

How Heterogeneity Impacts Learning

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Motivation

Social Learning Is Oddly Influential

Peers have limited experience

Authorities test recommendations extensively

Yet, both induce adoption at equal rates

- ▶ Krishnan and Patnam (2013)
- ▶ Takahashi, Mano, and Otsuka (2019)

Implies social learning is more influential *per data point*

What's the mechanism?

Natural questions:

- ▶ Why?

What's the mechanism?

Natural questions:

- ▶ Why?
- ▶ Is social learning special?

What's the mechanism?

Natural questions:

- ▶ **Why?**
- ▶ **Is social learning special?**
- ▶ **How can authorities improve?**

My Proposal: Context Uncertainty

Peer information comes with rich context

Information from authorities comes with little context

When weighing signals, we place weight on total uncertainty

Total Uncertainty = Context Uncertainty + Sampling Error

Related Literature

- ▶ Decision makers as statisticians
 - ▶ Steiner and Stewart (2008), Olea et al. (2021), Salant and Cherry (2020), etc..
- ▶ Social learning theory
 - ▶ Sethi and Yildiz (2016), Dasaratha et al (2022), Bala and Goyal (1998), etc...
- ▶ Information provision experiments
 - ▶ Jensen (2010), Chetty and Saez (2013), Binder (2020), etc...
- ▶ Role of heterogeneity in agents' responses to information
 - ▶ Armour (2018),
- ▶ Role of trust in agents' responses to information
 - ▶ asdf
- ▶ Agricultural technology adoption
 - ▶ asdf
- ▶ Agricultural extension design
 - ▶ asdf

Roadmap

Today:

- ▶ Relate question to agricultural technology adoption

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- ▶ Implications for farmers and policymakers

