in the next subsection. A similar analysis of a system of Bayesian signals can be done with any conjugate distribution.[7]

2.3 Learning About Her Own Return

Once translated, Agent A can use these modified signals, s_j^A for $j \in \{1, \dots, n, E\}$ to form her belief about θ_A. By Bayes' Rule, agent A's posterior belief about θ_A is proportional to her prior belief times the conditional likelihood of receiving her signals:

$$\Pr(\theta_A | s_1^A, \dots, s_n^A, s_E^A) \propto \Pr(s_1^A, \dots, s_n^A, s_E^A | \theta_A) \Pr(\theta_A).$$

Because she has little knowledge about the technology, we assume that agent A's prior for her marginal return to adoption θ_A is

$$\theta_A \sim_A \mathcal{N}(0, \sigma_0^2)$$

where σ_0 is sufficiently large so that the prior is weak and minimally informative.[8]

It follows from Bayes rule for linear Gaussian systems[9] that agent A's posterior is distributed

[7] See Rossi, Allenby, and McCulloch (2012) for an overview of conjugate distributions, solving these models analytically, cases when deference to numerical integration methods are needed, and how to do so.

[8] Alternatively, we can consider agent A's prior to be the improper prior, derived from the limit

$$\lim_{\sigma_0 \to \infty} \mathcal{N}(0, \sigma_0^2).$$

Because the maximum likelihood estimator is the maximum a posteriori estimator (Murphy 2012), agent A's posterior will be equivalent to the computed likelihood distribution under the limit. The parameters in equations 7 and 8 can then be replaced with their limits:

$$\tilde{\mu} = \tilde{\sigma}_0^2 \left(\frac{s_E^A}{\sigma_E^2 + (\sigma_E^\gamma)^2} + \sum_{j \in 1, \dots, n} \frac{s_j^A}{\sigma_j^2 + (\sigma_j^\gamma)^2} \right) \qquad \text{and} \qquad \tilde{\sigma}_0^2 = \left(\frac{1}{\sigma_E^2 + (\sigma_E^\gamma)^2} + \sum_{j \in 1, \dots, n} \frac{1}{\sigma_j^2 + (\sigma_j^\gamma)^2} \right)^{-1}.$$

[9] See Section 4.4 of Murphy (2012) for a more complete overview of linear Guassian systems and their properties.

$\mathcal{N}(\tilde{\mu}, \tilde{\sigma}_0^2)$ where

$$\tilde{\mu} = \tilde{\sigma}_0^2 \left(\frac{0}{\tilde{\sigma}_0^2} + \frac{s_E^A}{\sigma_E^2 + (\sigma_E^\gamma)^2} + \sum_{j \in 1,\dots,n} \frac{s_j^A}{\sigma_j^2 + (\sigma_j^\gamma)^2} \right) \tag{7}$$

and

$$\tilde{\sigma}_0^2 = \left(\frac{1}{\tilde{\sigma}_0^2} + \frac{1}{\sigma_E^2 + (\sigma_E^\gamma)^2} + \sum_{j \in 1,\dots,n} \frac{1}{\sigma_j^2 + (\sigma_j^\gamma)^2} \right)^{-1}. \tag{8}$$

We note that the posterior mean is the weighted average of the prior mean, the extension agent's translated signal, and the translated signal from each peer. An important observation is that the weight on each term is determined not only by the noise arising from sampling error, σ_j, but also the noise from context uncertainty, σ_j^γ. These context uncertainty values σ_j^γ also contribute to increasing the overall variance $\tilde{\sigma}_0^2$ of the posterior belief.

These posterior parameters contain this paper's primary message. It is evident, once we consider context uncertainty, why individuals do not learn more from sources such as extension agents. It is true that rigorous testing behind an extension agent's recommendation constitutes lower sampling uncertainty σ_E^2. However, his signal's total uncertainty $\sigma_E^2 + (\sigma_E^\gamma)^2$ may exceed those of peer villagers. Peer villagers may know one another's contexts extremely well, bringing context uncertainty as low as $\sigma_j^\gamma = 0$.

Given this, which source would a farmer listen to: her set of peers or the extension agent? Proposition 2.1 explains that, analogous to the issue of weighting signals in her posterior, the agent will always choose the signal with less total variance when forced to choose.

Proposition 2.1. *Let an agent A be a Bayesian expected utility maximizer choosing between the two signals:*

$$s_j^A \sim_A \mathcal{N}(\theta + \gamma_i, \sigma_j^2 + (\sigma_j^\gamma)^2) \qquad \textit{and} \qquad s_E^A \sim_A \mathcal{N}(\theta + \gamma_i, \sigma_E^2 + (\sigma_E^\gamma)^2).$$

The agent will choose the signal with lower total variance.

However, Proposition 2.1 does not imply that a higher level of adoption will be chosen. The following section will explain the adoption problem and provide the comparative statics of adoption after imposing the additional assumptions needed on our agent.

3 How Context Uncertainty Impacts Technology Adoption

Context uncertainty's impact on learning can be interesting in isolation. However, this paper's ultimate goal is understanding its ultimate impact on technology adoption behavior. Further, measuring respondents' probabilistic beliefs is an active area of research, in both economics (e.g. Manski 2004; Enke and Graeber 2019) and human-computer interaction (e.g. Koval and Jansen 2022; Greis et al. 2017; Greis et al. 2019), concerned with measurement error issues that could obfuscate real differences between priors and posteriors. Consequently, this section explains the impact of learning on the agent's technology adoption problem and derives the main results. Section 5 tests these propositions about adoption levels empirically.

3.1 The Agent's Problem

How does agent A use the signals shared with her by her peers and extension agent? She ultimately seeks to maximize her plot's yield by choosing the right level of adoption of the new technology, based on her beliefs about θ_A.

The agent's yield $Y_A(\alpha, \theta_A)$ is a function of the marginal impact θ_A of the new technology and the share of her plot $\alpha \in [0,1]$ on which she adopts it. Its functional form is the sum of her yield on the share of land where the technology was adopted, and is θ_A units higher (lower), and her yield on the land using the status quo technology:

$$Y_A(\alpha, \theta_A) \equiv \alpha(1 + \theta_A + \nu_A + \epsilon_{A,1}) + (1 - \alpha)(1 + \nu_A + \epsilon_{A,0}). \tag{9}$$

Yield is subject to two forms of shocks. $\nu_A \sim \mathcal{N}(0, \sigma_V)$ denotes a common shock to all parts of her land, such as unexpected weather conditions for the season. $\epsilon_{A,1} \sim \mathcal{N}(0, \sigma_A)$ and $\epsilon_{A,2} \sim \mathcal{N}(0, \sigma_A)$ are identically distributed shocks that are independent across the two fractions of land. These shocks can be interpreted as the average outcome of implementation idiosyncrasies, such as accidental variation in pesticide application.

