# Dev Patel

devapatel3@gmail.com
dev-patel.com
(303) 717-7724

## Academic Positions

Peggy and Henry D. Sharpe Jr. Assistant Professor of Economics and Environmental Science, Brown University 2026—
Prize Fellow in Economics, History, and Politics, Harvard University 2024—2026
Postdoctoral Fellow, Abdul Latif Jameel Poverty Action Lab (J-PAL), MIT 2024—2026

## Education

Ph.D. in Economics, Harvard University 2018—2024
A.B. in Economics, Harvard University 2012—2016

## Affiliations

Invited Researcher, Abdul Latif Jameel Poverty Action Lab (J-PAL) 2025—

## Working Papers

1. "Environmental Beliefs and Adaptation to Climate Change"
2. "Floods: Measurement, Impacts, and Adaptation"
3. "A Rosetta Stone for Human Capital," with Justin Sandefur
4. "Mis-Remembrance of Things Past: Memory and Adaptation to Climate Change"

## Publications

5. "What Jobs Come to Mind? Stereotypes about Fields of Study," with John J. Conlon, *Quarterly Journal of Economics*, Forthcoming
6. "Texts Don't Nudge: An Adaptive Trial to Prevent the Spread of COVID-19 in India," with Sebastian Bauhoff, Girija Bahety, and James Potter, *Journal of Development Economics*, 2021, vol. 153
7. "The New Era of Unconditional Convergence," with Justin Sandefur and Arvind Subramanian, *Journal of Development Economics*, 2021, vol. 152

## Other Writing

8. "We Were Wrong About Convergence," with Justin Sandefur and Arvind Subramanian, December 12, 2025
9. "A Requiem for Hyperglobalization," with Justin Sandefur and Arvind Subramanian, *Foreign Affairs*, June 12, 2024
10. "Everything You Know About Cross-Country Convergence Is (Now) Wrong," with Justin Sandefur and Arvind Subramanian

## Fellowships and Awards

Ana Aguado Prize, Harvard University, 2024
Fisher Prize, Harvard University, 2024

NBER Gender in the Economy Dissertation Fellowship, 2022-23
National Science Foundation Graduate Student Research Fellowship, 2018-23
Harvard University Certificate of Distinction in Teaching, 2020, 2021
John M. Olin Fellowship in Empirical Law and Finance, Harvard University, 2020

**Teaching**

Living in a Warming World: The Economics of Climate Adaptation (Brown, Undergraduate), 2027
Gender Inequality Around the World (Harvard, Undergraduate), 2021
Behavioral Development Economics (Harvard, Graduate), *Teaching Fellow*, 2021
Development Economics (Harvard, Graduate), *Teaching Fellow*, 2020

**Academic Service**

Reviewer for *American Economic Review*, *American Economic Review: Insights*, *American Economic Journal: Applied Economics*, *American Economic Journal: Economic Policy*, *American Journal of Health Economics*, *Econometrica*, *Economic Journal*, *Economics Letters*, *Economics of Education Review*, *Higher Education*, *Journal of Applied Econometrics*, *Journal of the Association of Environmental and Resource Economists*, *Journal of Comparative Economics*, *Journal of Development Economics*, *Journal of Economic Geography*, *Journal of Economic Growth*, *Journal of Environmental Economics and Management*, *Journal of Health Economics*, *Journal of Human Resources*, *Journal of Political Economy*, *Journal of Public Economics*, *Journal of Urban Economics*, *Management Science*, *PLOS One*, *Review of Economics and Statistics*, *Scandanavian Journal of Economics*, *Quarterly Journal of Economics*, *World Development*

Conference Organizer/Reviewer for LSE Environment Week (2024, 2025, 2026), SITE—Social Structures and Economic Development (2026), NEUDC (2026)

Funding Reviewer for J-PAL AI at Work, J-PAL Partnership for AI Evidence, USAID Development Innovation Ventures, World Bank Research Support Grants

Discussant for NEUDC (2019), ASSA (2019), ASSA (2026, x2), NBER Summer Institute—Energy and Environmental Economics (2026)

**Invited Seminars (including scheduled)**

Boston University, Brown University, Center for Global Development, Centre International de Recherche sur l'Environnement et le Développement, Columbia University, Cornell University, Duke University, Georgetown University, Indian Institute of Management Bangalore, International Monetary Fund, London School of Economics, Microsoft Research, Northwestern University, Paris School of Economics, Stanford University, TREE Seminar (Duke/North Carolina State/RTI International), Tufts University, University of California Berkeley, University of California Berkeley Agricultural and Resource Economics, University of Chicago Booth, University of Chicago Harris, University of Oxford, University of Pennsylvania Wharton, University of Rochester, University of Virginia, World Bank, Yale University

**Conference Presentations (including scheduled)**

NEUDC (2019), APPAM (2019), ASSA (2020), LSE Environment Camp (2024), NBER Summer Institute—Education (2024), LSE Environment Week (2024), BREAD Asia (2024), KHIPU Latin American Meeting in Artificial Intelligence (2025), Northwestern GPRL Rookiefest (2025), NBER Environmental and Energy Economics (2025), Global Food+ Symposium (2025), Northeast Workshop on Energy Policy and Environmental Economics (2025), BFI Memory and Attention Conference (2025), Barcelona School of Economics Summer Forum—Machine Learning in Economics (2025), NBER Summer Institute—Development (2025), World Bank ABCDE (2025), SITE—Missing Markets (2025), ASSA (2026), Y-RISE (2026), EPIC Junior Workshop (2026), SITE—Social Structures and Economic Development (2026), LSE Environment Week (2026), BREAD/ITAM/CAF Conference on Development Economics (2026), Occasional Workshop in Environmental and Resource Economics (2026)

**Advising**

*Undergraduate Theses:* Taybah Crorie (Harvard), Charlotte Calkins (Brown)

*Last Updated:* September 2026

I would be thrilled to participate in this workshop as much of my research focuses on the intersection of networks and development.

In “The Ties That Bind and Unwind: Coordination vs. Free Riding in Information Markets,” I examine how social structure shapes the missing market for non-rival information. Networks underpin two opposing forces: connections can facilitate coordination to jointly purchase data, yet those same links enable free riding on information purchased by peers. The equilibrium regime hinges on a race between these dual channels: as coalitions expand, the share of total fixed costs faced by an individual falls while the set of informed peers from whom to free ride grows. When this latter force dominates, the market can fully unravel because the ease of observing shared information outpaces the network's ability to exclude those who do not pay, ultimately preventing the purchase of information in the first place. I empirically test this framework by examining the network origins of the missing market for spatially covarying environmental data in rural Bangladesh. Exogenous decreases in social learning costs depress market demand. Consistent with the model's predictions, better connected farmers report *higher* coordination frictions when attempting to pool funds---particularly those embedded in more heterogeneous information environments and with denser local networks.

In “Adapting Alone, Coping Collectively: Equilibrium Risk Sharing Amid Environmental Threats”, I study the inherently geographic aspect of environmental risk by asking how poor households cope with this spatial covariance. I study how two margins of climate adaptation---within and across households---interact in the face of environmental threats to determine the overall degree of consumption smoothing. As the spatial concentration of agricultural shocks increases, households face incentives to self-insure via their own labor supply decisions. This individual-level adaptation has community-wide effects in general equilibrium because the benefits of a more diversified household extend through potential informal insurance network links. Theoretically, I show that whether equilibrium risk-sharing rises or falls with spatial covariance hinges on the relative risk of individual climate adaptation. I survey farmers in Bangladesh to test this model and find that households facing more concentrated environmental risk change the geographic nature of their self-insurance, shifting away from *local* production---crop diversification and non-agricultural employment within the village---to *distant* production via temporary migration. Because of the earnings uncertainty associated with urban work, higher spatial covariance ultimately strengthens risk sharing networks within villages.

Finally, in the on-going project I would hope to present at the workshop, titled “Who Wants to Talk to Whom? Diffusion and the Social Value of Social Learning” with Jimena Romero Pinto, we examine how non-information aspects of social learning impact the spread of information. I have attached an extended abstract, along with a model sketch and the current set of results.

References:

Emily Breza, Arun Chandrasekhar, Asim Khwaja, and Gautam Rao

# Who Wants to Talk to Whom?
# Diffusion and the Social Value of Social Learning

Dev Patel Jimena Romero Pinto

September 16, 2026

Extended Abstract & Key Results*

**Abstract**

The act of social learning involves more than just the mechanical transmission of information. How do these non-instrumental aspects of interacting with another person in the course of spreading knowledge shape diffusion? We study this question empirically amid the introduction of a new climate adaptation product among farmers in Bolivia. Using incentivized elicitations of supply and demand for sharing knowledge at the dyad level, we calculate match-specific surplus—the gap between the receiver's willingness-to-pay to learn and the sender's willingness-to-accept to teach. Experimentally arranging these missing conversations shows that *low* surplus dyads spur information diffusion across the network the most, an effect driven by the demand side. We present evidence suggesting the people value non-information aspects of social learning—such as popularity and prestige—that negatively correlate with high-quality knowledge transmission.

*We thank Nava Ashraf, Arun Chandrasekhar, Luisa Cefala, Kyle Emerick, Kelsey Jack, Sylvia Klosin, Eliana La Ferrara, and Nicholas Swanson for comments that greatly improved this paper. This research underwent Human Subjects Review at Harvard University, Cornell University, and Brown University. We are grateful to Sergio De Marco, Diego Delgado, Daniel Hernandez Aldaco, and especially Mario Gonzales Lelarge for their help in executing the surveys and to Rodrigo Garcia and Fernando Yu for their guidance on the climate adaptation products. This study was pre-registered here.

# 1 Introduction

The act of social learning involves more than than the pure transfer of information. When people interact to transfer knowledge, they spend time together, engage with the other person's personality, and inherently navigate the larger social fabric. These non-learning aspects of knowledge spread may shape who learns from whom: people may prefer to talk to their friends, seek opportunities to spend time with popular or prestigious individuals, and avoid conversations with those whom they find unpleasant.

In this paper, we examine how the non-learning component inherent to the act of social learning shapes the diffusion of information. We study this empirically by tracing knowledge about new climate adaptation technology among Bolivian farmers. Our design combines dyad-level incentivized measures of the demand and supply of social learning with a field experiment that exogenously arranged conversations to spread information. We find that people want to learn from those who tend to be popular and socially central, at the expense of their ability to communicate information well, with important negative externalities on the rest of the network.

We begin by measuring demand and supply for social learning using a Becker-DeGroot Marschak method to incentivize the elicitation. We sample nodes across village networks, and for each $i$ and $j$, we measure willingness-to-pay (WTP) for $i$ to learn from $j$ and willingness-to-accept (WTA) for $j$ to teach $i$. We can therefore classify links into three categories. First, *free-flowing* links feature positive demand and negative supply costs such that even in the absence of market forces, learning may still take place. Second, *market* links have positive WTA for the teacher to inform the listener, but demand exceeds this cost, implying that a price exists that could facilitate a conversation. Finally, *blocked* links include supply costs that exceed demand, so no price would clear the market because either demand is negative or WTP is lower than WTA. Our first result shows that while the majority of links are free-flowing, about about 30% are blocked and 15% are market links. Second, link type is often asymmetric, highlighting the importance of treating the network as a directed graph: many $i$ to $j$ links of one type are a different type from $j$ to $i$. Third, we document substantial heterogeneity in surplus, defined as the difference between WTP and WTA. Fourth, while the majority of variation in WTP and WTA stems from the respondent, about a quarter arises from the match itself, indicating an important match-specific component.

We next examine predictors of demand and supply for social learning. Similarity matters: farmers cultivating the same crop or sharing demographic characteristics (gender, age, or language) exhibit systematically higher surplus. Older, more socially central people are in highest demand.

To quantify the importance of different links for learning, we experimentally arrange conversations. We randomly seed two farmers in each village with information about a new crop insurance and extreme weather early warning system that a firm was considering introducing in the areas. In a randomly selected third of villages assigned to a control group, that initial seeding of information was the only component of the intervention. In the remaining two thirds of villages, we additionally arranged conversations between the two seeded individuals and two others in our sample, based on the WTP and WTA elicited via the BDM exercise. We then followed up with all respondents several days later to measure comprehension and knowledge about these products.

We find that knowledge is substantially higher in villages where we arranged conversations. Out of eight comprehension questions about the climate products, non-seeded individuals answered about half right in the control villages. In treated villages, those assigned to learn from the seeded individuals answered about one question more correctly ($p$-value $< .01$). We find spillovers across the graph: even those not targeted answered about half a question more correctly ($p$-value $< .1$).

We next examine heterogeneity in these treatment effects based on the type of conversation that we randomly selected. Using the same measure of surplus (WTP - WTA) as before, we find that the increased learning is entirely driven by low surplus matches. One standard deviation lower surplus increases the amount of learning by about 50%, both among targetted listeners and spillovers.

These effects suggest people's demand for learning does not only reflect the information transmission technology of the match. To examine this in our data, we turn to comprehension questions we administered to the seeded individuals immediately following the initial provision of information. These questions—the same comprehension questions of our main outcomes—measure the respondent's ability to understand and retain the information they were just provided about the climate technology. We find this measure negatively correlates with other respondents' WTP to learn from that person. In other words, people are willing to pay more to learn from people who happen to understand the information worse.

What other factors contribute to demand if not the seeds' comprehension ability? We measure other aspects of each person's social standing, and find that people want to learn from those who are popular both socially and in terms of giving agricultural advice.

In future work, we plan on measuring beliefs about comprehension ability to understand if people know who is skilled at retaining information, and also vary directly the non-information component of social learning to test whether that impacts diffusion and knowledge.