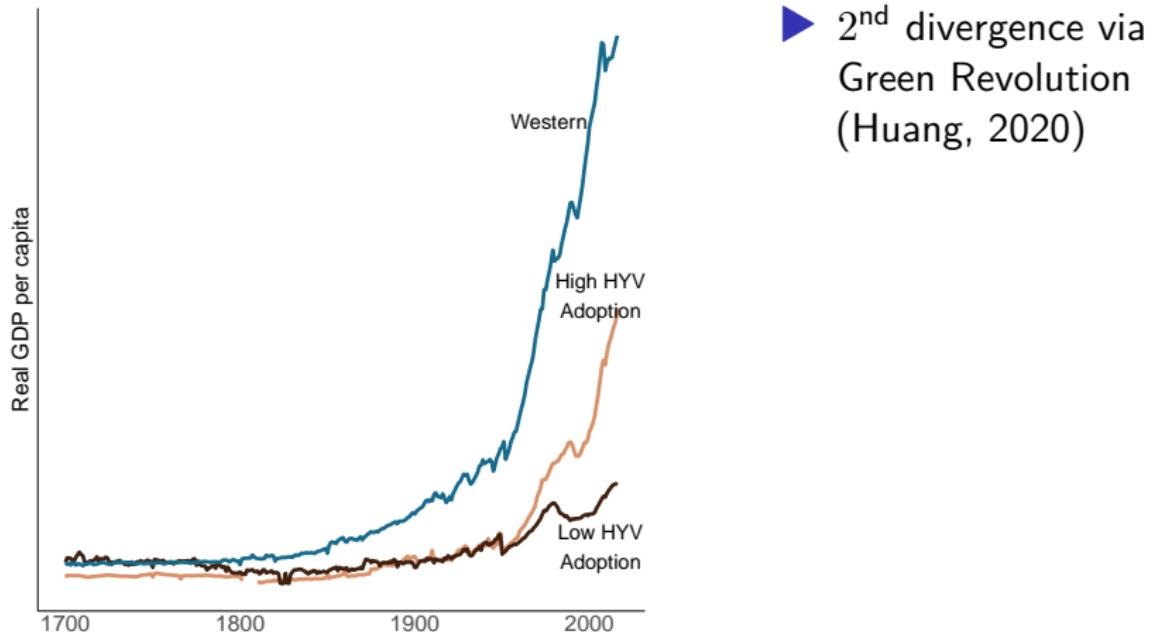
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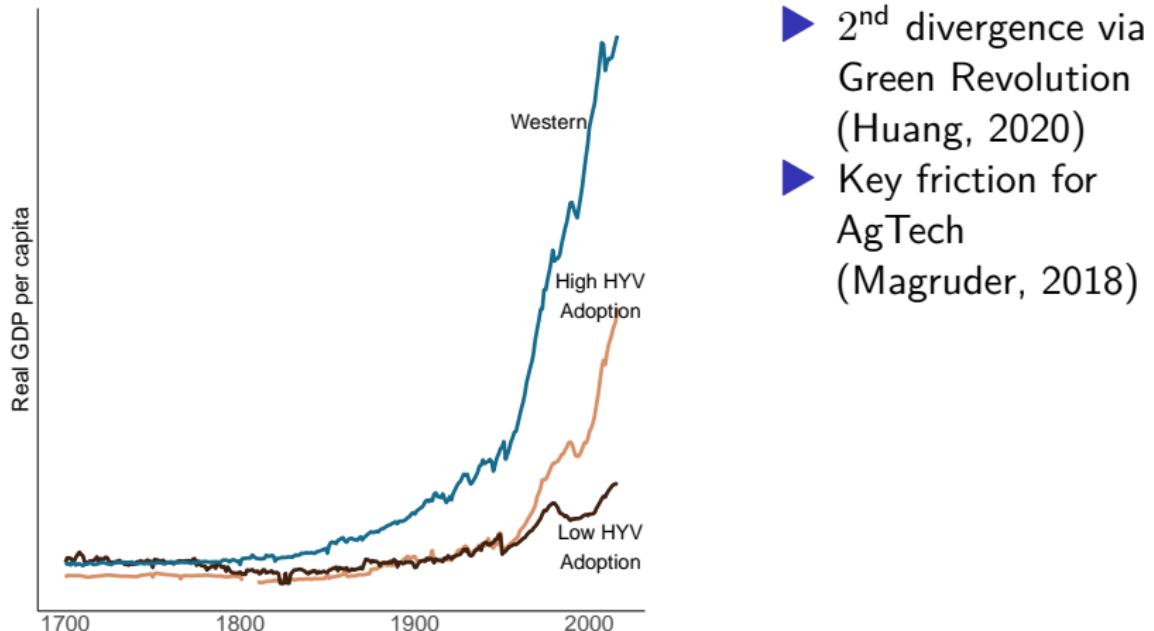
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- ▶ Implications for farmers and policymakers
- ▶ Upcoming extensions

Setting

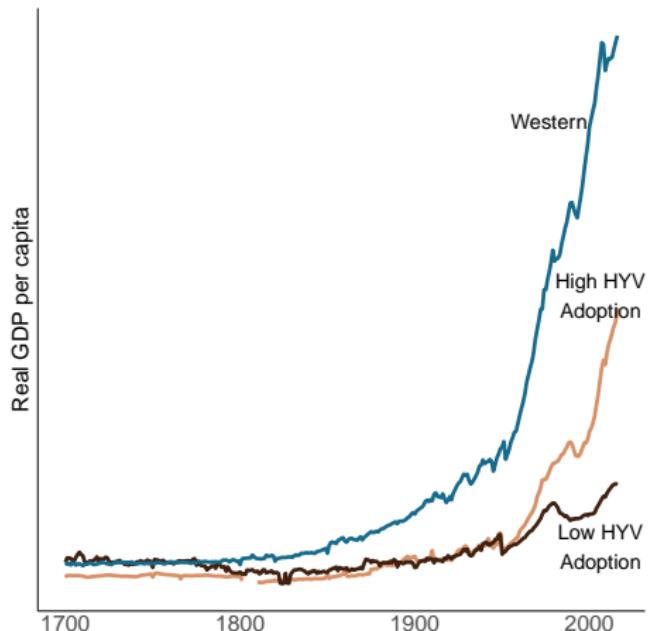
Low AgTech Adoption Is A Major Issue



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Low AgTech Adoption Is A Major Issue