We assume that the risk averse agent A has a utility function

$$u(Y_A(\alpha, \theta_A))$$

where u is nondecreasing and concave. Her goal is to choose a level of adoption α^* that maximizes the her expected utility over her distribution of possible yields:

$$\alpha^* = \arg\max_{\alpha} E[u(Y_A(\alpha, \theta_A))]. \tag{10}$$

Agent A's posterior beliefs over θ_A follow the distribution $\mathcal{N}(\tilde{\mu}, \tilde{\sigma}_0^2)$ with parameters as defined in equations 7 and 8. To focus on the impact of context uncertainty on adoption and ignore issues of particular signal draws, we assume that $s_j^A = \bar{\mu} \in \mathbb{R}^{++}$ for all $j \in \{1, \ldots, n, E\}$ so all individuals have the same positive signal draw and the mean of the belief distribution is $\tilde{\mu} = \bar{\mu}$.[10]

3.2 Adoption Dynamics

Our principal goal is showing that the agent's optimal level of adoption is a function of beliefs over θ_A, particularly that α^* weakly increases when context uncertainty decreases for any signal s_j^A received. This result is formalized in Proposition 3.1.[11] A stronger version of this result can be obtained for strictly risk averse agents. The proof for this case is analogous.

Proposition 3.1. *Consider a risk averse agent A with utility u, which is nondecreasing and concave, selecting a level of adoption to solve Equation 10. The agent's optimal level of adoption α^* is nonincreasing in context uncertainty from any signal.*

So far, we have restricted our focus to the impact of context uncertainty in isolation. However, it is also important to understand the interaction between context uncertainty and uncertainty arising from sampling error. It turns out that, for certain agents, these two forms of uncertainty are decision complementary, as defined in Definition 3.1[12]: when the agent faces less of one form of uncertainty, the marginal reduction in the other form of uncertainty has greater impact on α.

Definition 3.1. Two inputs x and y are **decision complementary** if, for an agent selecting an optimal α to maximize their expected utility, the optimal decision rule α^* has increasing differences

[10] The true marginal return to the technology is perhaps the optimal candidate for $\bar{\mu}$. It coincides with the expected value of each translated signals s_j^A. This is not set explicitly, both for the purpose of generality and to avoid confusion in notation between the true value of θ_A and agent A's beliefs about the parameter.

[11] Proposition 3.1 makes provides sufficient, but not necessary, conditions for this comparative statics result. However, these weaker conditions require greater exposition. Readers interested in weakening these conditions on the utility function, or on signal's distribution, should consult Section 4 of Athey (2002).

[12] This definition of complementary is stronger than pairwise increasing differences in the utility function U amongst parameters α, σ_j, and σ_j^γ. The difference is most easily understood in the continuous case. Pairwise increasing differences is a statement about the set of second partial derivatives $\frac{\partial^2 U}{\partial\alpha\partial\sigma_j}$, $\frac{\partial^2 U}{\partial\alpha\partial\sigma_j^\gamma}$, and $\frac{\partial^2 U}{\partial\sigma_j\partial\sigma_j^\gamma}$. By contrast, Definition 3.1 is a statement about the third derivative $\frac{\partial^3 U}{\partial\alpha\partial\sigma_j\partial\sigma_j^\gamma}$.

in x and y:

$$\alpha^*(x'', y'') - \alpha^*(x'', y') \geq \alpha^*(x', y'') - \alpha^*(x', y')$$

for all $x'' \geq x'$ and $y'' \geq y'$.

As Proposition 3.2 documents, decision complementarity requires stronger assumptions about our agents preferences. For differentiable utility, this assumption is a restriction on the third derivative, U'''. This captures the skewness of the utility function. However, utility need not be differentiable. Definition 3.2 provides a general definition for our restriction, allowing us to continue using the lattice toolkit of monotone comparative statics.

Definition 3.2. Let $g_\epsilon(x) = x - \epsilon$. An agent's utility u satisfies **decreasing absolute risk aversion (DARA)** if the function $v(x) \equiv u(g_\epsilon(x))$ is a concave transformation of $u(x)$ for all $\epsilon > 0$.

Proposition 3.2. *Consider a risk averse agent A with DARA utility u, and is selecting a level of adoption to solve Equation 10. For any given signal s_j, context uncertainty $(\sigma_j^\gamma)^2$ and sampling uncertainty σ_j^2 are decision complementary.*

These theoretical results have important implications for policymakers encouraging adoption of technologies. First, if the target of an information campaign is risk averse, then the information campaign should provide contextual data about where the testing occurred. For example, provide details about the plot traits such as soil nutrition and weather relative to the plot of the targeted individual.

Second, for policymakers deciding whether their information campaigns will be more influential with greater data, the answer depends on the agent's preferences. If individuals exhibit decreasing absolute risk aversion, then the marginal impact of additional data is greater when more information about context is revealed. Depending on the cost of providing additional context data from existing testing versus conducting more testing, an information campaign can mimic the effect of additional testing just by revealing context.

4 Experimental Design

This lab-in-the-field experiment recruited 1,600 small and marginal farmers in Odissa, India. Testing context uncertainty as a mechanism requires introducing variation that does not affect other, related factors. I tackle this difficulty by designing a mobile game where I completely control the information available.

The game has a simple premise: the farmer must decide how intensively to adopt a hypothetical technology on his plot. Before making his decision, the farmer has access to information from several fictional characters. Each character tested the technology in the previous season and privately gives the farmer their impression. The farmer's real payout is based on how effectively his own yield is maximized by choosing the right level of technology adoption.

The experiment proceeded as follows. First, respondents participated in a survey to collect information about their perception of peers, extension agents, and other sources of information about farming. After the survey was completed, an enumerator provided each participant with a scripted explanation of the game and compensation structure. The participant then begins by playing a five round practice module of the game, during which they are allowed to ask any questions about the game. At the end of the practice module, all remaining rounds are played in the order randomly assigned to the participant. When the player has completed all rounds, they are paid based on their performance and their participation is complete. Results of the game are only revealed through the final compensation to avoid ongoing learning.

The following subsection details the game's overall design. Subsequently, I describe the individual game modules used to create different forms of identifying variation. Then, I describe the randomization procedure. The final subsection provides characteristics of the participants in the sample.

4.1 Game Design

This subsection provides details on the game design. All the information in this subsection is also provided to the participant.

Setting

The participant plays a multiple-round game. In each round of the game, he lives in a hypothetical village with hypothetical fellow villagers, referred to as *characters*. He is considering adoption of a hypothetical agricultural technology. The technology, village, and the characters are different in each round. In each round, he has not yet adopted this technology, and has no direct experience with it. However, some of the other characters in the game experimented with the technology last season. The participant's goal is to use the information shared with him by these characters to decide how intensively to adopt the new technology on his own plot.

Signals

Each character privately shares his experience with the technology with the participant. These private signals are shared using emojis from a 7-point Likert scale, reflecting their perceived value of the technology over the status quo alternative.[13] The scale is illustrated in Figure 6.