# 2 Model of Social Learning with Match Effects

This section develops a simple model in which individuals choose whom to learn from and whom to teach. The central distinction is between a dyad's *information transmission technology* and the utility that the two individuals derive from interacting. This distinction allows willingness to pay to learn and willingness to accept to teach to be imperfect measures of how productive a social-learning relationship is for information diffusion.

## 2.1 Environment

There is a finite set of individuals $N$ connected by a social network $G = (N, E)$. For any pair $i$ and $j$ connected in the network, $i$ can potentially learn from $j$. We use $(i, j)$ to denote the directed learning relationship in which $i$ is the learner and $j$ is the teacher.

At date 0, a set $S \subset N$ is exogenously informed. In the experiment, $S$ corresponds to the randomly selected information seeds.

Suppose that $j$ is informed and $i$ is not. If $i$ and $j$ engage in a social-learning interaction, information is successfully transmitted from $j$ to $i$ with probability

$$\theta_{ij} \in [0, 1].$$

We refer to $\theta_{ij}$ as the *diffusion productivity* of the dyad. It may depend on the teacher's ability to communicate, the learner's ability to understand the teacher, or features of their relationship.

Becoming informed has instrumental value $B_i > 0$ to learner $i$.

The learner may also derive utility directly from interacting with $j$. Let

$$s_{ij} \in \mathbb{R}$$

denote this non-instrumental social value. For example, $s_{ij}$ may be high because $i$ enjoys spending time with $j$, because $j$ is popular or high status, or because interacting with $j$ is otherwise socially valuable independently of the information transmitted.

Similarly, let $c_{ji}$ denote $j$'s cost of teaching $i$, and let

$$r_{ji} \in \mathbb{R}$$

denote the non-instrumental benefit that $j$ receives from the interaction.

Consider a generalized transfer $x$ from $i$ to $j$. The transfer is a device for allocating the surplus from an interaction and need not be monetary; it can represent time, favors,

reciprocity, or other relational accommodations. Prior to the realization of information transmission, the two agents' expected utilities from the interaction are

$$u_{ij}^{L}(x) = B_i\theta_{ij} + s_{ij} - x, \tag{1}$$

$$u_{ji}^{T}(x) = x + r_{ji} - c_{ji}. \tag{2}$$

It follows immediately that $i$'s willingness to pay to learn from $j$ is

$$W_{ij} \equiv B_i\theta_{ij} + s_{ij}, \tag{3}$$

while $j$'s willingness to accept to teach $i$ is

$$A_{ji} \equiv c_{ji} - r_{ji}. \tag{4}$$

Note that neither of these match-specific objects are in general a sufficient statistic for information transmission. WTP combines the expected informational benefit from the interaction with the learner's direct utility from socializing with the teacher, while WTA combines the cost of teaching with the teacher's direct utility from the interaction.

Let $\kappa_{ij} \geq 0$ denote the search, coordination, and other costs required for the pair to interact. Define the net surplus from an endogenous social-learning interaction as

$$X_{ij} \equiv W_{ij} - A_{ji} - \kappa_{ij} = B_i\theta_{ij} + s_{ij} + r_{ji} - c_{ji} - \kappa_{ij}. \tag{5}$$

A social-learning interaction occurs endogenously whenever

$$X_{ij} \geq 0. \tag{6}$$

The key feature of (5) is that individuals select social-learning relationships according to the *utility* generated by those relationships rather than according to their diffusion productivity alone.

## 2.2 Willingness to pay need not rank information quality

Equations (3)–(5) immediately imply that an individual may have a high willingness to learn from someone who is relatively poor at transmitting information.

**Proposition 1 (Social value can reverse the ranking of teachers)** *Consider learner*

*$i$ and two potential teachers $j$ and $k$. Suppose*

$$\theta_{ij} < \theta_{ik}.$$

*Nevertheless,*

$$W_{ij} > W_{ik}$$

*if and only if*

$$s_{ij} - s_{ik} > B_i\left(\theta_{ik} - \theta_{ij}\right). \tag{7}$$

*More generally,*

$$(W_{ij}, \theta_{ij} \mid i) = B_i(\theta_{ij} \mid i) + (s_{ij}, \theta_{ij} \mid i). \tag{8}$$

*Hence WTP and diffusion productivity can be negatively related when social value is sufficiently negatively correlated with information-transmission quality.*

The result captures, for example, an environment in which people especially value learning from popular individuals, but popularity is not positively related to the ability to transmit the information. A learner can then rationally prefer a socially desirable teacher even though another teacher would be more likely to transmit the information successfully.

An analogous force operates through WTA. A teacher may be particularly willing to teach a given person because she enjoys the interaction, even if that dyad is not especially productive at communicating the information.

## 2.3 Random matching

We next introduce the experimental intervention. For a randomly selected set of seed–recipient pairs $\mathcal{M}$, the experiment arranges a social-learning match.

We represent the intervention as increasing the surplus from interaction by $\lambda \geq 0$. This can capture a reduction in search and coordination costs, increased salience, or the experimenter's directly arranging an interaction. For an assigned pair,

$$X_{ij}^T = X_{ij} + \lambda. \tag{9}$$

The interaction therefore takes place under treatment if

$$X_{ij} + \lambda \geq 0.$$

The limiting case in which the experiment guarantees that an assigned pair meets is obtained by taking $\lambda$ sufficiently large.

Because $j$ is initially informed, the probability that information passes directly from $j$ to $i$ in the absence of treatment is

$$p_{ij}^0 = \theta_{ij}\mathbf{1}\{X_{ij} \geq 0\},$$

while for an assigned pair it is

$$p_{ij}^T = \theta_{ij}\mathbf{1}\{X_{ij} + \lambda \geq 0\}.$$

**Proposition 2 (The direct effect of randomized matching)** *For a randomly assigned seed–recipient pair $(i, j)$, the treatment-induced increase in the probability that $i$ becomes informed directly by $j$ is*

$$\begin{aligned}\Delta_{ij}^{\text{direct}} &\equiv p_{ij}^T - p_{ij}^0 \\ &= \theta_{ij}\mathbf{1}\left\{-\lambda \leq X_{ij} < 0\right\}. \end{aligned} \tag{10}$$

*If an assigned match guarantees interaction, this becomes*

$$\Delta_{ij}^{\text{direct}} = \theta_{ij}\mathbf{1}\{X_{ij} < 0\}. \tag{11}$$

The proposition separates two objects that are otherwise confounded in observational diffusion. The term $X_{ij}$ determines whether the dyad interacts endogenously, whereas $\theta_{ij}$ determines how much information is transmitted conditional on interaction.

Since $X_{ij}$ is increasing one-for-one in $W_{ij}$ and decreasing one-for-one in $A_{ji}$, randomized matching has the greatest scope to affect low-WTP and high-WTA relationships. Conditional on moving a dyad across the interaction threshold, however, the magnitude of the direct information effect is governed by $\theta_{ij}$ rather than by WTP or WTA.

## 2.4 From a single match to network diffusion

After an individual becomes informed, she may in turn transmit the information through her own social relationships. We assume that each newly informed individual receives one opportunity to transmit information along each active outgoing relationship. Conditional on an interaction, transmission along $(i, j)$ succeeds independently with probability $\theta_{ij}$.

This process has an equivalent "live-edge" representation: an endogenous directed edge $j \to i$ is live with probability

$$p_{ij}^0 = \theta_{ij}\mathbf{1}\{X_{ij} \geq 0\},$$

and information eventually reaches precisely those individuals connected to an initial seed by a path of live edges.

For a matched seed–recipient edge $j \to i$, let $\Gamma_{ij} \geq 0$ denote its *diffusion multiplier*: the expected number of final information statuses that change when the edge succeeds in transmitting, holding fixed the realizations of all other edges. This includes $i$ herself as well as any additional individuals reached through $i$.

**Proposition 3 (Total diffusion effect)** *For a single experimentally assigned seed–recipient pair,*

$$\Delta_{ij}^{\text{total}} = \theta_{ij} \mathbf{1}\left\{-\lambda \leq X_{ij} < 0\right\} \Gamma_{ij}. \tag{12}$$

*Under guaranteed interaction,*

$$\Delta_{ij}^{\text{total}} = \theta_{ij} \mathbf{1}\{X_{ij} < 0\} \Gamma_{ij}. \tag{13}$$

Thus, an experimentally induced interaction has a large effect on aggregate diffusion when three conditions coincide: the pair was unlikely to interact endogenously, the dyad is effective at transmitting the information, and the newly informed recipient occupies a position from which information can subsequently spread.

This decomposition also clarifies the interpretation of treatment-effect heterogeneity by WTP. A larger treatment effect among low-WTP dyads can arise because such relationships are less likely to occur endogenously. A stronger conclusion—that WTP favors people who are relatively poor transmitters—requires showing that, among experimentally generated interactions, diffusion productivity $\theta_{ij}\Gamma_{ij}$ is itself weakly or negatively related to WTP.

## 2.5 Mapping to the experiment

The experimental design separately identifies the objects appearing in the model. The elicitation exercises measure $W_{ij}$ and $A_{ji}$ for randomly sampled dyads. Random assignment of the initial seeds makes information availability exogenous. Random assignment of seed–recipient matches then generates variation in interaction that is independent of the dyad's endogenous social-learning surplus.

Proposition 2 predicts that induced matches should matter disproportionately for dyads with low WTP to learn or high WTA to teach, because these are precisely the dyads least likely to interact without the intervention.

Proposition 1 generates a stronger empirical implication. Among experimentally induced interactions, the amount of information ultimately generated by a match identifies its diffusion productivity rather than its social desirability. If dyads with lower measured WTP

generate at least as much—or more—subsequent diffusion than dyads with high measured WTP, then WTP cannot be interpreted as a measure of information quality alone. In the model, such a pattern requires the non-instrumental component $s_{ij}$ to be sufficiently important that willingness to learn and diffusion productivity are imperfectly aligned. “‘

# References

**Banerjee, Abhijit, Emily Breza, Arun G. Chandrasekhar, Gideon Moore, Rema Hanna, and Benjamin A. Olken**, "Target What? A Conceptual and Empirical Exploration of the Foundations of Poverty Targeting," 2026. Working paper.

**Chandrasekhar, Arun G., Matthew O. Jackson, Tyler H. McCormick, Karl Rohe, Jack Shane, and Brian Xu**, "On Tubes; or, Model-Building from Rich Data by Isolating Concepts," 2026. Working paper.

**Conley, Timothy G. and Christopher R. Udry**, "Learning about a New Technology: Pineapple in Ghana," *American Economic Review*, 2010, *100* (1), 35–69.

**Kaiser, Henry F.**, "The Varimax criterion for analytic rotation in factor analysis," *Psychometrika*, 1958, *23* (3), 187–200.

# 3 Figures and Tables

Table 1: Descriptive Statistics: Partner-Specific BDM Valuations

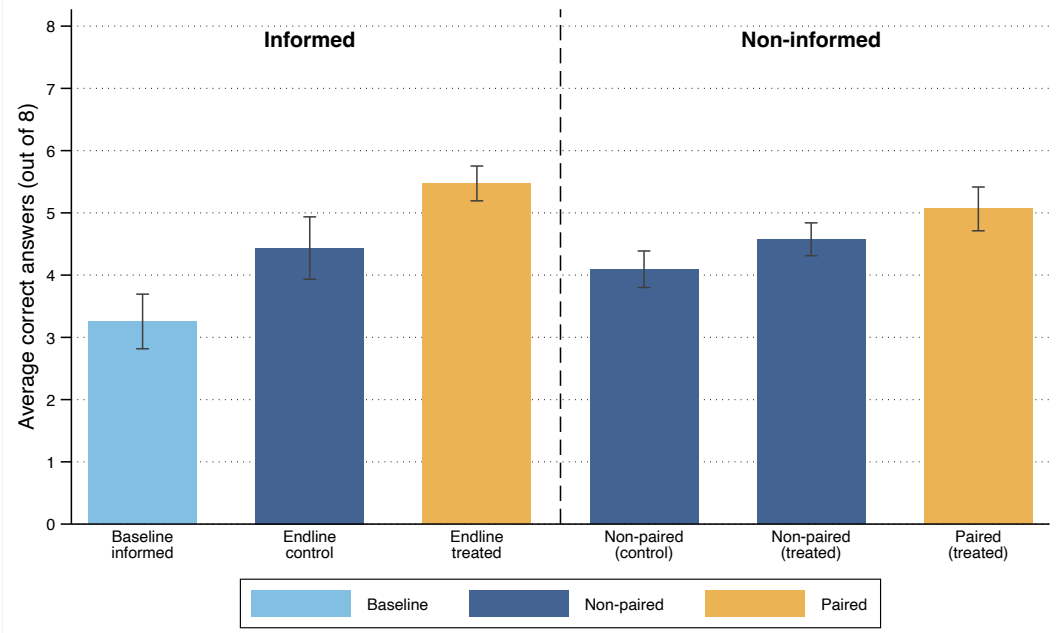
| | Mean | SD | Min | Median | Max | *N* |
|---|---|---|---|---|---|---|
| *Panel A: Listeners — WTP to learn from matched teacher* | | | | | | |
| WTP for matched teacher | 19.52 | 22.75 | 0.00 | 10.00 | 120.00 | 63 |
| Avg WTP across network | 17.60 | 18.95 | 0.00 | 10.00 | 120.00 | 63 |
| Difference (partner − avg) | 1.92 | 9.25 | -10.00 | 0.00 | 45.00 | 63 |
| *Panel B: Teachers — WTA to share with matched listener* | | | | | | |
| WTA for matched listener | 5.91 | 10.07 | 0.00 | 0.00 | 30.00 | 66 |
| Avg WTA across network | 7.12 | 10.62 | 0.00 | 0.00 | 34.29 | 67 |
| Difference (partner − avg) | -1.17 | 3.19 | -11.43 | 0.00 | 8.00 | 66 |
| *Panel C: Gains from trade (within matched pairs)* | | | | | | |
| Listener WTP − Teacher WTA | 12.71 | 26.77 | -30.00 | 10.00 | 120.00 | 59 |
| Share with WTP > WTA | | 57.6% (34 of 59 pairs) | | | | |
| Share with WTP = WTA | | 23.7% (14 of 59 pairs) | | | | |
| Share with WTP < WTA | | 18.6% (11 of 59 pairs) | | | | |
| *Panel D: Link classification* | | | | | | |
| Free-flowing (WTA = 0, neither side refused) | | 67.8% (40 of 59 pairs) | | | | |
| Norm-constrained (0 < WTA ≤ WTP) | | 13.6% (8 of 59 pairs) | | | | |
| Blocked (WTP < WTA or never willing) | | 18.6% (11 of 59 pairs) | | | | |