- ▶ 2nd divergence via Green Revolution (Huang, 2020)
- ▶ Key friction for AgTech (Magruder, 2018)
- ▶ Governments spend huge sums on extension (Akroyd and Smith, 2007)

Traditional Extension Design

- ▶ R&D at university or national research institute



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- ▶ Villagers have no clue about test conditions



Microfoundation

The Farmer's Problem

Problem:

$$\underset{\alpha}{\operatorname{argmax}} E[U(\alpha \cdot \theta_i) | s_1, \dots, s_n, s_E]$$

Decision: Fraction of investment $\alpha \in [0, 1]$

Heterogeneity:

$$\theta_i = \underbrace{\theta}_{\text{average return}} + \underbrace{\gamma_i}_{\text{context adjustment}}$$

Belief: Posterior $\tilde{\theta}_i$

Preferences: Risk averse so

$$E[U(\alpha \theta_i)] \leq U(\alpha E[\theta_i]).$$

Interpreting Signals from peers

Friend j shares signal

$$s_j = \underbrace{\theta}_{\text{Average Return}} + \underbrace{\gamma_j}_{\text{Agent } j\text{'s Context}} + \underbrace{\epsilon_j}_{\text{Agent } j\text{'s Sampling Error}}.$$

Farmer's belief about γ_j is

$$\gamma_j \sim \mathcal{N}(0, (\sigma_j^\gamma)^2).$$

Farmer knows friend j well, so context uncertainty σ_j^γ is low.

Interpreting Signals from Authorities

Extension agent E shares signal

$$s_E = \underbrace{\theta}_{\text{Average Return}} + \underbrace{\gamma_E}_{\text{Agent's Context}} + \underbrace{\epsilon_E}_{\text{Agent's Sampling Error}}.$$

Farmer's belief about γ_E is

$$\gamma_E \sim \mathcal{N}(0, (\sigma_E^\gamma)^2).$$

Farmer doesn't know any context, so σ_E^γ is high.

Adjusting Signals for Context

How does the farmer adapt the signal to his own context?

$$\begin{aligned}\text{Adjusted Signal} = & \text{Original Signal} \\ & + \text{Own Context Adjustment} \\ & - \text{Friend's Context Adjustment}\end{aligned}$$

Implication:

↑ context uncertainty ↑ variance in adjusted signal

Our Farmer's Posterior

Using information from all sources, farmer updates his belief.

$$\text{Mean} \propto \frac{0}{\text{Prior Var}} + \frac{\text{Ext Adj Signal}}{\text{Ext Sample Var} + \text{Ext Context Var}} \\ + \sum \frac{\text{Peer Adj Signal}}{\text{Peer Sample Var} + \text{Peer Context Var}}$$

Less Context → Less Investment

Consider a strictly risk averse agent with utility U solving

$$\operatorname{argmax}_{\alpha} E[U(\alpha \cdot \theta_i) | s_1, \dots, s_n, s_E].$$

The agent's optimal level of adoption α^* is decreasing in context uncertainty from any signal.

Sampling and Context Precision Are Complements

Consider a strictly risk averse agent with DARA utility U solving

$$\underset{\alpha}{\operatorname{argmax}} E[U(\alpha \cdot \theta_i) | s_1, \dots, s_n, s_E].$$

For any signal s_j , the amount that the agent's optimal level of adoption α^* increases from a unit increase in sampling precision $1/\sigma_j^2$, is increasing in context precision $(1/\sigma_j^\gamma)^2$ from that signal.