Figure 6: Signal Likert Scale

Character Types

There are two types of villagers: the 'orange' type and the 'blue' type. The participant is the orange type. Types denote contexts: two characters with the same type have all the opportunity costs, soil patterns, and other factors that could impact a technology's efficacy. Accordingly, the returns to the technology are identical within type.

However, signals are not identical across types. The hypothetical technology has less value for blue types. This disparity is expained using an example about rainwater catchment technology. In the example, blue types represent villagers with better alternative water access (e.g. adjacency to a river), while orange types represent those on more arid land. This highlights that the underlying value of the technology is unchanged, but the returns are heterogeneous based on plot type.

The participant is told the exact magnitude of this difference varies per module. All modules used for our main hypotheses provide full information about the translation. Section 4.2 provides additional details about individual modules.

Sampling Error

Two characters with the same type may share different signals with the participant. These differences arise due to *sampling error*. Sampling error is explained as a consequence of issues such

[13] There is a recent, extensive literature in the field of human-computer interaction on how to best visualize data, including visualizing uncertainty. One recent overview of trade-offs in this literature can be found in Kim, Moritz, and Hullman (2021). This project optimized visualization for its settings, where participants were not ubiquitously familiar with bar charts and had wide heterogeneity in education. While past research does feature concerns about emoji use, these concerns impact cross-sectional analysis (i.e. Alismail and Zhang 2020; Lu et al. 2016). I avoid these concerns by using a within-subject design, wherein I study the impact on differences in each participant's technology adoption across rounds.

as implementation error. These differences would disappear with greater testing. However, each character has only a single season of experience with the technology on a single plot of land.

Orange types experience the same amount of sampling error as blue types. The signal distribution for one type is therefore a scalar shift of the signal distribution for the other type. The scalar shift matches the difference in returns. For example, if the difference in returns across types is two units, the empirical distribution of signals seen from orange characters will be identical to that of blue characters, but shifted up by two units.

Context Uncertainty

Some fraction of characters will share their signal but their type is unknown. Visually, these characters appear as a gray, instead of blue or orange. The participant still sees the signal from these gray characters, but does not know whether their type is blue or orange. This is illustrated in Figure 7.

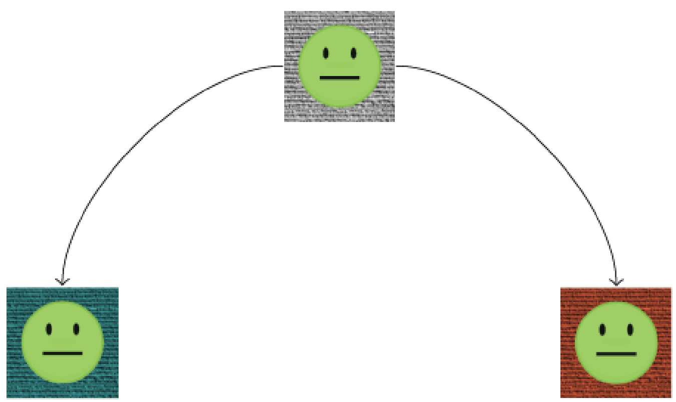


Figure 7: A Gray Character Has Context Uncertainty

A gray character is equally likely to be a blue or orange character. Consequently, the blue and orange distributions remain equivalent under a scalar shift. The percentage of gray characters will vary across rounds. This variation, within users but across rounds, is the main source of identification for testing behavior towards context uncertainty.

Adoption Decision

The participant's plot features ten rows. He must decide, given the information presented in a round, how many rows to adopt the hypothetical technology on. To ease the mapping between signals and adoption decisions, a Likert Scale is provided underneath the sliding tool used to select adoption intensity, as illustrated in Figure 8.

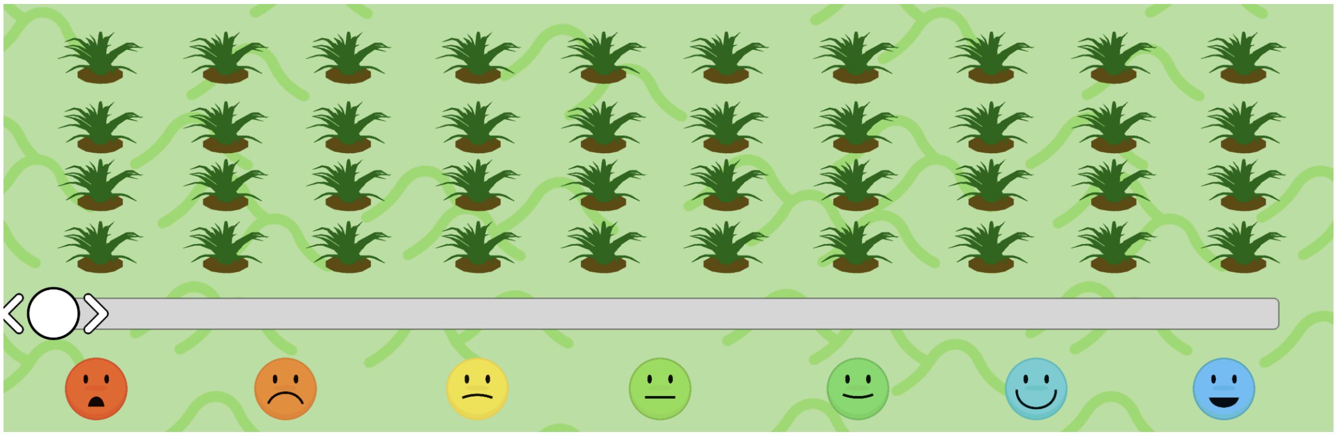


Figure 8: Sliding Scale For Selecting Adoption Intensity

Payout

The participant's total compensation for playing the game is between 100 and 300 rupees, depending on performance. Compensation is designed to average around 200 rupees, approximately a half day's wage. In each round, yield is maximized by selecting the intensity equal to the true underlying mean signal for the orange type. The mobile game computes the absolute deviation in each round and determines total compensation by adding performance across all rounds. The total compensation owed is provided once the participant completes the game.

4.2 Module Descriptions

The game is divided into seven modules. The first module consists of five rounds and is unincentivized; it serves as a practice module to familiarize participants with the game. All remaining modules are incentivized and consist of only two rounds.

I test my two primary hypotheses, the comparative statics results derived in Section 3, using only two of the seven modules. The remaining modules test various possible non-neoclassical behaviors outside the scope of my model, but that may affect participant behavior. These are described in Appendix Section B and analyzed in Appendix Section C.