*Notes:* WTP = willingness to pay to learn from a specific network member (BDM mechanism, bolivianos). WTA = willingness to accept to share knowledge with a specific network member (BDM mechanism, bolivianos). Partner-specific values correspond to the matched teacher/listener pair. Network averages are the respondent's mean BDM valuation across all 8 network members. Respondents who answered are classified as not willing to meet; their WTP/WTA is set to missing and they are excluded from Panels A–C summary statistics. Respondents who would pay to meet or share (small negative BDM values) are set to 0. Panels A–C condition on willingness to meet. Panel C computes gains from trade within each matched pair: listener's WTP minus teacher's WTA. Positive values indicate the listener values learning more than the teacher requires to share. Panel D classifies links by link type: free-flowing if teacher's WTA = 0 AND neither side refused (raw WTA = −888 or WTP = −999); norm-constrained if WTA > 0 and WTP ≥ WTA (gains from trade exist but social norm blocks payment); blocked if WTP < WTA or if either party is never willing to meet.

Table 2: Knowledge Retention by Treatment Status

| | Baseline | Endline | | | |
|---|---|---|---|---|---|
| | Informed | Informed | | Non-informed | |
| | | Non-paired village | Paired village | Non-paired village | Paired village |
| Q1: Shock covered | 0.416 | 0.565 | 0.703 | 0.507 | 0.628 |
| Q2: Crops covered | 0.453 | 0.717 | 0.802 | 0.601 | 0.720 |
| Q3: Insurance cost | 0.511 | 0.630 | 0.791 | 0.601 | 0.670 |
| Q4: When premium is paid | 0.467 | 0.696 | 0.868 | 0.645 | 0.728 |
| Q5: Payout trigger | 0.504 | 0.587 | 0.857 | 0.543 | 0.636 |
| Q6: EWS shocks alerted | 0.066 | 0.065 | 0.077 | 0.080 | 0.092 |
| Q7: Forecast lead time | 0.533 | 0.717 | 0.780 | 0.645 | 0.724 |
| Q8: Forecast accuracy | 0.307 | 0.457 | 0.593 | 0.471 | 0.494 |
| Total correct (out of 8) | 3.26 | 4.43 | 5.47 | 4.09 | 4.69 |
| | 137 | 46 | 91 | 138 | 261 |

*Notes:* Each cell reports the share answering correctly (for Q1–Q8) or the mean number correct out of 8 (for the total row). *Informed* refers to the two individuals per community who received information about insurance and EWS products during the baseline survey. *Non-informed* are the remaining respondents who did not receive this information. *Paired village* and *Non-paired village* refer to village-level treatment assignment (whether matched pairs were formed for facilitated conversations). **Questions and correct answers:** Q1: What type of climate shock does the insurance cover? (Correct: drought). Q2: Which crops are covered? (Correct: all crops). Q3: How much does insurance cost? (Correct: 5% of the insured value). Q4: When do you pay the premium? (Correct: at the beginning of the season). Q5: When is the payout triggered? (Correct: when satellite soil moisture data shows conditions far below normal). Q6: What shocks does the EWS alert? (Correct: hail and floods/excess rain, but not drought or wind). Q7: How far in advance can the EWS issue warnings? (Correct: 1–5 days; in an alternative survey version, an additional correct answer was accepted). Q8: How often are the forecasts correct? (Correct: 4/6 or 3/6 times; the definition of correct varies across survey versions to reflect the range of accuracy communicated during the intervention).




*Note*: Bars show group means; whiskers indicate 95% confidence intervals.
Bar 1 — Baseline informed: seeds, score from session questionnaire.
Bar 2 — Endline informed, control village: seeds in control villages at endline.
Bar 3 — Endline informed, treated village: seeds in treated villages at endline.
Bar 4 — Non-paired, control: non-seeds in control villages;.
Bar 5 — Non-paired, treated: non-seeds in treated villages who had no meeting.
Bar 6 — Paired, treated: non-seeds in treated villages who had a meeting.

Table 3: Effect on Teacher Knowledge

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Paired | 1.038*** | 1.098*** | 1.138*** | 1.146*** |
| | (0.362) | (0.375) | (0.385) | (0.387) |
| Eligibility FE (0–7) | No | Yes | Yes | Yes |
| Socioeconomic controls | No | No | Yes | Yes |
| Baseline teacher knowledge control | No | No | No | Yes |
| Control mean | 4.094 | 4.094 | 4.094 | 4.094 |
| Observations | 137 | 137 | 136 | 136 |

Dependent variable: total correct answers at endline (0–8).
Sample: teachers in treatment and control villages.
Standard errors clustered at the community level in parentheses.
Eligibility FE: fixed effects for number of community members teacher is willing to teach (WTA $\geq 0$), from 0 to 7.
Baseline teacher knowledge control: teacher's own baseline knowledge score (0–8).
Socioeconomic controls: age, gender, insurance history, land title, HH selection method.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect on Recipient Knowledge

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Paired | 0.969*** | 1.156*** | 1.262*** | 1.251*** |
| | (0.270) | (0.295) | (0.299) | (0.298) |
| Eligibility FE (0–2) | No | Yes | Yes | Yes |
| Socioeconomic controls | No | No | Yes | Yes |
| Baseline teacher knowledge control | No | No | No | Yes |
| Control mean | 4.094 | 4.094 | 4.094 | 4.094 |
| Observations | 201 | 201 | 201 | 201 |

Dependent variable: total correct answers at endline (0–8).
Sample: recipients and non-informed control village members.
Standard errors clustered at the community level in parentheses.
Eligibility FE: fixed effects for number of assigned teachers willing to teach this person (WTA $\geq 0$), from 0 to 2.
Socioeconomic controls: age, gender, insurance history, land title, HH selection method.
Baseline teacher knowledge control: average baseline knowledge score of teachers in community.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Spillover Effects on Knowledge — Teacher Willingness FE

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Matched village | 0.482* | 0.488* | 0.456* | 0.451* |
| | (0.260) | (0.250) | (0.239) | (0.238) |
| Eligibility FE (0–2) | No | Yes | Yes | Yes |
| Socioeconomic controls | No | No | Yes | Yes |
| Baseline teacher knowledge control | No | No | No | Yes |
| Control mean | 4.094 | 4.094 | 4.094 | 4.094 |
| Observations | 336 | 336 | 336 | 336 |

Dependent variable: total correct answers at endline (0–8).
Sample: community members who are neither teachers nor recipients.
Standard errors clustered at the community level in parentheses.
Eligibility FE: fixed effects for number of assigned teachers willing to teach this person (WTA $\geq 0$), from 0 to 2.
Socioeconomic controls: age, gender, insurance history, land title, HH selection method.
Baseline teacher knowledge control: average baseline knowledge score of teachers in community.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Teacher and Recipient Characteristics by Pair Link Type (Paired Arm)

| | Free-flowing | | | Norm-constrained | | | Blocked | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | N | Mean | SD | N | Mean | SD | N |
| **Panel A: Teachers** | | | | | | | | | |
| *Conversation & meeting* | | | | | | | | | |
| Had any conversation | 0.80 | ( 0.41) | 40 | 0.88 | ( 0.35) | 8 | 1.00 | ( 0.00) | 11 |
| Had multiple conversations | 0.12 | ( 0.33) | 40 | 0.25 | ( 0.46) | 8 | 0.09 | ( 0.30) | 11 |
| # conversations with partner | 1.07 | ( 0.97) | 40 | 1.25 | ( 0.89) | 8 | 1.18 | ( 0.60) | 11 |
| # conversations with others | 0.97 | ( 1.44) | 40 | 1.12 | ( 0.99) | 8 | 0.91 | ( 1.22) | 11 |
| Meeting took place | 0.93 | ( 0.25) | 30 | 0.83 | ( 0.41) | 6 | 1.00 | ( 0.00) | 10 |
| Meeting duration (minutes) | 4.21 | ( 2.45) | 28 | 4.00 | ( 1.22) | 5 | 4.40 | ( 2.41) | 10 |
| Clarity of explanation (1–4) | 2.57 | ( 0.57) | 28 | 2.80 | ( 0.84) | 5 | 2.40 | ( 0.52) | 10 |
| Comfort during meeting (1–4) | 2.82 | ( 0.48) | 28 | 2.80 | ( 0.45) | 5 | 2.90 | ( 0.32) | 10 |
| Talked about insurance | 0.72 | ( 0.46) | 39 | 0.88 | ( 0.35) | 8 | 0.64 | ( 0.50) | 11 |
| Talked about EWS | 0.67 | ( 0.48) | 39 | 0.88 | ( 0.35) | 8 | 0.82 | ( 0.40) | 11 |
| Talked about both | 0.59 | ( 0.50) | 39 | 0.88 | ( 0.35) | 8 | 0.55 | ( 0.52) | 11 |
| *Knowledge* | | | | | | | | | |
| Endline knowledge score (0–8) | 5.40 | ( 1.41) | 40 | 6.38 | ( 0.74) | 8 | 5.27 | ( 1.42) | 11 |
| *Demographics* | | | | | | | | | |
| Age | 47.23 | ( 14.33) | 40 | 42.38 | ( 11.45) | 8 | 53.82 | ( 7.57) | 11 |
| Male | 0.35 | ( 0.48) | 40 | 0.62 | ( 0.52) | 8 | 0.45 | ( 0.52) | 11 |
| Has land title | 0.72 | ( 0.46) | 39 | 0.88 | ( 0.35) | 8 | 0.82 | ( 0.40) | 11 |
| **Panel B: Recipients (Listeners)** | | | | | | | | | |
| *Conversation & meeting* | | | | | | | | | |
| Had any conversation | 0.90 | ( 0.30) | 40 | 0.75 | ( 0.46) | 8 | 0.82 | ( 0.40) | 11 |
| Had multiple conversations | 0.17 | ( 0.38) | 40 | 0.00 | ( 0.00) | 8 | 0.09 | ( 0.30) | 11 |
| # conversations with partner | 1.38 | ( 1.87) | 39 | 0.75 | ( 0.46) | 8 | 0.91 | ( 0.54) | 11 |
| # conversations with others | 0.65 | ( 0.86) | 40 | 0.38 | ( 0.74) | 8 | 0.73 | ( 0.90) | 11 |
| Meeting took place | 0.91 | ( 0.30) | 32 | 0.67 | ( 0.52) | 6 | 0.90 | ( 0.32) | 10 |
| Meeting duration (minutes) | 4.34 | ( 2.92) | 29 | 3.00 | ( 0.82) | 4 | 4.44 | ( 1.74) | 9 |
| Clarity of explanation (1–4) | 2.69 | ( 0.66) | 29 | 2.75 | ( 0.50) | 4 | 2.67 | ( 0.50) | 9 |
| Comfort during meeting (1–4) | 2.97 | ( 0.57) | 29 | 2.75 | ( 0.50) | 4 | 3.00 | ( 0.50) | 9 |
| Talked about insurance | 0.74 | ( 0.44) | 39 | 0.62 | ( 0.52) | 8 | 0.82 | ( 0.40) | 11 |
| Talked about EWS | 0.62 | ( 0.49) | 39 | 0.62 | ( 0.52) | 8 | 0.73 | ( 0.47) | 11 |
| Talked about both | 0.49 | ( 0.51) | 39 | 0.62 | ( 0.52) | 8 | 0.73 | ( 0.47) | 11 |
| *Knowledge* | | | | | | | | | |
| Endline knowledge score (0–8) | 5.00 | ( 1.50) | 40 | 5.00 | ( 1.07) | 8 | 5.45 | ( 1.29) | 11 |
| *Demographics* | | | | | | | | | |
| Age | 52.70 | ( 12.66) | 40 | 52.50 | ( 12.60) | 8 | 54.45 | ( 10.49) | 11 |
| Male | 0.42 | ( 0.50) | 40 | 0.50 | ( 0.53) | 8 | 0.45 | ( 0.52) | 11 |
| Has land title | 0.72 | ( 0.45) | 40 | 0.88 | ( 0.35) | 8 | 0.91 | ( 0.30) | 11 |

*Notes:* Sample restricted to teachers and matched recipients in paired (treatment) villages. Link types are assigned at the listener level using baseline BDM elicitations and propagated to the matched teacher: *Free-flowing* = teacher willing to share for free (WTA = 0) and neither party refused the link; *Norm-constrained* = teacher WTA > 0 and listener WTP ≥ teacher WTA; *Blocked* = price gap (listener WTP < teacher WTA), or one party refused the link entirely (teacher WTA = −888 or listener WTP = −999). Cells report mean, standard deviation in parentheses, and the number of non-missing observations. Number-of-conversations variables are based on endline self-reports ($16 for paired partner; 14 for other community members). Meeting variables are conditional on the respondent providing post-meeting answers.