Model Recap

- ▶ Heterogeneity can cause uncertainty about context

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- ▶ Heterogeneity can cause uncertainty about context
- ▶ Context uncertainty adds to signal noise
- ▶ Context can be adjusted for when certain
- ▶ **Hypothesis 1:** Higher context uncertainty reduces adoption if risk averse
- ▶ **Hypothesis 2:** Sampling and context precision are complements under DARA

Lab Experiment Design

Overview

- ▶ Lab-in-the-field experiment in rural Odissa

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- ▶ 1,600 small and marginal farmers

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Overview

- ▶ Lab-in-the-field experiment in rural Odissa
- ▶ 1,600 small and marginal farmers
- ▶ Decide whether to adopt a hypothetical technology
- ▶ Receive noisy signals from fictional characters
- ▶ Vary only context uncertainty
- ▶ Choose adoption level

Signals As Likert Scales

Everyone is learning about their θ_j

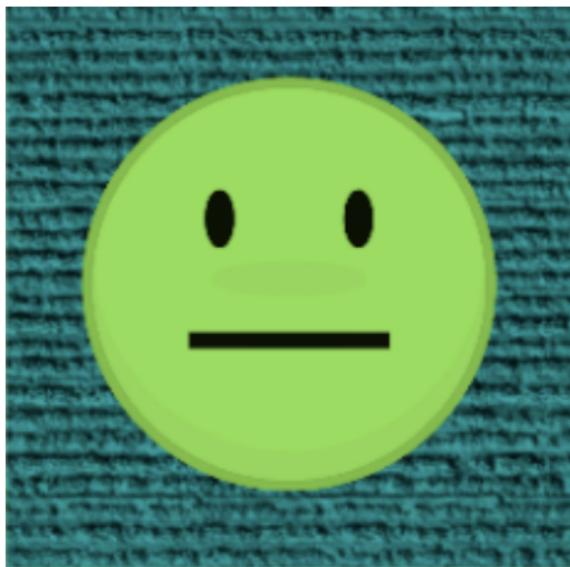
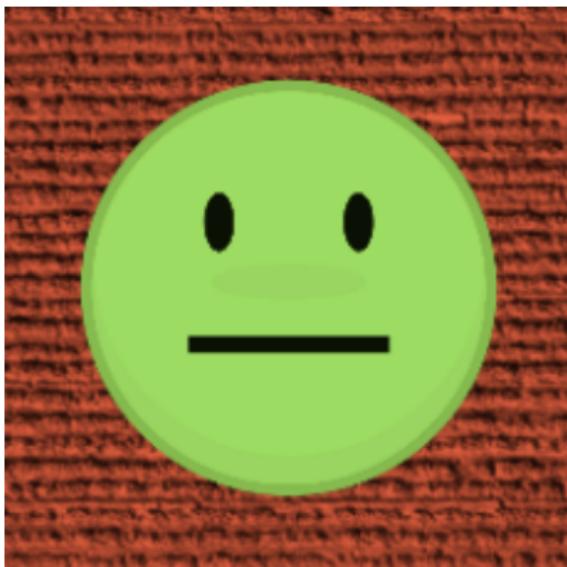
Report experience using an emoji Likert scale