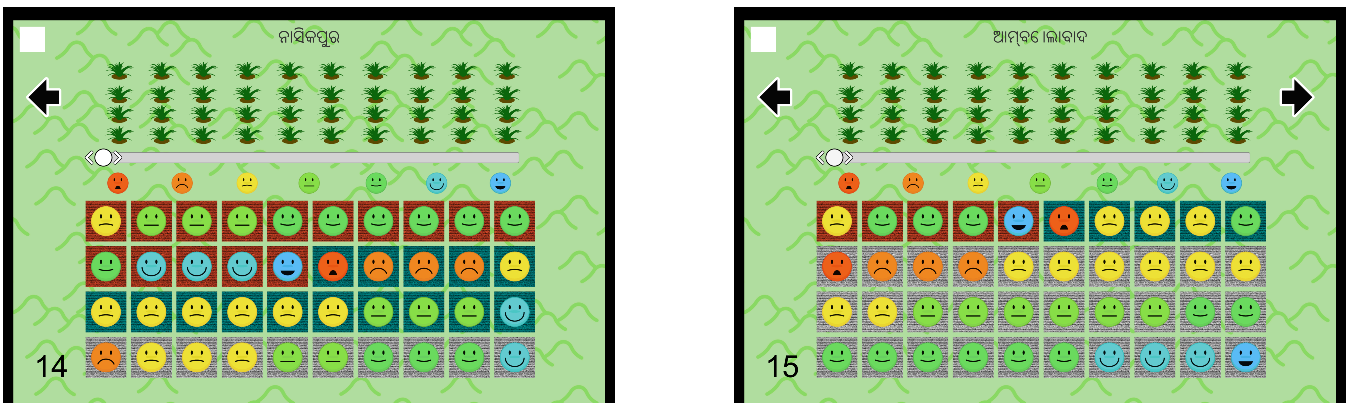
Context Uncertainty Under High Signal Error Module (CU:HSE)

In this module, participants are told that the technology works exactly two units better for orange types than blue types. This is visualized in Figure 9. I implement high signal error by setting a wider distribution of possible emoji signals within each type.[14] Both rounds feature 40 characters,

[14]The maximum signal error is limited by only having seven possible signal values. Signals have to be translatable

and an equal number of blue and orange type characters. One round features 30 characters with unknown (gray) type out of the 40 total characters. The other round features only 10 characters with unknown type. The two rounds are illustrated in Figure 10.

Figure 9: Signal Adjustment Across Types



(a) Low Context Uncertainty

(b) High Context Uncertainty

Figure 10: Rounds in the Context Uncertainty Under High Signal Error Module

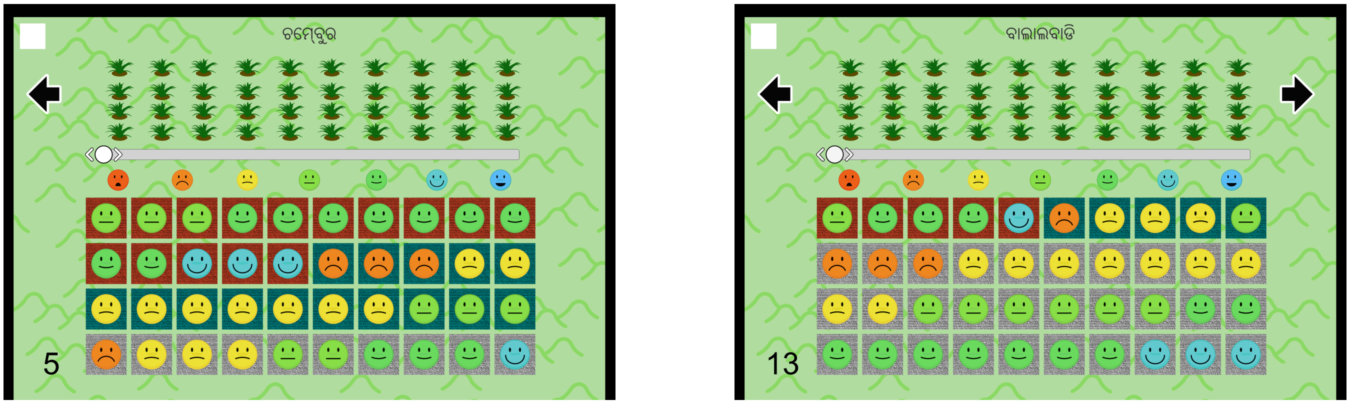
Context Uncertainty Under Low Signal Error Module (CU:LSE)

This module is identical to the previous module, except that signal error is lower. The two rounds are illustrated in Figure 11. As discussed in Section 4.3, the order of the rounds within and across modules is not kept constant; it is randomized across participants.

4.3 Randomization

My experimental design relies on identifying differences in adoption across rounds. To ensure I measure the impact of my variation, and not confounding factors, my experimental design randomizes the order of (i) the rounds being played, (ii) the technologies being adopted, and even (iii)

across types, and signals translate by two units across types. Consequently, the distribution of signals within each type is limited to existing on five units.



(a) Low Context Uncertainty (b) High Context Uncertainty

Figure 11: Rounds in the Context Uncertainty Under Low Signal Error Module

the names of the hypothetical villages. The order of each is randomized across participants and each is randomized separately.

Round order is perhaps the most important dimension for randomization. This is for multiple reasons. First, one could expect participants learning across rounds thus having different behavior in later rounds. Avoiding this requires randomizing how many rounds appear before the round of interest. Second, relative round order may also be important. For example, a participant may respond differently to a high context uncertainty round depending on whether or not it was preceded by the low context uncertainty round.

To avoid either of these channels, I randomize both the order of modules and the order of rounds within modules. Following the recommendation of McKenzie (2022), I implement a matched quartet design. The index assigned to each participant is based on data summarized in the following subsection on sample characteristics and collected during an initial listing survey. A detailed algorithm is provided in Section D.

4.4 Sample Characteristics

My experiment takes place in the state of Odissa, India. A listing survey was conducted in two districts, Khorda and Cuttack. During the listing, field staff identified 1,868 potential respondents meeting a set of five criteria. First, all individuals had to own five or fewer acres of land to meet the criteria of our population of interest, small or marginal farmers. Second, the individual needed to be the primary decision maker for their plot of land, and thereby be in charge of technology adoption decisions. A third restriction was placed on age: respondents could be a maximum of 60 years old. Early piloting suggested that individuals above this age often deferred actual control to younger members of the household, such as a son. Fourth, I also excluded individuals who did not primarily cultivate their own land, as sharecroppers face different incentives when deciding whether to adopt a new agricultural technology. Finally, potential respondents needed to be in contact with their extension agent, locally known as a Village Agricultural Worker (VAW), so that they could answer questions about how they perceive the VAW compared to other information sources.

Of the 1,868 identified individuals, 27 were dropped due to incomplete listing data. Table 1 summarizes the mean and standard deviation of the remaining individuals across a variety of attributes collected during the listing survey. The remaining individuals were randomly assigned to one of 64 treatment arms according to Section 4.3. 25 individuals per arm (1,600 in total) were designated as *primary* respondents at random. The remaining respondents were designated as backup respondents in the event that the enumeration team could not reach a primary respondent.

Table 1 illustrates a non-trivial amount of heterogeneity within our sample. This heterogeneity was used in two ways. First, these variables are used in Section 4.3 to create an index for stratified randomization. Second, Section 5 explores the heterogeneous impact of context uncertainty along these attributes.