Table 7: Knowledge by Role and Realised Surplus

| | (1) | (2) | (3) |
|---|---|---|---|
| Listener (paired) | 1.328*** | 1.189*** | 1.258*** |
| | (0.284) | (0.289) | (0.296) |
| Listener × own-pair surplus (sd) | -0.506*** | -0.210 | -0.365* |
| | (0.136) | (0.196) | (0.211) |
| Spillover (treated village) | 0.635** | 0.526** | 0.556** |
| | (0.260) | (0.254) | (0.239) |
| Spillover × village total surplus (sd) | -0.268 | -0.242 | -0.317* |
| | (0.183) | (0.176) | (0.170) |
| Spillover × seed surplus (through seeds, sd) | 0.017 | 0.098 | 0.052 |
| | (0.155) | (0.130) | (0.113) |
| Potential surplus with all others (sd) | | -0.265*** | -0.270** |
| | | (0.098) | (0.103) |
| Eligibility FE (0–2) | Yes | Yes | Yes |
| Potential-surplus control | No | Yes | Yes |
| Socioeconomic controls | No | No | Yes |
| Control mean | 4.094 | 4.094 | 4.094 |
| Observations | 395 | 395 | 395 |

Dependent variable: total correct answers at endline (0–8). Sample: all non-informed members; omitted group: non-informed control-village members. Own-pair surplus: the listener's WTP for their assigned teacher minus that teacher's WTA for them, in sd units of the listener distribution; 0 for non-listeners. Village total surplus: sum of pair surpluses in the village. Seed surplus: the potential gains from trade available THROUGH the village's seeds – for each seed, the sum over learners of max(0, learner WTP for the seed minus the seed's WTA), summed over the village's seeds; standardised. Potential-surplus control: the person's total potential surplus with ALL other community members as a recipient, $\sum_s \max(0, WTP_s - WTA_s)$, standardised. Standard errors clustered at the community level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Knowledge by Role: Surplus Split into WTP and WTA

| | (1) | (2) | (3) |
|---|---|---|---|
| Listener (paired) | 1.470*** | 1.250*** | 1.371*** |
| | (0.330) | (0.358) | (0.353) |
| Listener × own-pair WTP (sd) | -0.535*** | -0.312 | -0.419** |
| | (0.145) | (0.194) | (0.205) |
| Listener × own-pair teacher WTA (sd) | 0.029 | 0.049 | 0.088 |
| | (0.143) | (0.153) | (0.152) |
| Spillover (treated village) | 1.209*** | 1.085*** | 1.004*** |
| | (0.367) | (0.366) | (0.366) |
| Spillover × village total WTP (sd) | -0.180 | -0.170 | -0.207 |
| | (0.168) | (0.160) | (0.161) |
| Spillover × village total WTA (sd) | 0.195 | 0.199 | 0.220* |
| | (0.132) | (0.132) | (0.115) |
| Spillover × seed attractiveness / WTP to seeds (sd) | -0.249 | -0.194 | -0.177 |
| | (0.221) | (0.199) | (0.192) |
| Spillover × seed WTA (sd) | -0.379** | -0.382** | -0.288** |
| | (0.162) | (0.173) | (0.137) |
| Own WTP toward all others (sd) | | -0.208** | -0.209* |
| | | (0.102) | (0.107) |
| WTA others ask of person (sd) | | -0.027 | 0.061 |
| | | (0.095) | (0.097) |
| Eligibility FE (0–2) | Yes | Yes | Yes |
| Component-level potential controls | No | Yes | Yes |
| Socioeconomic controls | No | No | Yes |
| Control mean | 4.094 | 4.094 | 4.094 |
| Observations | 395 | 395 | 395 |

Dependent variable: total correct answers at endline (0–8). Same sample as the surplus table: all non-informed members; omitted group: control villages. Each surplus term is split into its components (sd units), relaxing the equal-and-opposite restriction the surplus imposes.
The potential controls are matched to the components: own WTP toward all potential teachers (the person's demand trait) and the total WTA all potential teachers ask of the person (the price the village puts on teaching them), both standardised. Refusal sentinels excluded throughout.
Standard errors clustered at the community level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Willingness to Pay for Central Teachers (Listener FE)

| | (1) W1 | (2) W2 | (3) W3 | (4) W4 | (5) W5 |
|---|---|---|---|---|---|
| Teacher j's diffusion centrality (z, free-text) | 0.565** | | | | |
| | (0.278) | | | | |
| Teacher j's degree (z, free-text) | | 0.606** | | | |
| | | (0.259) | | | |
| Teacher j is a nominated key informant | | | 1.766*** | | |
| | | | (0.618) | | |
| Teacher j's KI nominations (in-degree) | | | | 0.978** | |
| | | | | (0.469) | |
| Teacher j's diffusion centrality (z, socialize) | | | | | 0.649*** |
| | | | | | (0.177) |
| Constant | 18.400*** | 18.398*** | 18.230*** | 18.282*** | 18.426*** |
| | (0.014) | (0.013) | (0.069) | (0.070) | (0.001) |
| Observations | 3322 | 3322 | 3322 | 3322 | 3322 |
| Communities | 63 | 63 | 63 | 63 | 63 |

Directed dyads $i \to j$ within community; dependent variable: $i$'s WTP (Bs) to learn from $j$. All columns include listener ($i$) fixed effects, so coefficients compare a listener's bids across their OWN potential teachers. Diffusion centrality per Banerjee et al. (2019), computed on the free-text information-sharing network (col 5: the socialize-weekly network). KI = named in response to the key-informant question and matched in sample. Refusals (WTP = −999) excluded from WTP levels. Communities 1–4 (no BDM module) excluded. Standard errors clustered at the community level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# A Additional Tables and Figures

Table A.1: Sample Summary

| | Treatment | Control |
|---|---|---|
| Number of communities | 44 | 23 |
| *Teachers per community* | | |
| 0 teachers | 0 | 0 |
| 1 teacher | 0 | 0 |
| 2 teachers | 42 | 23 |
| 3+ teachers | 2 | 0 |
| *Listeners per community* | | |
| 0 listeners | 5 | 23 |
| 1 listener | 16 | 0 |
| 2 listeners | 22 | 0 |
| 3+ listeners | 1 | 0 |
| Total pairs | 65 | 0 |
| Total teachers | 91 | 46 |
| Total listeners | 63 | 0 |
| Total spillovers | 198 | 138 |
| Total individuals | 352 | 184 |

*Notes:* Teachers are those who received information at baseline. Listeners are non-informed individuals matched with an informed individual. Spillovers are individuals who are neither listeners nor teachers/seeds. Each pair consists of one teacher and one listener. In control villages, informed individuals were not matched with listeners.

Table A.2: Baseline Characteristics by Treatment Status and Sub-Groups

| | | | | Non-paired villages | | Paired villages | | |
|---|---|---|---|---|---|---|---|---|
| | All | Informed | Non-inf. | Inf. | Non-inf. | Sender | Listener | Non-matched |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Demographics* | | | | | | | | |
| Age (years) | 48.810 | 46.664 | 49.546 | 47.348 | 49.754 | 46.319 | 52.524 | 48.455 |
| Male | 0.502 | 0.445 | 0.521 | 0.457 | 0.594 | 0.440 | 0.413 | 0.505 |
| Agricultural income: Negative | 0.058 | 0.080 | 0.050 | 0.022 | 0.065 | 0.110 | 0.000 | 0.056 |
| Agricultural income: None | 0.078 | 0.080 | 0.078 | 0.174 | 0.065 | 0.033 | 0.111 | 0.076 |
| Agricultural income: Under 2,000 Bs | 0.493 | 0.474 | 0.499 | 0.413 | 0.442 | 0.505 | 0.508 | 0.535 |
| Agricultural income: 2,000–7,000 Bs | 0.278 | 0.285 | 0.276 | 0.304 | 0.297 | 0.275 | 0.317 | 0.247 |
| Agricultural income: Over 7,000 Bs | 0.093 | 0.080 | 0.098 | 0.087 | 0.130 | 0.077 | 0.063 | 0.086 |
| Has land title | 0.739 | 0.701 | 0.752 | 0.609 | 0.754 | 0.747 | 0.762 | 0.747 |
| Network size | 3.412 | 3.109 | 3.516 | 3.870 | 4.420 | 2.725 | 3.143 | 3.005 |
| Main language: Spanish | 0.606 | 0.606 | 0.607 | 0.609 | 0.659 | 0.604 | 0.571 | 0.581 |
| Main language: Quechua | 0.390 | 0.394 | 0.388 | 0.391 | 0.341 | 0.396 | 0.429 | 0.409 |
| Main language: Aymara | 0.004 | 0.000 | 0.005 | 0.000 | 0.000 | 0.000 | 0.000 | 0.010 |
| *Agriculture* | | | | | | | | |
| Grows corn | 0.590 | 0.577 | 0.594 | 0.674 | 0.543 | 0.527 | 0.683 | 0.601 |
| Grows potato | 0.513 | 0.518 | 0.511 | 0.630 | 0.536 | 0.462 | 0.508 | 0.495 |
| Grows vegetables | 0.509 | 0.526 | 0.504 | 0.500 | 0.536 | 0.538 | 0.540 | 0.470 |
| Number of crops | 3.735 | 3.599 | 3.782 | 4.435 | 3.884 | 3.176 | 3.952 | 3.657 |
| *Insurance* | | | | | | | | |
| Never had insurance | 0.974 | 0.978 | 0.972 | 0.978 | 1.000 | 0.978 | 0.984 | 0.949 |
| Currently has insurance | 0.006 | 0.007 | 0.005 | 0.000 | 0.000 | 0.011 | 0.016 | 0.005 |
| Insurance interest: Not at all | 0.103 | 0.095 | 0.105 | 0.109 | 0.080 | 0.088 | 0.079 | 0.131 |
| Insurance interest: Somewhat | 0.539 | 0.511 | 0.549 | 0.348 | 0.514 | 0.593 | 0.603 | 0.556 |
| Insurance interest: Very | 0.332 | 0.372 | 0.318 | 0.500 | 0.362 | 0.308 | 0.286 | 0.298 |
| Insurance interest: Extremely | 0.026 | 0.022 | 0.028 | 0.043 | 0.043 | 0.011 | 0.032 | 0.015 |
| *Weather worry* | | | | | | | | |
| Frost worry: Not at all | 0.216 | 0.182 | 0.228 | 0.217 | 0.261 | 0.165 | 0.254 | 0.197 |
| Frost worry: Somewhat | 0.386 | 0.409 | 0.378 | 0.348 | 0.377 | 0.440 | 0.413 | 0.369 |
| Frost worry: Very | 0.340 | 0.350 | 0.336 | 0.391 | 0.312 | 0.330 | 0.286 | 0.369 |
| Frost worry: Extremely | 0.058 | 0.058 | 0.058 | 0.043 | 0.051 | 0.066 | 0.048 | 0.066 |
| Drought worry: Not at all | 0.069 | 0.044 | 0.078 | 0.022 | 0.094 | 0.055 | 0.063 | 0.071 |
| Drought worry: Somewhat | 0.354 | 0.314 | 0.368 | 0.174 | 0.341 | 0.385 | 0.381 | 0.384 |
| Drought worry: Very | 0.502 | 0.540 | 0.489 | 0.696 | 0.507 | 0.462 | 0.476 | 0.480 |
| Drought worry: Extremely | 0.075 | 0.102 | 0.065 | 0.109 | 0.058 | 0.099 | 0.079 | 0.066 |
| Flood worry: Not at all | 0.332 | 0.299 | 0.343 | 0.196 | 0.326 | 0.352 | 0.397 | 0.338 |
| Flood worry: Somewhat | 0.362 | 0.380 | 0.356 | 0.435 | 0.399 | 0.352 | 0.254 | 0.359 |
| Flood worry: Very | 0.235 | 0.241 | 0.233 | 0.283 | 0.217 | 0.220 | 0.270 | 0.232 |
| Flood worry: Extremely | 0.071 | 0.080 | 0.068 | 0.087 | 0.058 | 0.077 | 0.079 | 0.071 |
| *Community characteristics* | | | | | | | | |
| Population (inhabitants) | 1574.111 | 1570.636 | 1575.307 | 1534.350 | 1534.350 | 1586.944 | 1609.500 | 1589.788 |
| Distance to capital (km) | 55.432 | 55.432 | 55.432 | 60.333 | 60.333 | 52.897 | 58.116 | 51.183 |
| Travel time to capital (min) | 94.545 | 94.545 | 94.545 | 90.667 | 90.667 | 96.552 | 104.186 | 94.046 |
| Rate of cold days (10y) | 0.020 | 0.020 | 0.020 | 0.019 | 0.019 | 0.020 | 0.020 | 0.021 |
| Rate of dry days (10y) | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.024 | 0.025 |
| Rate of extreme rainy days (10y) | 0.056 | 0.055 | 0.056 | 0.057 | 0.057 | 0.055 | 0.056 | 0.055 |
| $N$ | 536 | 137 | 399 | 46 | 138 | 91 | 63 | 198 |

*Notes:* Each cell reports the group mean. *Informed* = individuals who received information about insurance and EWS at baseline. *Non-informed* = individuals who did not receive this information. *Non-paired*/*Paired* refers to village-level treatment assignment (whether matched pairs were formed for facilitated conversations). *Sender* = informed individual in match villages assigned to share information. *Listener* = non-informed individual matched to receive information from a sender. *Non-matched* = non-informed individuals in match villages who were not assigned a conversation partner. Network size = number of named contacts reported in baseline survey.