Each signal s_j is shared only with the participant

Contexts As Types

Characters are one of two *types*: orange or blue



The participant is the orange type

Type is a summary of all dimensions of context

θ_O and θ_B are homogenous

Introducing Sampling Error

Even within type, s_j are not identical

Reflects idiosyncratic risk

Drawn from $\theta_O + \epsilon$ or $\theta_B + \epsilon$

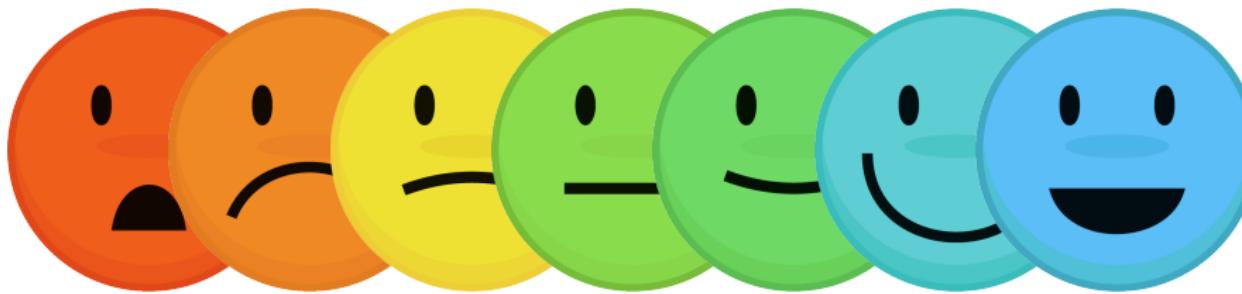
Error ϵ is identical and independent

Learning From Blue Types

Blue type always does worse

Provide story about rainwater catchment

Difference of two Emoji



What We Have So Far

So far, our game looks like this:



Where's the context uncertainty?

Where's the decision making?

Adding Context Uncertainty

Some characters have unknown type

They appear as gray

Could be either type



Deciding Adoption Intensity

Land divided into 10 rows

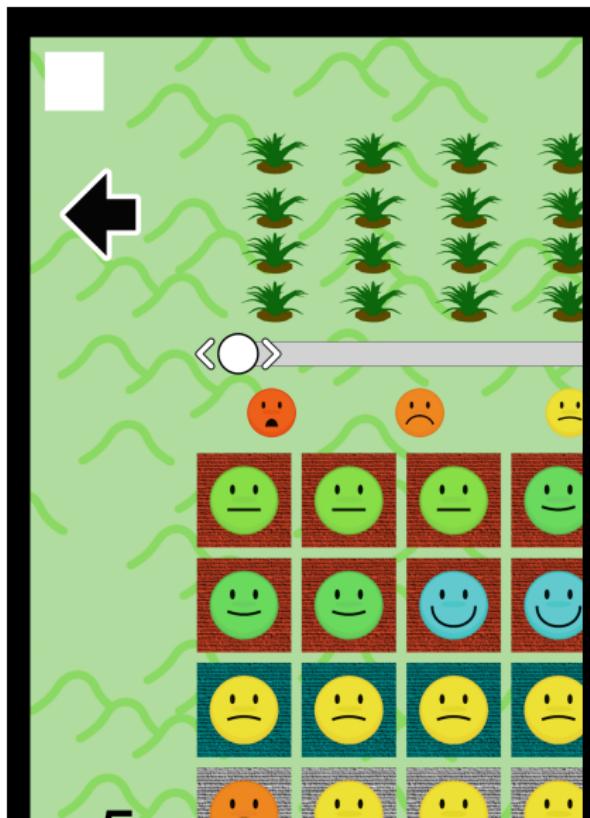
Must decide adoption maximizing yield

Mapped to Likert Scale



Bringing it all together

Player sees information and decides adoption level



Process and Randomization

- (1) Survey participant

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- (2) Read game script

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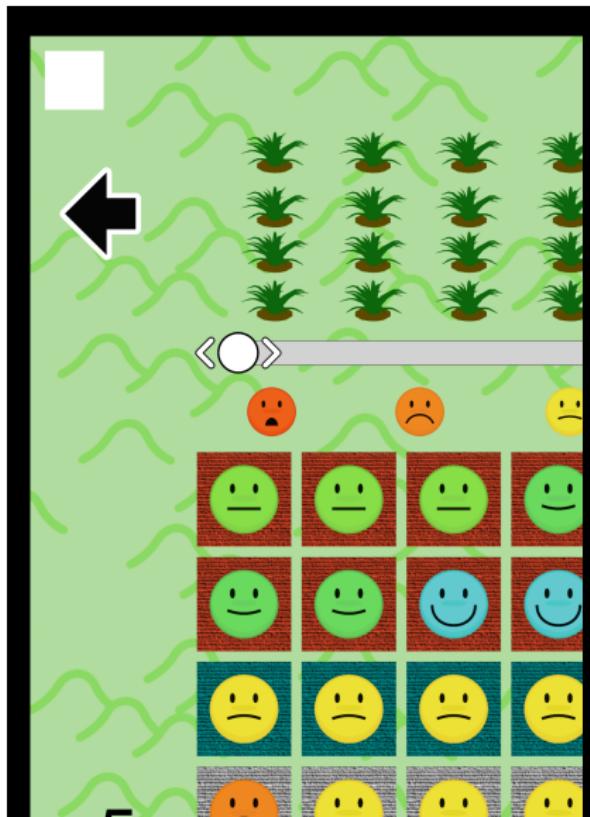
Process and Randomization