Table 1: Sample Characteristics

Characteristic	Mean (SD)
Age	44.48
	(8.14)
Monthly Expenses (INR)	$6,628.27$
	$(4,052.09)$
# Of Dependents	2.79
	(1.03)
# Of Crops Grown In Last 12 Months	4.40
	(3.43)
% Employed In Village During Lean Season	59.6
% Migrating Elsewhere During Lean Season	19.4
% Self-identifying As Early Adopters	50.0
% Married	93.5
% Completed School Until 12th Standard	24.7
Observations	1,841

Notes: This table shows means of key attributes for all eligible individuals from the listing survey. Standard deviations are in parenthesis. 1,600 individuals from this sample were designated as primary households. The remaining households were designated as backup households during randomization. Monthly expenses winsorized at 99th percentile.

5 Results

This section tests the reduced form implications derived from the model from Section 3 using data from the lab-in-the-field experiment. Because the participant population consists of small and marginal farmers, I assume that the minimal assumption imposed by the theoretical propositions are met. Namely, evidence shows that these farmers exhibit not only risk aversion but also decreasing absolute risk aversion (DARA) (Bar-Shira, Just, and Zilberman 1997).

Testing Proposition 3.1: Does Context Uncertainty Reduce Adoption?

The first hypothesis is that risk-averse individuals reduce adoption as context uncertainty increases. My results are consistent with this hypothesis: within each module, farmers adopt more intensively in rounds with lower context uncertainty.

Testing the hypothesis is straightforward under my experimental design. In each of the two modules discussed in Section 4.2, there were two maps: one with high context uncertainty and one with low context uncertainty. Exploiting this, we can use the following regression specification:

$$\text{Adoption Choice}_{i,t} = \beta_0 + \beta_1 \cdot \mathbb{1}(t = \text{High Context Uncertainty}) + u_i + \epsilon_{i,t}.$$

In this specification, $\mathbb{1}(t = \text{High Context Uncertainty})$ is a dummy variable for whether the data was collected in the high context uncertainty round. u_i is an individual level fixed effect, which is observed because each participant plays each round.

The hypothesis here is directional: if context uncertainty reduces adoption, $\beta_1 < 0$. I test this hypothesis with data from three cases. First, I test it using data from the high signal error module. Second, I test it separately using data from the low signal error module. Third, I pool the data from both modules.[15] The results of these regressions are illustrated in Figure 12. A table is

[15] Pooling across modules with different levels of signal error does not impact interpretation of magnitudes. This is because the high context uncertainty round in both modules are identical in all aspects except within-type variance of emoji, and the same is true for the low context uncertainty rounds. As a result, the change in the level of context uncertainty is the same across modules: participants see either 10 or 30 characters with unknown (gray) type.

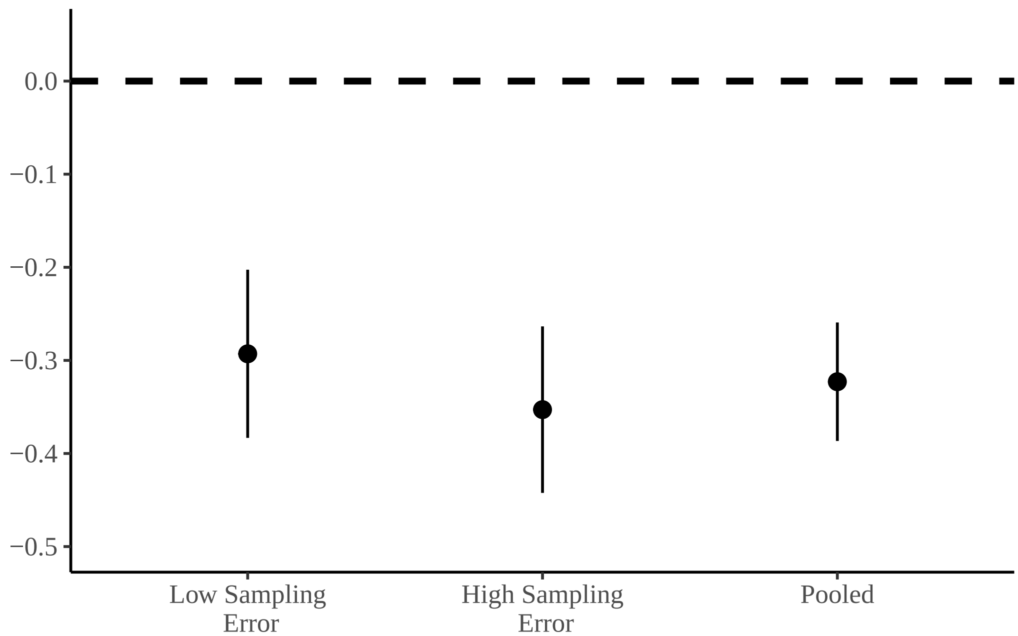


Figure 12: Coefficients for effect of increasing context uncertainty on adoption intensity

also provided in Table A1. All three specifications show evidence that context uncertainty reduces adoption.

How did this impact the distribution of adoption? Figure 13 provides histograms of adoption intensity by participants in each module, comparing adoption under high versus low context uncertainty. The results of the one-sided Kolmogorov–Smirnov test in each module are significant. Further, it is possible visually inspect and see the distribution shifting towards lower levels of adoption intensity under higher context uncertainty in each module.

These results cumulatively suggest that the main hypothesis holds: higher context uncertainty leads to lower levels of adoption.

Future work in this section will explore the heterogeneity of this effect. Using gathered data on traits such as level of consumption and education, I will explore the relationships between these traits and in-game behavior within these modules.

Testing Proposition 3.2: Are Context Uncertainty and Sampling Error Complements?

The second hypothesis has to do with the relationship between context uncertainty and sampling error. A more general interpretation of Proposition 3.2 is that the relationship between context uncertainty and sampling error have on jointly impacting adoption intensity depends on an in-