Table A.3: Teacher Knowledge by Link Type (Separate Samples) — Raw (no controls)

| | (1) Free-flowing | (2) Blocked | (3) Norm-constrained |
|---|---|---|---|
| Paired | 0.965** | 0.838 | 1.940*** |
| | (0.412) | (0.582) | (0.419) |
| Control mean | 4.094 | 4.094 | 4.094 |
| Observations | 86 | 57 | 54 |

Dependent variable: total correct answers at endline (0–8).
Sample: teachers in treatment and control villages.
Standard errors clustered at the community level in parentheses.
No controls, no eligibility FE, no baseline-knowledge control.
Each column restricts treatment teachers to those whose
paired recipient has the indicated link type.
All control village teachers are included in every column.
*Free-flowing*: teacher WTA $\leq 0$ (intrinsically motivated to share).
*Blocked*: listener WTP $<$ teacher WTA.
*Norm-constrained*: teacher WTA $> 0$ but listener WTP $\geq$ teacher WTA.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table A.4: Teacher Knowledge by Link Type (Separate Samples)

| | (1) Free-flowing | (2) Blocked | (3) Norm-constrained |
|---|---|---|---|
| Paired | 1.484*** | -0.441 | 1.138 |
| | (0.472) | (0.700) | (0.863) |
| Link-type exposure controls | Yes | Yes | Yes |
| Socioeconomic controls | Yes | Yes | Yes |
| Baseline teacher knowledge control | Yes | Yes | Yes |
| Control mean | 4.094 | 4.094 | 4.094 |
| Observations | 85 | 57 | 54 |

Dependent variable: total correct answers at endline (0–8).
Sample: teachers in treatment and control villages.
Standard errors clustered at the community level in parentheses.
Each column restricts treatment teachers to those whose
paired recipient has the indicated link type.
All control village teachers are included in every column.
*Free-flowing*: teacher WTA $\leq 0$ (intrinsically motivated to share).
*Blocked*: listener WTP $<$ teacher WTA.
*Norm-constrained*: teacher WTA $> 0$ but listener WTP $\geq$ teacher WTA.
Link-type exposure controls: for each person, the number of potential partners
(0–7) of the relevant link type, counted over all community members from baseline
WTA/WTP. A partner is counted only if it would be matchable under the assignment
rule (04_meeting_treatment_assignments.do): teacher WTA in $[0, 30]$ and partner
WTP $\geq 0$, with either-side refusals ($-888/-999$) excluded. Free: teacher WTA
$= 0$; Norm-constrained: teacher WTA $> 0$ and partner WTP $\geq$ teacher WTA; Blocked:
teacher WTA $> 0$ and $0 \leq$ partner WTP $<$ teacher WTA. Computed identically in
Each column controls for the teacher's count of potential recipients of its own link type:
the Free-flowing column for free-flowing recipients, the Blocked column for blocked
recipients, and the Norm-constrained column for norm-constrained recipients (fixed effects).
Baseline teacher knowledge control: teacher's own baseline knowledge score (0–8).
Socioeconomic controls: age, gender, insurance history, land title, HH selection method.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Recipient Knowledge by Link Type (Separate Samples) — Raw (no controls)

| | (1) Free-flowing | (2) Blocked | (3) Norm-constrained |
|---|---|---|---|
| Paired | 0.906*** | 1.360*** | 0.906** |
| | (0.315) | (0.412) | (0.411) |
| Control mean | 4.094 | 4.094 | 4.094 |
| Observations | 178 | 149 | 146 |

Dependent variable: total correct answers at endline (0–8).
Sample: recipients and non-informed control village members.
Standard errors clustered at the community level in parentheses.
No controls, no eligibility FE, no baseline-knowledge control.
Each column restricts recipients to those whose own pair
has the indicated link type.
All non-informed control village members are included in every column.
*Free-flowing*: teacher WTA $\leq 0$ (intrinsically motivated to share).
*Blocked*: listener WTP $<$ teacher WTA.
*Norm-constrained*: teacher WTA $> 0$ but listener WTP $\geq$ teacher WTA.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table A.6: Recipient Knowledge by Link Type (Separate Samples)

| | (1) Free-flowing | (2) Blocked | (3) Norm-constrained |
|---|---|---|---|
| Paired | 1.198*** | 2.014*** | 1.008* |
| | (0.346) | (0.591) | (0.547) |
| Link-type exposure controls | Yes | Yes | Yes |
| Socioeconomic controls | Yes | Yes | Yes |
| Baseline teacher knowledge control | Yes | Yes | Yes |
| Control mean | 4.094 | 4.094 | 4.094 |
| Observations | 178 | 149 | 146 |

Dependent variable: total correct answers at endline (0–8).
Sample: recipients and non-informed control village members.
Standard errors clustered at the community level in parentheses.
Each column restricts recipients to those whose own pair
has the indicated link type.
All non-informed control village members are included in every column.
*Free-flowing*: teacher WTA $\leq 0$ (intrinsically motivated to share).
*Blocked*: listener WTP $<$ teacher WTA.
*Norm-constrained*: teacher WTA $> 0$ but listener WTP $\geq$ teacher WTA.
Link-type exposure controls: for each person, the number of potential partners
(0–7) of the relevant link type, counted over all community members from baseline
WTA/WTP. A partner is counted only if it would be matchable under the assignment
rule (04_meeting_treatment_assignments.do): teacher WTA in $[0, 30]$ and partner
WTP $\geq 0$, with either-side refusals ($-888/-999$) excluded. Free: teacher WTA
$= 0$; Norm-constrained: teacher WTA $> 0$ and partner WTP $\geq$ teacher WTA; Blocked:
teacher WTA $> 0$ and $0 \leq$ partner WTP $<$ teacher WTA. Computed identically in
Each column controls for the count of available teachers of its own link type: the
Free-flowing column for free-flowing teachers, the Blocked column for blocked teachers,
and the Norm-constrained column for norm-constrained teachers (entered as fixed effects).
Baseline teacher knowledge control: average baseline knowledge score of teachers in community.
Socioeconomic controls: age, gender, insurance, land title, HH selection method.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table A.7: Spillover Effects by Link Type (Separate Samples) — Raw (no controls)

| | (1) Free-flowing | (2) Blocked | (3) Norm-constrained |
|---|---|---|---|
| Matched village | 0.525* | 0.590 | 0.656 |
| | (0.296) | (0.346) | (0.578) |
| Control mean | 4.094 | 4.094 | 4.094 |
| Observations | 277 | 157 | 146 |

Dependent variable: total correct answers at endline (0–8).
Sample: community members who are neither teachers nor recipients.
Standard errors clustered at the community level in parentheses.
No controls, no eligibility FE, no baseline-knowledge control.
Each column restricts treatment villages to those where the community's dominant link type matches the column heading.
All control village non-informed members are included in every column.
*Free-flowing*: teacher WTA $\leq 0$ (intrinsically motivated to share).
*Blocked*: listener WTP $<$ teacher WTA.
*Norm-constrained*: teacher WTA $> 0$ but listener WTP $\geq$ teacher WTA.
Community link type assigned by dominance hierarchy: free-flowing > norm-constrained > blocked.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table A.8: Spillover Effects by Link Type (Separate Samples)

| | (1) Free-flowing | (2) Blocked | (3) Norm-constrained |
|---|---|---|---|
| Matched village | 0.408 | 1.425*** | 0.421 |
| | (0.263) | (0.431) | (0.573) |
| Link-type exposure controls | Yes | Yes | Yes |
| Socioeconomic controls | Yes | Yes | Yes |
| Baseline teacher knowledge control | Yes | Yes | Yes |
| Control mean | 4.094 | 4.094 | 4.094 |
| Observations | 277 | 157 | 146 |

Dependent variable: total correct answers at endline (0–8).
Sample: community members who are neither teachers nor recipients.
Standard errors clustered at the community level in parentheses.
Each column restricts treatment villages to those where the
community's dominant link type matches the column heading.
All control village non-informed members are included in every column.
*Free-flowing*: teacher WTA $\leq 0$ (intrinsically motivated to share).
*Blocked*: listener WTP $<$ teacher WTA.
*Norm-constrained*: teacher WTA $> 0$ but listener WTP $\geq$ teacher WTA.
Community link type assigned by dominance hierarchy:
free-flowing $>$ norm-constrained $>$ blocked.
Link-type exposure controls: for each person, the number of potential partners
(0–7) of the relevant link type, counted over all community members from baseline
WTA/WTP. A partner is counted only if it would be matchable under the assignment
rule (04_meeting_treatment_assignments.do): teacher WTA in $[0, 30]$ and partner
WTP $\geq 0$, with either-side refusals ($-888/-999$) excluded. Free: teacher WTA
$= 0$; Norm-constrained: teacher WTA $> 0$ and partner WTP $\geq$ teacher WTA; Blocked:
teacher WTA $> 0$ and $0 \leq$ partner WTP $<$ teacher WTA. Computed identically in
Each column controls for the count of available teachers of its own link type: the
Free-flowing column for free-flowing teachers, the Blocked column for blocked teachers,
and the Norm-constrained column for norm-constrained teachers (entered as fixed effects).
Baseline teacher knowledge control: average baseline knowledge score of teachers in community.
Socioeconomic controls: age, gender, insurance, land title, HH selection method.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## A.1 Results by Knowledge

### A.1.1 category 1

- Remember (Q1, Q2, Q4, Q8): factual recall — covered risk, covered crops, purchase timing, EWS lead time (0–4).
- Understand (Q3, Q6): interpretation — premium amount, non-covered risks (0–2).
- Analyze (Q5, Q7): causal reasoning — payout trigger, basis risk (0–2)

Table A.9: Teacher Knowledge by Cognitive Process

| | (1) Remember | (2) Understand | (3) Analyze |
|---|---|---|---|
| Paired | 0.628*** | 0.148 | 0.370** |
| | (0.235) | (0.102) | (0.148) |
| Eligibility FE (0–7) | Yes | Yes | Yes |
| Socioeconomic controls | Yes | Yes | Yes |
| Baseline teacher knowledge control | Yes | Yes | Yes |
| Control mean | 2.225 | 0.681 | 1.188 |
| Observations | 136 | 136 | 136 |

Dependent variable: sum of correct answers within each cognitive category.
Remember (Q1, Q2, Q4, Q8): factual recall — covered risk, covered crops, purchase timing, EWS lead time (0–4).
Understand (Q3, Q6): interpretation — premium amount, non-covered risks (0–2).
Analyze (Q5, Q7): causal reasoning — payout trigger, basis risk (0–2).
Sample: teachers in treatment and control villages.
Standard errors clustered at the community level in parentheses.
Eligibility FE: fixed effects for number of community members teacher is willing to teach (WTA $\geq 0$), from 0 to 7.
Baseline teacher knowledge control: teacher's own baseline knowledge score (0–8).
Socioeconomic controls: age, gender, insurance history, land title, HH selection method.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table A.10: Recipient Knowledge by Cognitive Process

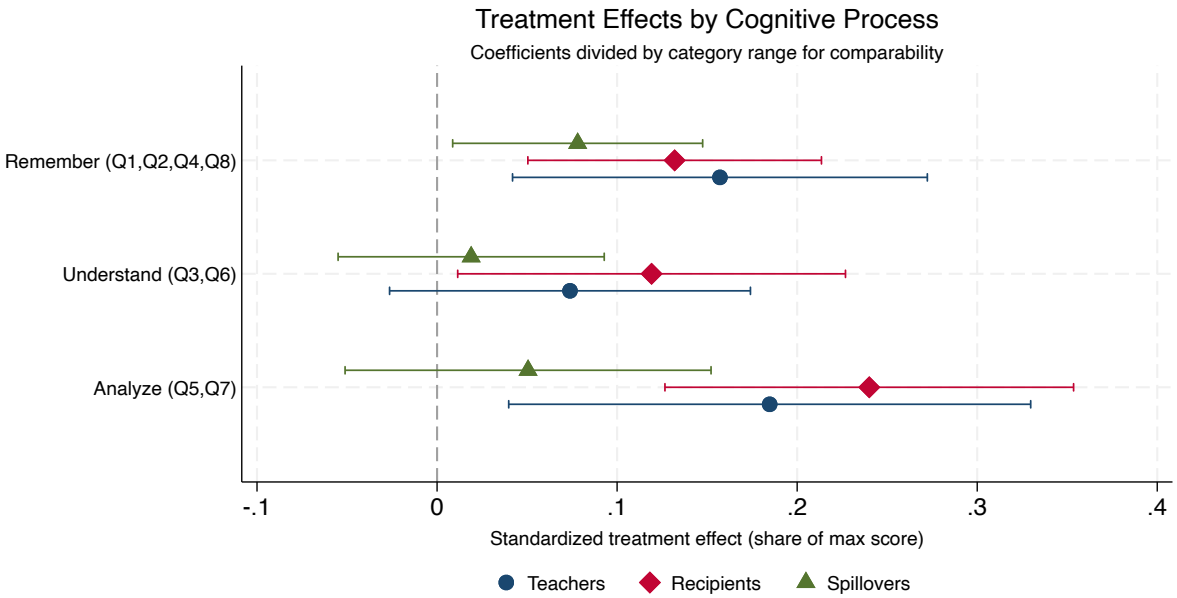
| | (1) Remember | (2) Understand | (3) Analyze |
|---|---|---|---|
| Paired | 0.528*** | 0.238** | 0.480*** |
| | (0.166) | (0.110) | (0.116) |
| Eligibility FE (0–2) | Yes | Yes | Yes |
| Socioeconomic controls | Yes | Yes | Yes |
| Baseline teacher knowledge control | Yes | Yes | Yes |
| Control mean | 2.225 | 0.681 | 1.188 |
| Observations | 201 | 201 | 201 |

