How Uncertainty About Heterogeneity Impacts Technology Adoption*

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Hossein Alidaee†

Abstract

Despite being supported by small sample sizes, peers' recommendations of new technologies are effective at disseminating information and inducing adoption. I propose one potential mechanism, which I refer to as context uncertainty. Because returns are heterogeneous across types or "contexts", individuals place more weight on recommendations from peers, whose contexts they know well compared to other information providers. I test this mechanism via a lab-in-the-field experiment with a sample of smallholder farmers. This mechanism provides a framework for central sources, such as government agencies, to improve their own informational interventions.

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†Northwestern University. Email: hossein.alidaee@kellogg.northwestern.edu

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 is uncertainty arising 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. 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 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 correlation neglect (Enke and Zimmermann 2019).[1] 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.

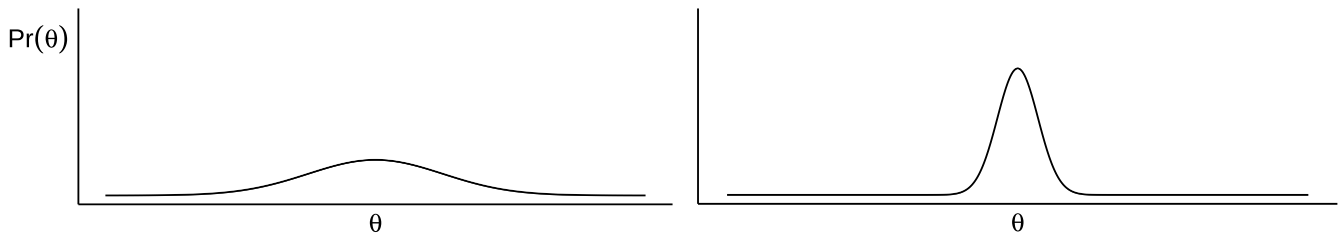
The analysis of the experiment and the survey data are consistent with the model: farmers prefer information from sources whose contexts they know well. Further, uncertainty from sampling error and context uncertainty are complements: the value of tighter statistical distribution is higher when the context 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.

First, consider a world with homogenous types. Here, all agents are interested in learning a single

[1] 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

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

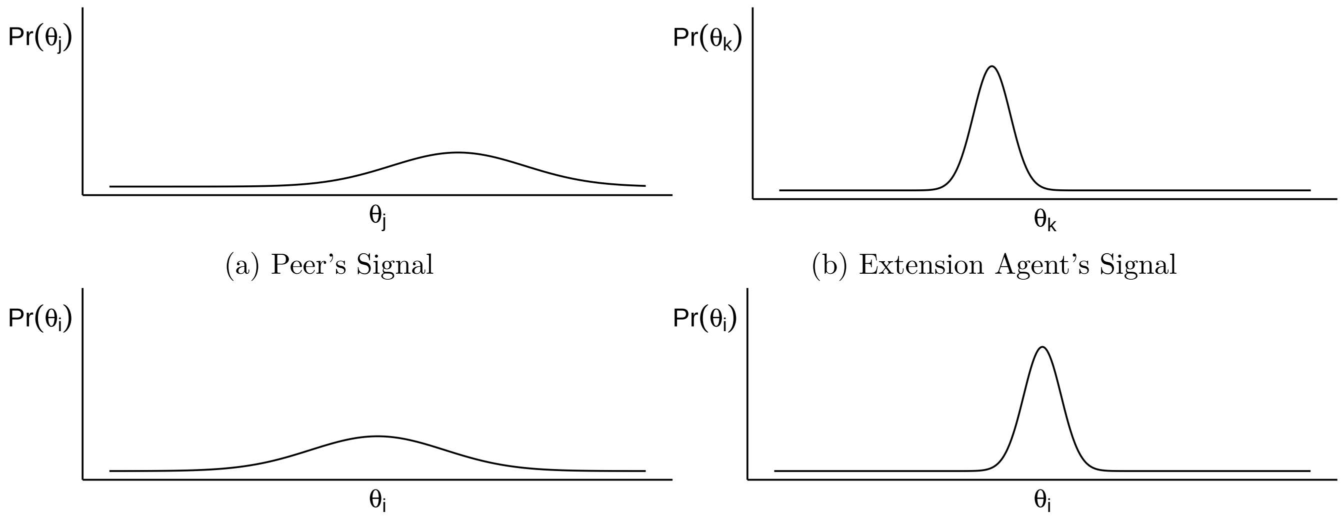
$$\underbrace{\theta_j}_{\text{Agent } j\text{'s Return}} = \underbrace{\theta}_{\text{Average Return}} + \underbrace{\gamma_j}_{\text{Agent } j\text{'s Context}} . \tag{1}$$

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.