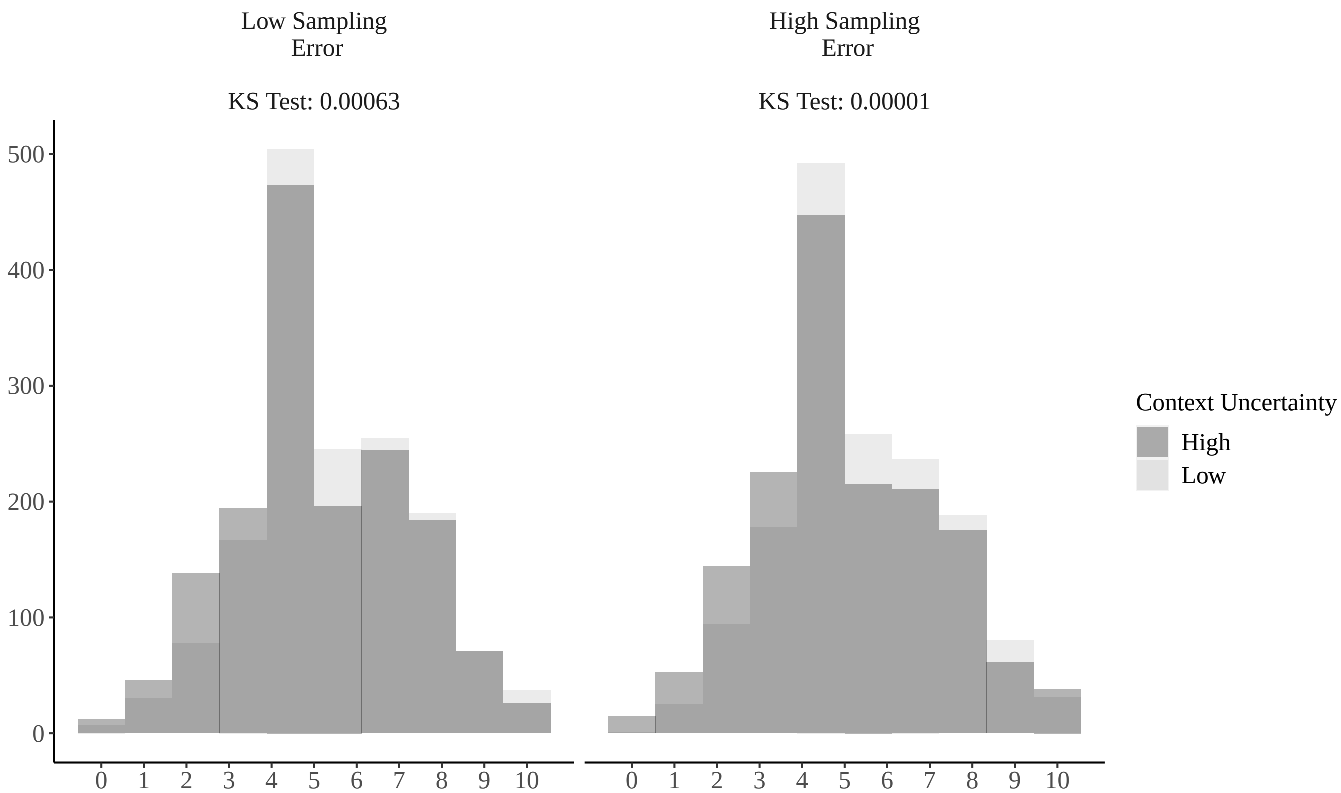


Figure 13: Histograms of Adoption Intensity by Level of Context and Signal Uncertainty

dividual's risk preferences. If the individual has decreasing absolute risk aversion (DARA), the theorem states that these two forms of uncertainty are complements. Alternatively, under increasing absolute risk aversion (IARA), these two forms of uncertainty are substitutes. Finally, if an individual's absolute risk aversion is constant (CARA), we expect the two forms of uncertainty to be independent.

Following prior work on testing complementarities [e.g. Athey and Stern (1998); Cassiman and Veugelers (2006)][16], I test for complementarity using a difference-in-difference approach. This approach is illustrated in Table 2, where each α parameter denotes the level of adoption chosen by participants in a given information environment. The ultimate parameter of interest is the sign of $(\alpha_{HH} - \alpha_{HL}) - (\alpha_{HL} - \alpha_{LL})$. If negative, it provides evidence in favor of DARA and complementarity.

The specification for this test can be written as:

[16] These prior works often focused on testing complementarities in organization design as it pertains to firm performance. My method has been referred to in this literature as the "direct approach" or the "production approach" to testing complementarity. The direct approach does face endogeneity issues in that literature, because firm design and innovation strategy are often endogenous. However, endogeneity is not an issue in my analysis because my dimensions of interest have been randomized.

Table 2: Difference in Difference Design for Testing Complementarity

		Context Uncertainty		
		Low	High	Difference
Sampling Error	Low	α_{LL}	α_{LH}	$\alpha_{LH} - \alpha_{LL}$
	High	α_{HL}	α_{HH}	$\alpha_{HH} - \alpha_{HL}$
	Difference	$\alpha_{HL} - \alpha_{LL}$	$\alpha_{HH} - \alpha_{LH}$	$(\alpha_{HH} - \alpha_{HL}) - (\alpha_{HL} - \alpha_{LL})$

$$
\begin{aligned}
\text{Adoption Choice}_{i,t} = \beta_0 &+ \beta_1 \cdot \mathbb{1}(t = \text{High Context Uncertainty}) \cdot \mathbb{1}(t = \text{High Sampling Error}) \\
&+ \beta_2 \cdot \mathbb{1}(t = \text{High Context Uncertainty}) \cdot \mathbb{1}(t = \text{Low Sampling Error}) \\
&+ \beta_3 \cdot \mathbb{1}(t = \text{Low Context Uncertainty}) \cdot \mathbb{1}(t = \text{High Sampling Error}) \\
&+ \beta_4 \cdot \mathbb{1}(t = \text{Low Context Uncertainty}) \cdot \mathbb{1}(t = \text{Low Sampling Error}) \\
&+ u_i + \epsilon_{i,t}.
\end{aligned}
$$

However, this formulation can be difficult to interpret. It features multiple events, each with a different coefficient whose sign and magnitude both matter for the final test. Instead, I formulate a variable combining multiple dummy terms from the above specification:

$$
\begin{aligned}
\text{Difference}_{i,t} = &[\mathbb{1}(t = \text{High Context Uncertainty}) \cdot \mathbb{1}(t = \text{High Sampling Error}) \\
&- \mathbb{1}(t = \text{High Context Uncertainty}) \cdot \mathbb{1}(t = \text{Low Sampling Error})] \\
&- [\mathbb{1}(t = \text{Low Context Uncertainty}) \cdot \mathbb{1}(t = \text{High Sampling Error}) \\
&- \mathbb{1}(t = \text{Low Context Uncertainty}) \cdot \mathbb{1}(t = \text{Low Sampling Error})].
\end{aligned}
$$

Using this new term, we can rewrite our specification as:

$$
\text{Adoption Choice}_{i,t} = \beta_0 + \beta_1 \cdot \text{Difference}_{i,t} + u_i + \epsilon_{i,t}.
$$

As a consequence of this specification, complementarity is now succicinctly tested by whether $\beta_1 < 0$. The result of this estimation is in Table 3. While the coefficient is suggestive of complementarity, the standard error implies a low level of statistical significance. Similarly, a one tailed test yields a p-value of 0.177.

Table 3: Regression output for test of complementarity

	(1)
Difference	-0.0150
	(0.0162)
R^2	0.33917
Observations	6,336
Individual fixed effects	✓

It is possible that these two sources of uncertainty are not complements. If so, this has important implications for those designing information provision: a reduction in context uncertainty will not increase the marginal value of reducing sampling error. However, two separate issues with the experiment suggest that the test is simply underpowered.