Dependent variable: sum of correct answers within each cognitive category.
Remember (Q1, Q2, Q4, Q8): factual recall — covered risk, covered crops, purchase timing, EWS lead time (0–4).
Understand (Q3, Q6): interpretation — premium amount, non-covered risks (0–2).
Analyze (Q5, Q7): causal reasoning — payout trigger, basis risk (0–2).
Sample: recipients and non-informed control village members.
Standard errors clustered at the community level in parentheses.
Eligibility FE: fixed effects for number of assigned teachers willing to teach this person (WTA $\geq 0$), from 0 to 2.
Baseline teacher knowledge control: category-specific teacher baseline knowledge score.
Socioeconomic controls: age, gender, insurance history, land title, HH selection method.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: Spillover Effects on Knowledge by Cognitive Process

| | (1) Remember | (2) Understand | (3) Analyze |
|---|---|---|---|
| Matched village | 0.312** | 0.038 | 0.101 |
| | (0.142) | (0.075) | (0.104) |
| Eligibility FE (0–2) | Yes | Yes | Yes |
| Socioeconomic controls | Yes | Yes | Yes |
| Baseline teacher knowledge control | Yes | Yes | Yes |
| Control mean | 2.225 | 0.681 | 1.188 |
| Observations | 336 | 336 | 336 |

Dependent variable: sum of correct answers within each cognitive category.
Remember (Q1, Q2, Q4, Q8): factual recall — covered risk, covered crops, purchase timing, EWS lead time (0–4).
Understand (Q3, Q6): interpretation — premium amount, non-covered risks (0–2).
Analyze (Q5, Q7): causal reasoning — payout trigger, basis risk (0–2).
Sample: community members who are neither teachers nor recipients.
Standard errors clustered at the community level in parentheses.
Eligibility FE: fixed effects for number of assigned teachers willing to teach this person (WTA $\geq 0$), from 0 to 2.
Baseline teacher knowledge control: category-specific teacher baseline knowledge score.
Socioeconomic controls: age, gender, insurance history, land title, HH selection method.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$




Bars show 95% CIs. SEs clustered at community level.
Categories follow Bloom's revised taxonomy.

# WTP for insurance

Table A.12: Effect on Teacher Willingness to Pay

| | (1) Insurance | (2) EWS | (3) Bundle |
|---|---|---|---|
| Paired | 6.509 | -28.705 | 0.235 |
| | (7.417) | (28.966) | (24.956) |
| Eligibility FE (0–7) | Yes | Yes | Yes |
| Socioeconomic controls | Yes | Yes | Yes |
| Control mean (Bs) | 39.913 | 77.246 | 179.935 |
| Observations | 136 | 136 | 136 |

Dependent variable: endline willingness to pay (Bolivianos) for each product.
Sample: teachers in treatment and control villages.
Standard errors clustered at the community level in parentheses.
Eligibility FE: fixed effects for number of community members teacher is willing to teach (WTA $\geq 0$), from 0 to 7.
Socioeconomic controls: age, gender, insurance history, land title, HH selection method.
No baseline WTP was elicited, so no baseline-outcome control is included.
Control mean: mean WTP among non-informed individuals in control villages.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table A.13: Effect on Recipient Willingness to Pay

| | (1) Insurance | (2) EWS | (3) Bundle |
|---|---|---|---|
| Paired | -1.879 | -62.228* | -63.669 |
| | (5.918) | (33.618) | (75.619) |
| Eligibility FE (0–2) | Yes | Yes | Yes |
| Socioeconomic controls | Yes | Yes | Yes |
| Control mean (Bs) | 39.913 | 77.246 | 179.935 |
| Observations | 201 | 201 | 201 |

Dependent variable: endline willingness to pay (Bolivianos) for each product.
Sample: recipients and non-informed control village members.
Standard errors clustered at the community level in parentheses.
Eligibility FE: fixed effects for number of assigned teachers willing to teach this person (WTA $\geq 0$), from 0 to 2.
Socioeconomic controls: age, gender, insurance history, land title, HH selection method.
No baseline WTP was elicited, so no baseline-outcome control is included.
Control mean: mean WTP among non-informed individuals in control villages.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.14: Spillover Effects on Willingness to Pay

| | (1) Insurance | (2) EWS | (3) Bundle |
|---|---|---|---|
| Matched village | -7.552* | -39.596 | -67.563 |
| | (3.921) | (26.048) | (48.597) |
| Eligibility FE (0–2) | Yes | Yes | Yes |
| Socioeconomic controls | Yes | Yes | Yes |
| Control mean (Bs) | 39.913 | 77.246 | 179.935 |
| Observations | 336 | 336 | 336 |

Dependent variable: endline willingness to pay (Bolivianos) for each product.
Sample: community members who are neither teachers nor recipients.
Standard errors clustered at the community level in parentheses.
Eligibility FE: fixed effects for number of assigned teachers willing to teach this person (WTA $\geq 0$), from 0 to 2.
Socioeconomic controls: age, gender, insurance history, land title, HH selection method.
No baseline WTP was elicited, so no baseline-outcome control is included.
Control mean: mean WTP among non-informed individuals in control villages.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# Is WTP driven by connection or by knowledge transmission

Dependent variable: WTP Sample: All dyadic pairs Variables based on alter' popularity or endline knowledge

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Key-informant mentions (0–7) | 1.152** | | | | 0.767* |
| | (0.520) | | | | (0.409) |
| Socialize-with in-degree (0–7) | | 0.643*** | | | 0.553*** |
| | | (0.175) | | | (0.170) |
| Named-in-network in-degree (0–7) | | | 0.797** | | 0.367 |
| | | | (0.353) | | (0.333) |
| Endline knowledge (0–8) | | | | -0.083 | -0.090 |
| | | | | (0.098) | (0.092) |
| Ego (listener) FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 3528 | 3528 | 3528 | 3528 | 3528 |

Dyadic regressions: outcome is ego $i$'s WTP (Bs) to learn from alter $j$ (3528 directed dyads, all roster members, 63 communities; refusals floored to 0). Same full sample in every column. All columns include ego fixed effects: coefficients compare the SAME listener's WTP across partners; village differences are absorbed. In-degrees are ex-ante baseline nominations received. Endline knowledge is measured for everyone but AFTER the experiment (WTP was elicited at baseline): read it as a proxy for the partner's general knowledge type, partly moved by experimental roles, not as information the bidder observed. The alter component of WTP is a small share of its total variance; the table speaks to WHAT the partner premium loads on, not to its overall size. SEs clustered by community.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: WTP Sample: All pairs with teachers and seeds Variables based on seeds' popularity or endline knowledge

| | Alter is a seed (same sample in all columns) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Key-informant mentions (0–7) | -0.590 | | | | -2.523 |
| | (1.613) | | | | (1.533) |
| Socialize-with in-degree (0–7) | | 0.277 | | | 0.093 |
| | | (0.727) | | | (0.755) |
| Named-in-network in-degree (0–7) | | | 1.728 | | 2.833 |
| | | | (1.937) | | (2.032) |
| Baseline knowledge (0–8) | | | | -0.262 | -0.096 |
| | | | | (0.374) | (0.331) |
| Listener FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 903 | 903 | 903 | 903 | 903 |

Dyadic regressions: outcome is listeners $i$'s WTP (Bs) to learn from seed or teacher $j$; refusals floored to 0. ALL columns use the same sample: dyads whose alter is a seed – baseline knowledge was only elicited for the informed, and holding the sample fixed keeps the columns comparable. All columns include ego fixed effects, so coefficients compare the SAME listener's WTP across different partners; village differences are absorbed. With ∼2 seed alters per ego, within-ego variation is thin – estimates are imprecise by construction. Alter attributes are ex ante: key-informant mentions, weekly-socializing and free-list nominations received, and the alter's baseline knowledge score (0–8). The alter component of WTP is a small share of its total variance (see the variance decomposition); the table speaks to WHAT the partner premium loads on, not to its overall size. SEs clustered by community.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

| | All alters (endline knowledge) | | Seed alters (baseline knowledge) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| High popularity (index > median) | 1.190** | 1.201** | 0.891 | 0.271 |
| | (0.494) | (0.498) | (1.641) | (1.733) |
| High knowledge (> median) | | 0.267 | | -2.540 |
| | | (0.473) | | (1.771) |
| Self (listener) FE | Yes | Yes | Yes | Yes |
| Observations | 3528 | 3528 | 903 | 903 |

Dyadic regressions with ego FE; outcome is ego $i$'s WTP (Bs) for alter $j$, refusals floored to 0; SEs clustered by community. POPULARITY INDEX: the equal-weighted average of the z-scores of three nomination counts received at baseline (key-informant mentions, network free-list namings, weekly-socializing links); the three correlate 0.17–0.31 and their first principal component (∼51% of variance) loads on them near-equally. Dummies are strictly > the estimation sample's median. Cols. (1)-(2): all roster alters, knowledge measured at ENDLINE (post-experiment – a proxy for the partner's knowledge type, not information the bidder observed). Cols. (3)-(4): alters who are seeds – the only people with elicited BASELINE knowledge; ∼2 seed alters per ego leaves thin within-ego variation there.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Self's own tie to the seed | 1.797 | | | 1.582 |
| | (1.368) | | | (1.311) |
| Seed is high-popularity | | 0.891 | | -0.193 |
| | | (1.641) | | (1.763) |
| Seed is high-knowledge | | | -2.667* | -2.493 |
| | | | (1.560) | (1.721) |
| Self (listener) FE | Yes | Yes | Yes | Yes |
| Observations | 903 | 903 | 903 | 903 |

Outcome: self's WTP (Bs) to learn from a SEED alter (903 dyads; refusals floored to 0); self FE, SEs clustered by community. All regressors ex ante. Own tie = the self named the seed in their free-list or socializes weekly with them (32.3% of dyads; dyad-specific). High-popularity = the seed's nomination index (equal-weighted mean of z-scored KI mentions, free-list namings and socialize links received, village-wide) above the sample median (-0.31). High-knowledge = baseline knowledge above the sample median (4.00 of 8); seeds are the only people with elicited baseline knowledge. Column (4) races the three: the popularity premium is absorbed by the own tie (they correlate 0.35) – a seed commands a premium only from their own friends – while the knowledge coefficient is negative.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Self's own tie to the alter | 1.363** | | | 1.095* |
| | (0.528) | | | (0.562) |
| Alter is high-popularity | | 1.190** | | 0.910* |
| | | (0.494) | | (0.531) |
| Alter is high endline knowledge | | | 0.218 | 0.262 |
| | | | (0.476) | (0.474) |
| Self (listener) FE | Yes | Yes | Yes | Yes |
| Observations | 3528 | 3528 | 3528 | 3528 |

Outcome: self's WTP (Bs) to learn from each roster member (3528 dyads; refusals floored to 0); self FE, SEs clustered by community. Own tie = the self named the alter in their free-list or socializes weekly with them (33.7% of dyads; dyad-specific, ex ante). High-popularity = the alter's nomination index (equal-weighted mean of z-scored KI mentions, free-list namings and socialize links received, village-wide, ex ante) above the sample median (-0.08). High endline knowledge = above the sample median (5.00 of 8); measured for everyone but POST-experiment – a proxy for the partner's knowledge type, not information the bidder observed. Column (4) races the three.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Who are high in popularity?

| | Low popularity | High popularity | Diff. | (SE) |
|---|---|---|---|---|
| Age | 47.48 | 51.27 | 3.79*** | ( 1.26) |
| Male | 0.45 | 0.60 | 0.15*** | ( 0.05) |
| Has land title | 0.75 | 0.72 | -0.03 | ( 0.04) |
| Never had insurance | 0.98 | 0.96 | -0.03 | ( 0.02) |
| Income above 7000 Bs | 0.07 | 0.13 | 0.06** | ( 0.03) |
| Diversified crops | 0.83 | 0.90 | 0.07** | ( 0.03) |
| Is a seed | 0.28 | 0.22 | -0.06 | ( 0.04) |
| Endline knowledge (0 8) | 4.72 | 4.51 | -0.21 | ( 0.19) |
| Own mean WTA (Bs) | 8.18 | 7.96 | -0.22 | ( 1.43) |
| Own mean WTP (Bs) | 16.51 | 18.91 | 2.40 | ( 2.02) |
| Socialize out degree | 2.08 | 2.65 | 0.57*** | ( 0.18) |
| Named out degree | 0.22 | 0.42 | 0.20*** | ( 0.06) |
| Good communicator nominations | 1.82 | 1.90 | 0.07 | ( 0.12) |
| Advice nominations | 2.45 | 2.66 | 0.22 | ( 0.16) |
| Respect nominations | 3.20 | 3.40 | 0.20 | ( 0.16) |
| Individuals | 348 | 188 | | |

High popularity = the nomination index (equal-weighted mean of z-scored key-informant mentions, free-list namings and socialize links RECEIVED at baseline) strictly above the median. Diff. from an OLS of the characteristic on the High dummy, SEs clustered by community. Own mean WTA/WTP: the person's average stated price over their ∼7 partners, refusals floored to 0. Out-degrees: nominations the person GIVES. Communicator/advice/ respect: nominations RECEIVED on the perceived-skill roster questions.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Are there just certain people everyone wants to learn from? Or is there a lot of variation within person?