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- (4) Game modules
 - ▶ Randomize round order via matched quartets
 - ▶ Randomize technology order
 - ▶ Randomize village name order
- (5) Payout

Results

How Context Uncertainty Aversion Is Tested

Identification: Two game rounds. Only change % gray



Farmers Prefer More Context



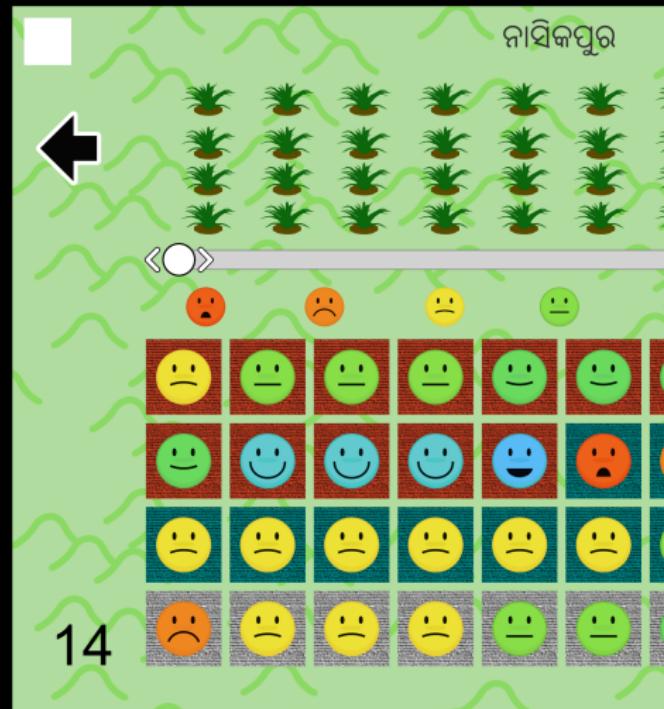
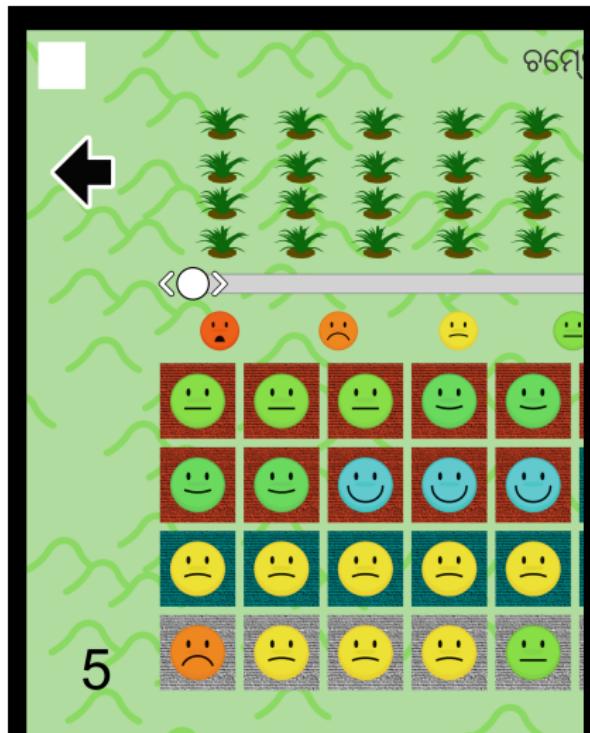
Shifts in Adoption

Low Sampling
Error

High Sampling
Error

How Complementarity Is Tested

Identification: Two modules. Low vs high sampling error.