Because this specification involves testing an interaction, a much larger sample size is needed for the same level of statistical power(i.e. Gelman, Hill, and Vehtari 2020; Gelman 2018). One issue impacting power in this design is the desired effect size being measured. While context uncertainty could be substantially varied across rounds, switching from 25% to 75% of characters being of unknown types, the sampling error could not be as dramatically altered. This issue arose due to the combination of having a limited number of possible signal values, the limited number of tiles that fit on a tablet screen, and the requirement that the empirical distribution remain the same across types and context uncertainty rounds. Even if participants' utility functions exhibit the curvature needed for DARA, they may still be locally linear given the small difference in sampling error.

Another issue impacting power is noise. The experiment relied heavily on enumerators providing proper instructions to participants, ensuring that all relevant details were provided. Poor instructions lead to a form of measurement error that also reduces statistical power. Out of twenty five enumerators, three were eventually dismissed due to their performance in providing instructions in the field. Table A2 shows the impact of dropping data from these enumerators. This table provides an estimate that is both more negative and more statistically significant, with a one-tailed p-value of 0.062.

Overall, these results are suggestive of complementarity, but highlight the need for future work replicating this test. The ramifications for policymakers are substantial: understanding whether context uncertainty impacts how sampling error is perceived is important for designing information provision, especially when the cost of additional testing is high.

6 External Validity

This section will be updated in the future to include a discussion of external validity. I will do so using two distinct approaches. First, I will use survey data collected from experiment participants about their beliefs and perceptions of different sources of information when making real life decisions about agricultural technology adoption. Second, I overview a variety of agricultural extension program designs in the literature and show that the history of which designs are effective is consistent with this paper's model of context uncertainty.

7 Estimating Context Uncertainty Aversion

Throughout the paper, I have modeled context uncertainty as an additional form of risk. An implication of this modeling approach is that, because expected utility models agents as having a single risk aversion parameter, I have been unable to compare aversion to context uncertainty versus aversion to sampling error. However, my experimental design allows me to identify these parameters separately. This section will be expanded in the future to use the nested approach of Klibanoff, Marinacci, and Mukerji (2005) for modeling smooth ambiguity, developing a structural model that separately tests aversion to each form of uncertainty compare these parameters.

8 Conclusion

This paper presents evidence that context uncertainty is a significant factor in how individuals weigh signals when learning about new technologies. I show that this behavior exists in a well identified laboratory setting. I also provide evidence of external validity to farmers' real world decisions about agricultural technologies and recommendations provided by extension agents.

One weakness of this paper's approach is that it does not provide a new, actionable design for policymakers. An important direction for future field research is understanding how to most efficiently design information provision to reduce context uncertainty. A companion project is currently under development to address this question.

Further, this project focuses on agricultural technology adoption in developing countries. However, examples of potential context uncertainty aversion can be found in a variety of settings, most recently in medicine (Alsan et al., n.d.). However, there is evidence of agents exclusively caring about sampling error in other contexts, such as policymaking (Hjort et al. 2021). An open area for future research is understanding both which settings context uncertainty is important within and the reasons for these differences.

A related area of importance is better understanding the relationship between education and context uncertainty aversion. Do certain forms of education increase an individual's ability to extrapolate information from sources with different characteristics? Do individuals highly educated in statistics, such as the policymakers in Hjort et al. (2021), learn to neglect context uncertainty?

The interaction between homophily and context uncertainty is another important area of exploration. Related questions have been explored theoretically, including Sethi and Yildiz (2016) and Baccara and Yariv (2013). However, several open questions remain about how the arrival of new technologies impacts homophily. For example, if an individual anticipates a high rate of new technologies arriving in the future, and expects to be uncertain about how to translate signals from other sources, are they more likely to form homophilous ties? Is this tendency reduced by improving education? Each of these questions poses interesting avenues for future theoretical and empirical research.

Overall, this project provides an important first step in a research agenda formally studying a common feature in previously effective information provision designs. Having been identified in a lab, there are now a number of useful extensions for future work. This project will hopefully also help information provision designers to better understand why certain designs have worked more effectively in the past and more efficiently modify future designs.

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A The Impact of Priors on Measuring Adoption

B Design of Behavioral Modules

C Results from Behavioral Modules

D Randomization Algorithm

E Tables for Primary Hypotheses

Table A1: Regression output for effect of increasing context uncertainty on adoption intensity

	Low Sampling Error (1)	High Sampling Error (2)	Pooled (3)
High Context Uncertainty	-0.2929***	-0.3529***	-0.3229***
	(0.0461)	(0.0456)	(0.0325)
R^2	0.81466	0.82333	0.34465
Observations	3,168	3,168	6,336
Individual fixed effects	✓	✓	✓

Table A2: Regression output for test of complementarity without dropped enumerators

	(1)
Difference	-0.0253
	(0.0164)
R^2	0.34177
Observations	5,936
Individual fixed effects	✓

F Proofs

Proof of Proposition 2.1

Proof. The distributions of each signal is centered at $\theta + \gamma_i$. Assume without loss of generality that the extension agent's signal, S_E^A, has greater variance. We can parameterize the difference in variance between the signals as

$$\delta = (\sigma_E^2 + (\sigma_E^\gamma)^2)) - \left(\sigma_j^2 + (\sigma_j^\gamma)^2)\right).$$

Next, consider a signal $s_k^A = s_j^A + \zeta$ where $\zeta \sim \mathcal{N}(0, \delta)$ and independent of all other random variables composing s_j^A. Because ζ is independent Gaussian noise with mean 0, s_k^A is considered a *garbling* of s_j^A. This is equivalent to the agent preferring s_j^A over s_k^A by Blackwell's Theorem (Blackwell 1951, 1953). Next, observe that $s_k^A \sim_A \mathcal{N}(\theta + \gamma_i, \sigma_j^2 + (\sigma_j^\gamma)^2 + \delta)$. By construction of δ, this implies $s_k^A \sim_A \mathcal{N}(\theta + \gamma_i, \sigma_E^2 + (\sigma_E^\gamma)^2)$, and so s_k^A and s_E^A are equivalent signals about θ_A. By transitivity, the agent prefers s_j^A over s_E^A.