# Is it WTP or WTA

Among non informed, having more wanted seeds (higher WTP) or seeds that are more willing to teach (low WTA) improved knowledge learning?

| | Mean | SD | Min | p25 | Med | p75 | Max | At 0 |
|---|---|---|---|---|---|---|---|---|
| Supply: share taught free (WTA = 0) | 0.619 | 0.373 | 0.00 | 0.33 | 0.64 | 1.00 | 1.00 | 8 |
| Supply: share matchable (WTA $\leq$ 30) | 0.880 | 0.229 | 0.00 | 0.83 | 1.00 | 1.00 | 1.00 | 1 |
| Demand: share with positive WTP for seeds | 0.749 | 0.190 | 0.17 | 0.67 | 0.75 | 0.92 | 1.00 | 0 |
| Flatness: share of villagers flat on WTA | 0.615 | 0.243 | 0.00 | 0.40 | 0.67 | 0.83 | 1.00 | 1 |
| Flatness: share of villagers flat on WTP | 0.464 | 0.224 | 0.12 | 0.33 | 0.43 | 0.62 | 1.00 | 0 |

53 villages with at least 6 measured seed-to-villager links.

Links run from a drawn teacher to a non-teacher villager; a refusal counts as unwilling.

Corr with flat-WTA share: supply 0.362, demand 0.226; with flat-WTP share:
supply 0.119, demand 0.120.

corr(supply share, demand share) = -0.041. A flat schedule at zero forces the
free-share to 1 and a flat positive schedule forces it to 0, so the supply measure
is heavily contaminated by the elicitation artifact; the demand measure is not.

- Supply: share taught free (WTA = 0): From the two seeds and their links to other villagers, what fraction of links have WTA =0
- Supply: share matchable (WTA $\leq$ 30): From the two seeds and their links to other villagers, what fraction of links have WTA less than 30
- Demand: share with positive WTP for seeds. What share of villagers links with seeds have WTP positive

Regressor village level: free-share (what fraction of villagers would the two seeds teach for nothing or share of villagers with WTA = 0 from seeds) and posWTP-share (what fraction of villagers would pay something to learn from the seeds or WTP >0). Output: Endline score

Table A.15: Diffusion by the Seeds' Supply and Demand Position

| | (1)<br>All non-informed | (2)<br>Spillovers only |
|---|---|---|
| Treatment | 0.717*** | 0.585** |
| | ( 0.261) | ( 0.282) |
| Free-share (supply) | -0.365** | -0.365** |
| | ( 0.182) | ( 0.182) |
| Treatment × Free-share | 0.350 | 0.300 |
| | ( 0.243) | ( 0.256) |
| PosWTP-share (demand) | -0.416** | -0.416** |
| | ( 0.165) | ( 0.165) |
| Treatment × PosWTP-share | 0.152 | 0.076 |
| | ( 0.248) | ( 0.245) |
| Villages | 53 | 53 |

Village-level regressions: the dependent variable is the village mean of endline knowledge (0–8) over non-informed members, unweighted. Column (1): all non-informed. Column (2): the mean additionally excludes matched listeners (organic spillovers only). Robust standard errors in parentheses.
*Free-share*: share of non-teacher villagers the two randomly drawn seeds would teach at WTA = 0. *PosWTP-share*: share of villagers with strictly positive WTP to learn from the seeds. Both standardised to sd = 1 across villages. Seeds were drawn uniformly at random within village, so the interactions identify the effect of the luck of the draw; the share main effects are cross-sectional village correlations and carry no causal interpretation.
POWER: the minimum detectable interaction (80% power, 5% level) in column (1) is 0.681 (supply, 95% of the treatment effect) and 0.695 (demand, 97%). A null interaction is therefore uninformative about moderation smaller than the main effect itself.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.16: Conversations by the Seeds' Supply and Demand Position

| | (1)<br>All non-informed | (2)<br>Spillovers only |
|---|---|---|
| Treatment | 0.047 | 0.028 |
| | ( 0.123) | ( 0.126) |
| Free-share (supply) | 0.175* | 0.175* |
| | ( 0.094) | ( 0.094) |
| Treatment × Free-share | -0.125 | -0.124 |
| | ( 0.113) | ( 0.116) |
| PosWTP-share (demand) | -0.060 | -0.060 |
| | ( 0.079) | ( 0.079) |
| Treatment × PosWTP-share | -0.053 | -0.043 |
| | ( 0.104) | ( 0.119) |
| Villages | 53 | 53 |

Village-level regressions (same construction as the knowledge table): the dependent variable is the unweighted village mean of the count of conversations about the insurance product (end_q14) over non-informed members. Column (2) excludes matched listeners from the mean. The share main effects are control-village cross-sectional correlations; only the treatment interactions carry a causal reading. Robust SEs.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# Diffusion centrality

Three questions:

- do community members recognize who has higher diffusion centrality?
- are community members willing to pay more to meet those with higher diffusion centrality?
- are higher centrality members better at difussion of infomration?

## Diffusion centrality measures

Based on three measures of linkage between the 8 community members:

- Free-text = the person appears in your written list of who you share information with (freely named)
- Socializes = the person socializes weekly (asked per person)

Either direction is counted (i to j OR j to i): $G_{ij} = 1$ if either $i$ or $j$ named the other.

Table A.17: Centrality Measures: Descriptive Statistics

| | Mean | SD | Min | Median | Max | Share zero |
|---|---|---|---|---|---|---|
| Diffusion centrality (free-text) | 0.739 | 1.232 | 0.00 | 0.000 | 5.98 | 0.64 |
| Diffusion centrality (socialize) | 2.191 | 1.063 | 0.00 | 2.094 | 6.10 | 0.04 |
| Degree (free-text) | 0.537 | 0.868 | 0.00 | 0.000 | 4.00 | 0.64 |
| Degree (socialize) | 3.541 | 1.755 | 0.00 | 3.000 | 7.00 | 0.04 |
| Nominated KI (0/1) | 0.106 | 0.309 | 0.00 | 0.000 | 1.00 | 0.89 |
| KI in-degree | 0.140 | 0.482 | 0.00 | 0.000 | 5.00 | 0.89 |

One row per sampled person ($N = 536$; 67 communities $\times$ 8 members).
Networks OR-symmetrized (a link exists if either side names the other).
Diffusion centrality per Banerjee et al. (2019): $q = 1/\lambda_1$, $T$ = diameter. Eigenvector centrality sums to 1 within community. KI = key-informant nomination matched among the sampled 8 (a lower bound on nominations).

**Diffusion centrality**: Based on Banerjee's gossip paper: seed information at this person, let it pass along links with probability q for T rounds, and count the expected number of times it reaches others. Higher = information planted here travels further. Diffusion centrality is the *expected* number of times the information gets received by others:

$$DC_i \;=\; \Big[\textstyle\sum_{t=1}^{T}(qG)^t\,\mathbf{1}\Big]_i,$$

- Free-text: The median villager sits outside the information network entirely, while a small minority reaches DC of 5–6. Information flow runs through a few hubs
- Socialize: Almost everyone is connected, and centrality is spread smoothly around the middle

**Degree**: It is the raw link counts (0–7) $deg_i = \sum_j G_{ij} \in \{0, \ldots, 7\}$. At $T = 1$, diffusion centrality reduces to $q \cdot deg_i$, so degree is the one-round version of $DC$.

**Eigenvector**: Recursive measure where being linked to well-linked people counts extra, normalized so each community's scores sum to 1 — read it as this person's share of their village's total centrality (0.125 = an even one-eighth share). An individual's score is proportional to the sum of their neighbors' scores,

$$c_i \;=\; \frac{1}{\lambda_1}\sum_j G_{ij}\,c_j \qquad \Longleftrightarrow \qquad G\,c = \lambda_1 c,$$

where $c$ is the leading eigenvector of $G$. We normalize $c$ to sum to one within each community, so $c_i$ reads as person $i$'s *share* of the village's total centrality (0.125 = an even one-eighth share).

**A worked example.** To understand the measures, consider a community of three people, $A$, $B$, and $C$, where $A$ talks to $B$ and $B$ talks to $C$. The adjacency matrix is

$$G \;=\; \begin{array}{c} \\ A \\ B \\ C \end{array}\!\!\begin{array}{c} \begin{array}{ccc} A & B & C \end{array} \\ \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix} \end{array}$$

Each cell $G_{ij}$ indicates whether $i$ and $j$ are connected — here, whether either named the other in response to the question "With whom do you share information?"[1] The diagonal is zero, since a person's link to themselves does not count.

**Degree.** Degree is the row sum: for each person, the number of connections. Here $\deg(A) = 1$, $\deg(B) = 2$, $\deg(C) = 1$, so $B$ has the highest degree. Degree measures how many people one's news can potentially reach in a *single* round of conversation.

**The passing probability $q$.** Diffusion centrality discounts each conversation by $q$, the probability that a given link actually transmits the news in a given round. We set $q = 1/\lambda_1$, where $\lambda_1$ is the largest eigenvalue of $G$: $\lambda_1$ is the network's natural growth rate — on average, how many new ears each round of gossip reaches — because repeated transmission through the network expands the volume of circulating news by a factor of $\lambda_1$ per round. In the example, $\lambda_1 = \sqrt{2}$, so $q \approx 0.71$.

**Diffusion centrality.** Start with $x_0 = (1, 1, 1)'$: every person holds one unit of news. Each round, the news a person holds is the news held by all of their neighbors in the previous round, discounted by $q$:

$$x_t \;=\; q\,G\,x_{t-1}.$$

In round 1,

$$x_1 = q\,G x_0 = q\,(1,\ 2,\ 1)' \approx (0.71,\ 1.41,\ 0.71)',$$

[1] Links are OR-symmetrized: a link exists if *either* member reports it, so $G$ is symmetric ($G_{ij} = G_{ji}$).

where $Gx_0$ counts each person's neighbors and $q$ shrinks the count because not every conversation happens. In round 2 we compound again:

$$x_2 = q\,Gx_1 = q^2G^2x_0 \approx (1,\ 1,\ 1)',$$

so news traveling two hops is discounted by $q$ twice. We repeat this $T$ times, where $T$ is the network's *diameter* — the longest shortest path between any two members ($T = 2$ here, since $A$ reaches $C$ only through $B$) — i.e., just enough rounds for news to be able to cross the entire community. Diffusion centrality sums the rounds:

$$DC \ = \ \sum_{t=1}^{T}(qG)^t\,\mathbf{1} \ = \ x_1 + x_2 \ \approx \ (1.71,\ 2.41,\ 1.71)'.$$

$B$'s higher value reflects that news seeded at $B$ circulates more widely than news seeded at the peripheral members $A$ and $C$: $DC_i$ measures the expected volume of news transmission generated over $T$ rounds when person $i$ is the source.

Regression on teacher's centrality measure (including listener's FE) for all pairs:

reghdfe wtp [centrality of teacher j], absorb(listenerid) cluster(community)

There is a premium on the listener on Teacher's centrality measures. Listeners value centrality on information-network position and sociability.

Central teachers don't charge more.

Table A.18: Willingness to Pay for Central Teachers (Listener FE)

| | (1) W1 | (2) W2 | (3) W3 | (4) W4 | (5) W5 |
|---|---|---|---|---|---|
| Teacher j's diffusion centrality (z, free-text) | 0.565** | | | | |
| | (0.278) | | | | |
| Teacher j's degree (z, free-text) | | 0.606** | | | |
| | | (0.259) | | | |
| Teacher j is a nominated key informant | | | 1.766*** | | |
| | | | (0.618) | | |
| Teacher j's KI nominations (in-degree) | | | | 0.978** | |
| | | | | (0.469) | |
| Teacher j's diffusion centrality (z, socialize) | | | | | 0.649*** |
| | | | | | (0.177) |
| Constant | 18.400*** | 18.398*** | 18.230*** | 18.282*** | 18.426*** |
| | (0.014) | (0.013) | (0.069) | (0.070) | (0.001) |
| Observations | 3322 | 3322 | 3322 | 3322 | 3322 |
| Communities | 63 | 63 | 63 | 63 | 63 |

Directed dyads $i \to j$ within community; dependent variable: $i$'s WTP (Bs) to learn from $j$. All columns include listener ($i$) fixed effects, so coefficients compare a listener's bids across their OWN potential teachers. Diffusion centrality per Banerjee et al. (2019), computed on the free-text information-sharing network (col 5: the socialize-weekly network). KI = named in response to the key-informant question and matched in sample. Refusals (WTP = −999) excluded from WTP levels. Communities 1–4 (no BDM module) excluded. Standard errors clustered at the community level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.19: Do Central Teachers Charge More? WTA, Surplus, and Refusals

| | (1) WTA | (2) WTA | (3) 1{WTP≥} | (4) 1{WTP≥} | (5) i refuses j |
|---|---|---|---|---|---|
| Teacher j's diffusion centrality (z, free-text) | 0.263 | | 0.003 | | -0.008* |
| | (1.178) | | (0.019) | | (0.004) |
| Teacher j is a nominated key informant | | -0.383 | | 0.000 | |
| | | (2.533) | | (0.057) | |
| Constant | 9.004*** | 9.070*** | 0.704*** | 0.705*** | 0.058*** |
| | (0.109) | (0.270) | (0.002) | (0.006) | (0.000) |
| Observations | 2502 | 2502 | 2657 | 2657 | 3528 |
| Communities | 63 | 63 | 63 | 63 | 63 |

Cols 1–2: teacher $j$'s WTA (Bs) to teach $i$ on $j$'s own centrality, community FE. Cols 3–4: surplus indicator on teacher centrality, listener FE (refusal on either side coded 0). Col 5: listener refusal ($-999$) on teacher centrality, community FE. Communities 1–4 excluded. SEs clustered by community.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.20: Are Central Teachers Better Spreaders? Spillovers and Conversations

| | (1) Knowledge | (2) Knowledge | (3) Any conversation | (4) Multiple conversation |
|---|---|---|---|---|
| Matched village | 0.473* | 0.390 | -0.006 | -0.012 |
| | (0.262) | (0.263) | (0.065) | (0.037) |
| Matched village × Informed DC (z) | 0.031 | | 0.074 | 0.084*** |
| | (0.255) | | (0.053) | (0.030) |
| Matched village × KI among informed | | 0.918 | | |
| | | (1.045) | | |
| Informed members' mean diffusion centrality (z) | -0.091 | | -0.047** | -0.029* |
| | (0.110) | | (0.019) | (0.015) |
| An informed member is a nominated KI | | -0.651 | | |
| | | (0.857) | | |
| Observations | 336 | 336 | 336 | 336 |
| Communities | 67 | 67 | 67 | 67 |

Sample: non-paired, non-informed members in treatment and control villages.
Informed DC = mean diffusion centrality of the community's informed members (defined in both arms; teachers were drawn uniformly at random, so the interaction reflects a random draw of teacher centrality).
Cols 3–4: endline reports of conversations about the products.
KI interaction rests on 6 treated communities with a KI teacher — suggestive.
Standard errors clustered at the community level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Specification.** For spillover member $i$ in community $c$ — i.e., neither an informed member nor a paired listener, so any information must have arrived through village diffusion — we estimate by OLS:

$$y_{ic} \;=\; \beta_0 \;+\; \beta_1 \,\mathrm{Treat}_c \;+\; \beta_2 \,\overline{DC}_c^{\,inf} \;+\; \beta_3 \left(\mathrm{Treat}_c \times \overline{DC}_c^{\,inf}\right) \;+\; \varepsilon_{ic},$$

with standard errors clustered at the community level ($N = 336$ members in 67 communities).