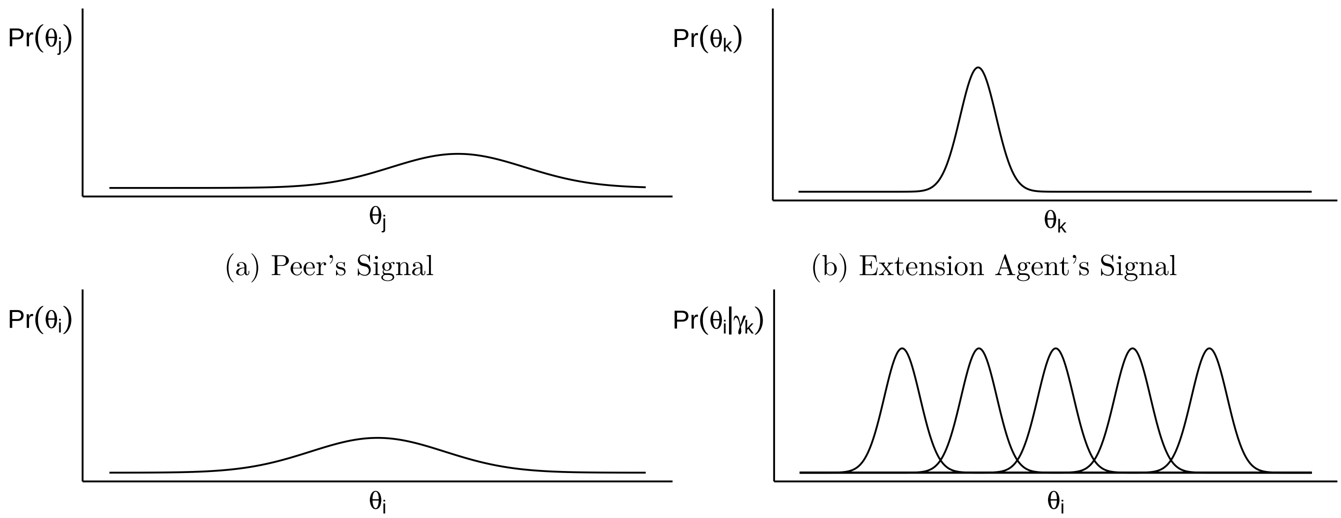
(a) Peer's Signal (b) Extension Agent's Signal

(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.



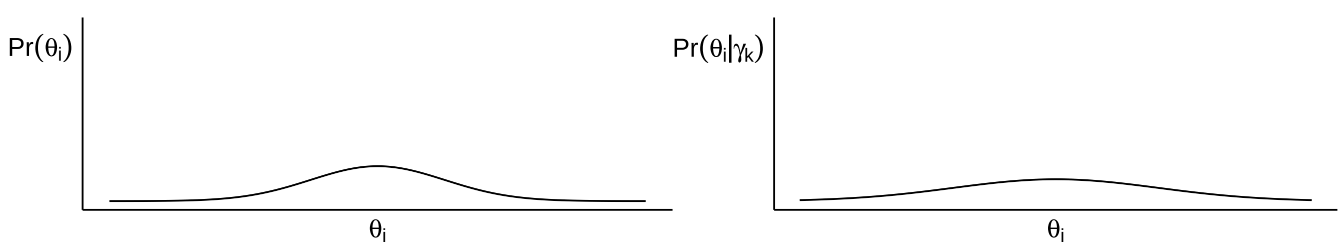
(a) Peer's Signal (b) Extension Agent's Signal

(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).[2] Prior work has also studied 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 [i.e. Athey (2002), Athey and Levin (2018), Shannon (1995)]. Unlike the stan-

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

dard 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 (n.d.) 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 $N = \{1, \dots, n\}$. 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.

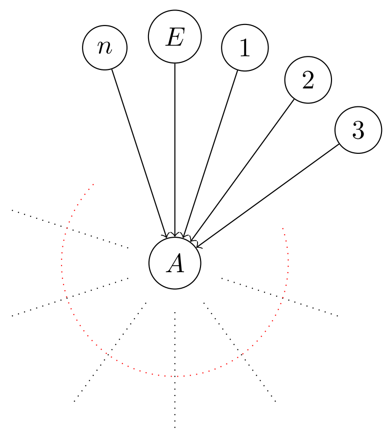


Figure 5: Signal Sharing Network S_{n+1}

Each individual $j \in \{1, \dots, n, E\}$ 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.[3] 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.[45]

2.2 Signal Translation

Before she can use the information from her peers, agent A first needs to 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 $\bar{\gamma}_j$ 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

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

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

[5]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.

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.[6]

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 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.[7]

It follows from Bayes rule for linear Gaussian systems[8] that agent A's posterior is distributed $\mathcal{N}(\tilde{\mu}, \tilde{\sigma}_0^2)$ where

[6] 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.

[7] 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:

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

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

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

and

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

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 the 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 $\sigma_j^\gamma = 0$.

A similar question asks which source a farmer would choose to listen to: her set of peers or the extension agent? Theorem 2.1 explains that, analogous to the issue of weighting signals in her posterior, the agent will always choose the signal with less variance.

Theorem 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 variance.

Proof. Both signals are distributions are 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.

□

However, Theorem 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 the final 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 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 $j \in \{1, \dots, n, E\}$ so all individuals have the same positive signal draw and the mean of the belief distribution is $\tilde{\mu} = \bar{\mu}$.[9]

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 Theorem 3.1.[10] A stronger version of this result can be obtained for strictly risk averse agents. The proof for this case is analogous.

Theorem 3.1. *Consider a risk averse agent A with utility u, which is nondecreasing and concave, and is 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.*

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

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

[9] 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.

[10] Theorem 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).

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.

□

So far, we have restricted our focus to the impact of context uncertainty in isolation.

Consider a risk averse agent A with utility u, which is nondecreasing and concave, 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 complementary: The agent's optimal level of adoption α^* is nonincreasing in context uncertainty from any signal.

4 Experimental Design

5 Results

6 External Validity

7 Estimating Context Uncertainty Aversion

8 Conclusion

9 References

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A The Impact of Priors on Measuring Adoption

B Proofs