□

Proof of Proposition 3.1

Proof. Note that the decision problem in Equation 10 can be expanded to

$$\alpha^* = \arg\max_{\alpha} \int_{\theta_A} \int_{\epsilon_{A,1}} \int_{\epsilon_{A,0}} \int_{\nu_A} u\left(1 + \nu_A + \epsilon_{A,0} + \alpha(\theta_A + \epsilon_{A,1} - \epsilon_{A,0})\right) dF_{\nu_A} dF_{\epsilon_{A,0}} dF_{\epsilon_{A,1}} dF_{\theta_A}.$$

Integrating over the distributions of our independent exogenous shocks $\epsilon_{A,0}, \epsilon_{A,1}$, and ν_A yields

$$\alpha^* = \arg\max_{\alpha} \int_{\theta_A} E\left[u\left(1 + \nu_A + \epsilon_{A,0} + \alpha(\theta_A + \epsilon_{A,1} - \epsilon_{A,0})\right)\middle|\, \epsilon_{A,0}, \epsilon_{A,1}, \nu_A\right] dF_{\theta_A}.$$

The precision of a univariate distribution is simply the inverse of its variance. To compress notation and focus on our parameters α and θ_A, we let

$$v(Y_A(\alpha, \theta_A)) \equiv E\left[u\left(1 + \nu_A + \epsilon_{A,0} + \alpha(\theta_A + \epsilon_{A,1} - \epsilon_{A,0})\right)\middle|\, \epsilon_{A,0}, \epsilon_{A,1}, \nu_A\right]$$

and rewrite our maximization problem as

$$\alpha^* = \arg\max_{\alpha} \int_{\theta_A} v(Y_A(\alpha, \theta_A)) f_{\theta_A}(t; 1/\tilde{\sigma}_0^2) dt$$

where $f_{\theta_A}(t; 1/\tilde{\sigma}_0^2)$ denotes the probability density function of θ_A as a function of precision in the posterior belief, $1/\tilde{\sigma}_0^2$.

Our proof will take three steps. First, we will show that α^* is nondecreasing in the overall precision of the posterior $1/\tilde{\sigma}_0^2$. Because precision is the inverse of variance, this immediately implies that α^* is nonincreasing in variance $\tilde{\sigma}_0^2$. Finally, we will show that this implies it is also nonincreasing in context uncertainty $(\sigma_j^\gamma)^2$ from any signal.

Recall that u is nondecreasing and concave. The conditional expectation is a linear operator. Thus, these properties are preserved; v is also nondecreasing and concave. This observation will be used shortly.

Note that Y_A is a linear function of the random variable θ_A. Consequently, for two values x'' and x', if the distribution $F_{\theta_A}(x')$ is a mean preserving spread of $F_{\theta_A}(x'')$, then $F_{Y_A}(\alpha, x')$ is a mean preserving spread of $F_{Y_A}(\alpha, x'')$. Because F_{θ_A} is parameterized by its precision, this is true whenever $x'' > x'$.

If a distribution B is a mean preserving spread of another distribution A, then A second-order stochastically dominates B. Further, a distribution A dominates B in the the second order if and only if $E[u(A)] \geq E[u(B)]$ for all functions u that are nondecreasing and concave.

We have now proven three facts. First, our function v is nondecreasing and concave. Second, for $x'' > x'$, $F_{Y_A}(\alpha, x')$ is a mean preserving spread of $F_{Y_A}(\alpha, x'')$. Third, if a distribution B is a mean preserving spread of another distribution A, then $E[v(A)] \geq E[v(B)]$ for all functions v that are non-decreasing and concave. Together, these imply that

$$E[v(F_{Y_A}(\alpha, x''))] \geq E[v(F_{Y_A}(\alpha, x'))].$$

Next, we borrow standard notation from expected utility theory and state that $U(\alpha, x) = E[v(F_{Y_A}(\alpha, x))]$. Therefore, we have proven that $U(\alpha, x'') - U(\alpha, x') \geq 0$ whenever $x'' > x'$. Shannon (1995) proves that α^* is nondecreasing in x if $U(\alpha, x)$ obeys the *weak single crossing property* in (α, x): for any $\alpha'' > \alpha'$ and $x'' > x'$,

$$U(\alpha', x'') \geq U(\alpha', x') \Longrightarrow U(\alpha'', x'') \geq U(\alpha'', x').$$

The weak single crossing property is trivially true for U in (α, x), because we proved that $U(\alpha, x'') \geq U(\alpha, x')$ whenever $x'' > x'$, regardless of α. Thus, we have proven that the agent's optimal share of adoption α^* is nondecreasing in the overall precision of the posterior, $1/\tilde{\sigma}_0^2$.

Because the precision is the inverse of the variance, it immediately follows that the agent's optimal share of adoption α^* is nonincreasing in the overall variance of the posterior, $\tilde{\sigma}_0^2$. Finally, it is immediate from Equation 8 that, all else held constant, $\tilde{\sigma}_0^2$ is increasing in the context uncertainty $(\sigma_j^\gamma)^2$ regarding any individual j. Because this relationship is monotonic, our comparative static is preserved: the agent's optimal share of adoption α^* is nonincreasing in the context uncertainty $(\sigma_j^\gamma)^2$ regarding any individual j.

□

Proof of Proposition 3.2

Proof. To show that, for an agent with DARA preferences, context uncertainty $(\sigma_j^\gamma)^2$ and sampling uncertainty σ_j^2 are decision complementary, we must show that the optimal level of adoption α^* is has the property

$$\alpha^*(\sigma_j^{\gamma''}, \sigma_j'') - \alpha^*(\sigma_j^{\gamma''}, \sigma_j') \geq \alpha^*(\sigma_j^{\gamma'}, \sigma_j'') - \alpha^*(\sigma_j^{\gamma'}, \sigma_j')$$

for all $\sigma_j^{\gamma''} \geq \sigma_j^{\gamma'}$ and $\sigma_j'' \geq \sigma_j'$.

If the agent's utility is thrice differentiable, then DARA implies $U''' > 0$. If so, the third partial derivative $\frac{\partial^3 U}{\partial\alpha\partial\sigma_j\partial\sigma_j^\gamma} > 0$. Our inequality immediately follows.

If the agent's utility is not thrice differentiable, we can still show decision complementarity. Assume for the sake of contradition that our inequality did not hold. Then for some $\sigma_j^{\gamma''} \geq \sigma_j^{\gamma'}$ and $\sigma_j'' \geq \sigma_j'$, we have

$$\alpha^*(\sigma_j^{\gamma''}, \sigma_j'') - \alpha^*(\sigma_j^{\gamma'}, \sigma_j'') < \alpha^*(\sigma_j^{\gamma''}, \sigma_j') - \alpha^*(\sigma_j^{\gamma'}, \sigma_j').$$

But, consider the impact of context uncertainty on any given realization of signal noise. Because the agent's preferences exhibit DARA, the agent is more risk averse at lower realizations than at higher realizations. Consequently, at high realizations of signal noise, the increase in context uncertainty will impact the agent's optimal adoption choice less at lower realizations.

Next, we can interpret an increase in signal noise as a mean preserving spread moving weight away from the mean and towards the tails, increasing the likelihood of extreme values. Because of DARA, this means that the impact, measured as the difference in optimal adoption as context uncertainty changes, is greater below the mean than above the mean.

Above mean realizations of signal noise, the impact of context uncertainty at the margin is reduced by the mean preserving spread. This is because the weight of the distribution is going towards higher signal error realizations where risk aversion is lower and context uncertainty has less impact. Below the mean, weight is being moved towards lower signal error realizations where risk aversion is higher and context uncertainty has more impact.

However, the mean preserving spread is more impactful below the mean than above the mean because DARA implies there is more concavity below the mean. Thus, a mean preserving spread redistributes weight towards realizations where changes in context uncertainty have greater impact.

It follows that our inequality cannot hold.

□