Change % gray within each.

How Complementarity Is Tested

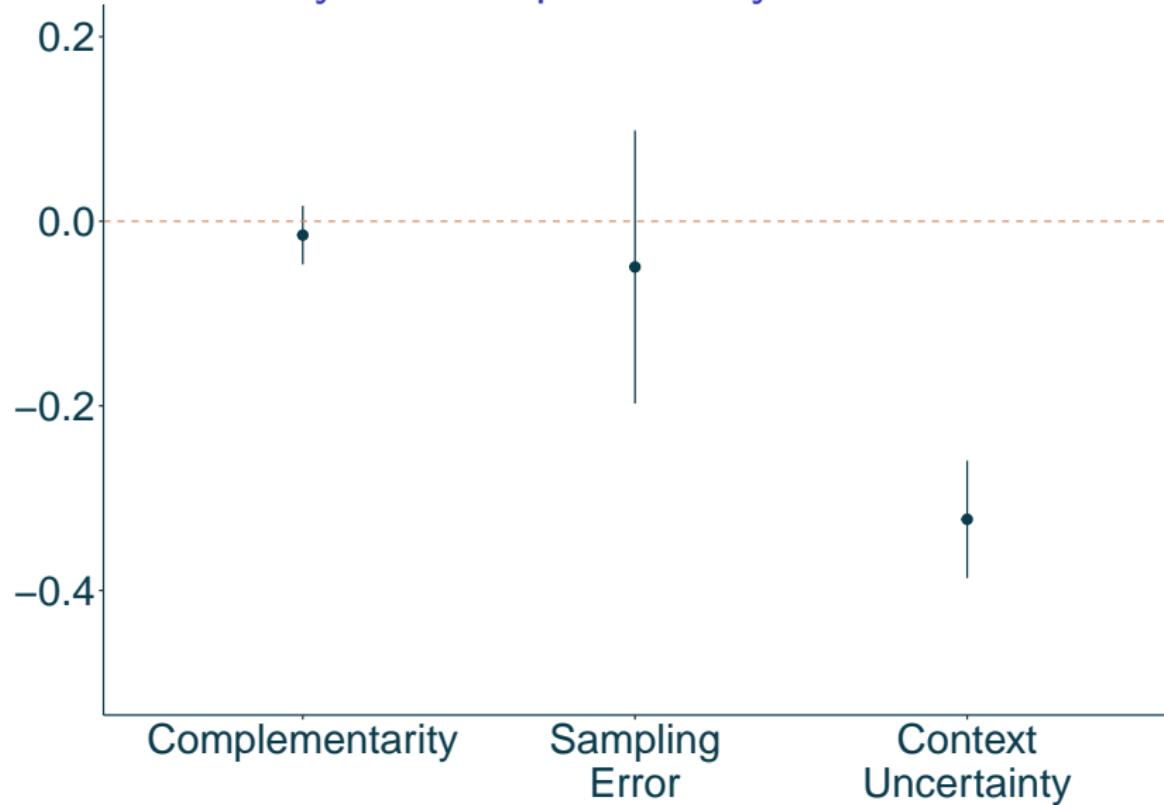
Specification: Use diff-in-diff (i.e. Athey and Stern, 1998)

Sampling Error

Low
High
Difference

$$AdoptionLevel_{it} = \text{Whoops!} + \eta_i + \epsilon_{it}$$

Uncertainties May Be Complementary



Dropped Enumerators Improve Significance

0.2

External Validity: Survey Evidence