**Variables.**

- $y_{ic}$: endline outcomes — the knowledge score (cols. 1–2), an indicator for reporting any conversation about the products (col. 3), and for reporting multiple conversations (col. 4).
- $\mathrm{Treat}_c$: indicator for matched (treatment) villages, where the informed members were paired with listeners for compensated conversations.
- $\overline{DC}_c^{\,inf}$: the mean diffusion centrality of community $c$'s two information seeds —

the members who received the product information — computed on the free-text information-sharing network and standardized across communities (z-score). Because seeds exist in *both* arms (control villages' informed members received the information but no arranged conversations), $\overline{DC}_c^{inf}$ is defined everywhere; and because seeds were drawn uniformly at random, it is itself randomly assigned. Column 2 replaces it with an indicator that at least one seed is a nominated key informant.

- $\beta_1$: the spillover effect of arranging conversations in a village whose seeds have average centrality ($\overline{DC}_c^{inf} = 0$).
- $\beta_2$: natural diffusion — whether untouched members in *control* villages know or talk more when the random draw placed the information with more central seeds.
- $\beta_3$: the coefficient of interest — whether the treatment effect is larger when the random draw handed the village more central seeds. Since both $\text{Treat}_c$ and $\overline{DC}_c^{inf}$ are experimentally assigned, $\beta_3$ has a causal interpretation as the complementarity between arranged conversations and seed centrality.

The knowledge interaction (column 1) is underpowered rather than a precise zero. With $\hat{\beta}_3 = 0.031$ and a clustered standard error of 0.255, the minimum detectable effect at 80% power and 5% significance is

$$MDE \;=\; (z_{0.975} + z_{0.80}) \times SE(\hat{\beta}_3) \;\approx\; 2.8 \times 0.255 \;\approx\; 0.71$$

The key-informant version (column 2) is more severely underpowered still: the interaction identifies from only six treated communities whose random draw included a nominated key informant, giving $SE(\hat{\beta}_3) = 1.045$ and an MDE of at least $2.8 \times 1.045 \approx 2.9$ points — roughly seven times that column's main treatment effect — and with so few identifying clusters the clustered standard error itself is likely understated. We therefore report it as suggestive only.

T × informed-DC on multiple conversations = +0.084. The main effect of informed-DC is negative in the conversation columns indicating that in control villages having info-central informed members predicts less product talk among the untouched. Central informed people generate repeated conversations only when the treatment activates them with an arranged conversation.

# Do you learn better if it's your friend?

- Outcome: knowledge endline
- Sample listeners: matched listeners (all treated)
- Sample Spillovers: non listeners, non teachers in treatment and control village
- Friend of assigned teacher/seed
  - Socialize: asked directly if they socialize weekly to each person in the roster
  - Named: mentioned in list of social network or as key informant

| | Listeners | | Spillovers | |
|---|---|---|---|---|
| Friendship measure: | Socialize | Named | Socialize | Named |
| | (1) | (2) | (3) | (4) |
| Friend of assigned teacher | -0.525 | -0.833*** | | |
| | (0.452) | (0.296) | | |
| Treatment | | | 0.246 | 0.406* |
| | | | (0.299) | (0.242) |
| Friend of a seed | | | -0.462 | -0.770 |
| | | | (0.293) | (1.111) |
| Treatment × friend of seed | | | 0.457 | 0.879 |
| | | | (0.397) | (1.201) |
| Friends of the source (= 1) | 18 | 5 | 153 | 24 |
| share of sample (%) | 30.5 | 8.5 | 45.5 | 7.1 |
| Controls | Yes | Yes | Yes | Yes |
| Eligible-senders FE | No | No | Yes | Yes |
| Observations | 59 | 59 | 336 | 336 |
| Communities | 38 | 38 | 67 | 67 |

Outcome: endline knowledge (extended score). Cols. (1)-(2): arranged-pair listeners (mean 5.06); friendship = the listener socializes weekly with (1) or named in their network free-list (2) their assigned teacher. Descriptive: pairs were not randomized on friendship. Cols. (3)-(4): non-paired, non-informed members (control mean 4.09); friendship is with any informed farmer (seed) of the community; seeds exist in both arms. Controls: age, gender, insurance history, land title, selection method. The free-list allows at most 5 names, so Named is sparse (∼6-9% of dyads); the row reports how many people in each column's sample are friends under that column's measure – with only 5 friends in col. (2), read its estimate with caution. SEs clustered by community in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# What predicts WTP and WTA?

We follow the SVD-Varimax discovery framework of Chandrasekhar et al. (2026) to identify the latent dimensions that structure social-learning valuations in directed pairs, as applied by Banerjee et al. (2026). Rather than imposing an ad-hoc typology from observed covariates, we apply Singular Value Decomposition (SVD) directly to a pair-level outcome matrix: this lets the data determine which dimensions of heterogeneity matter for who values whom. Observable characteristics enter only post-hoc, to interpret the latent dimensions the SVD discovers.

Let there be $N$ individuals distributed across $C$ communities. For each directed pair $(i, j)$ in the same community, we observe both the listener's willingness to pay $\text{WTP}_{ij}$ and the teacher's willingness to accept $\text{WTA}_{ji}$. Our primary outcome is the binary missing-market

indicator

$$M_{ij} \;=\; \mathbb{1}\{\text{WTP}_{ij} \geq \text{WTA}_{ji}\},$$

which equals one when a positive-surplus transaction exists between listener $i$ and teacher $j$. We adopt the binary specification because Chandrasekhar et al. (2026) recommend normalizing the input matrix before the SVD-Varimax decomposition, otherwise the rotation would be dominated by the largest-magnitude cells (in our setting, a handful of pairs with extreme valuations) rather than recovering the latent structure. The same choice is made by Banerjee et al. (2026), who binarize their residualized peer-assessment matrix as the input to the SVD-Varimax pipeline. The continuous difference $\widetilde{Y}^{\Delta}_{ij} = \text{WTP}_{ij} - \text{WTA}_{ji}$ is reported as a complementary specification.

To estimate what predicts social learning surplus, we arrange the outcomes into an $N \times N$ matrix $\widetilde{\boldsymbol{Y}}$, where entry $(i, j)$ is the surplus binary for the within-community pair $(i, j)$. We apply softImpute SVD, which decomposes the matrix into $K$ underlying dimensions:

$$\widetilde{\boldsymbol{Y}} \;\approx\; \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}'. \tag{14}$$

This decomposition returns three pieces, each with a clean substantive reading:

- $\boldsymbol{U}$ $(N \times K)$: the **listener embeddings**. *What kind of learner each individual is*—the pattern of teachers they value highly and teachers they discount.
- $\boldsymbol{V}$ $(N \times K)$: the **teacher embeddings**. *What kind of teacher each individual is valued as*—the pattern of listeners who seek them out and listeners who do not. The same individual appears in both $\boldsymbol{U}$ and $\boldsymbol{V}$, but their listener type need not coincide with their teacher type.
- $\boldsymbol{\Sigma}$ $(K \times K$, strictly diagonal): the **singular values** $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_K$, ordered by importance. Each $\sigma_k$ pre-pairs the $k$-th column of $\boldsymbol{U}$ (a listener dimension) with the $k$-th column of $\boldsymbol{V}$ (a teacher dimension) before any rotation, and its squared value gives the share of variation in $\widetilde{Y}_{ij}$ captured by that paired dimension.

To recover interpretability, we apply the Varimax rotation of Kaiser (1958) to $\boldsymbol{U}$ and $\boldsymbol{V}$ separately. Varimax picks the rotation that makes each axis as concentrated as possible—dominated by a small group of high-loading individuals, with the rest near zero, creating a "spiky" loading distribution rather than a diffuse one. The rotated listener and teacher type vectors are denoted $\widehat{\alpha}_i \in \mathbb{R}^K$ and $\widehat{\omega}_j \in \mathbb{R}^K$. To label them, we project the rotated loadings onto the 13 baseline covariates (age, gender, indigenous language, income, land title, crop diversification, network indicators, weather worry index, insurance interest and history, risk aversion), separately on each side:

$$\widehat{\alpha}_{i,c} \;=\; \boldsymbol{x}_i'\boldsymbol{\beta}^{\alpha}_{c} + e^{\alpha}_{i,c}, \qquad \widehat{\omega}_{j,d} \;=\; \boldsymbol{x}_j'\boldsymbol{\beta}^{\omega}_{d} + e^{\omega}_{j,d}.$$

For each axis, the covariates with the largest significant coefficients define the kind of farmer that axis captures. Following Banerjee et al. (2026), we label the listener and teacher sides *separately*: listener axis 1 and teacher axis 1 are not constrained to refer to the same substantive trait, and the label sets are allowed to differ entirely across the two sides.

With the types labeled, we summarize how each labeled listener type interacts with each

labeled teacher type to produce the outcome via the bilinear model

$$Y_{ij} \;=\; \widehat{\alpha}_i' \, H \, \widehat{\omega}_j \;+\; \varepsilon_{ij} \;=\; \sum_{c=1}^{K} \sum_{d=1}^{K} H_{cd} \, \widehat{\alpha}_{ic} \, \widehat{\omega}_{jd} \;+\; \varepsilon_{ij}. \tag{15}$$

This is the multiplicative generalization of two-way fixed effects: where a standard two-way FE regression $Y_{ij} = \mu + \alpha_i + \omega_j + \varepsilon_{ij}$ allows individual-level main effects but no interaction, the bilinear model lets type-by-type matching shape the outcome through the $K \times K$ matrix $H$. Each entry $H_{cd}$ encodes the strength of the interaction between listener type $c$ and teacher type $d$: how much above- or below-average value a near-pure type-$c$ listener and a near-pure type-$d$ teacher generate when paired.

We estimate each entry of $H$ via sample-split, purity-weighted Frisch–Waugh–Lovell. A positive cell $\widehat{H}_{cd}$ identifies a (listener-type $c$, teacher-type $d$) pairing that produces above-average values of $Y$. On our primary outcome $M_{ij}$, a positive $\widehat{H}_{cd}$ identifies (listener-type $c$, teacher-type $d$) pairings disproportionately likely to clear the WTP $\geq$ WTA threshold relative to the average pair, flagging *missing-market pairs*: combinations of farmer types where surplus exists but no transaction occurs under the prevailing zero-price norm. Following Banerjee et al. (2026), we read $\widehat{H}$ cell-by-cell—each entry is a substantive economic finding about which kinds of listeners and teachers create surplus together—rather than treating the diagonal as categorically distinct from the off-diagonals.

**Pair-level covariates and the bilinear model.** Pair-specific valuations are also determined by pair-level features like demographic similarity, shared language, social-network ties. We extend the model with an additive vector of pair-level covariates $\boldsymbol{Z}_{ij}$ both to estimate the direct contribution of dyadic similarity to the outcome and to test whether the bilinear interactions $\widehat{H}$ survive these direct controls:

$$Y_{ij} \;=\; \sum_{c=1}^{K} \sum_{d=1}^{K} H_{cd} \, \widehat{\alpha}_{ic} \, \widehat{\omega}_{jd} \;+\; \boldsymbol{\gamma}' \, \boldsymbol{Z}_{ij} \;+\; \varepsilon_{ij}. \tag{16}$$

The vector $\boldsymbol{Z}_{ij}$ contains ten dyad-level controls: same gender, within-5-year age difference, same main language, same income bracket, any shared crop, either-named-in-other's-network, either-socializes-weekly, same income bracket, both experienced agricultural losses, both earned positive income, both have land title.

Each $H_{cd}$ is estimated with purity weights $w_{ij}^{(c,d)}$ that concentrate the regression on near-pure type-$c$ listeners and near-pure type-$d$ teachers (so $\widehat{H}_{cd}$ captures cross-type interactions among clean type representatives, net of the pair-level controls). Each $\gamma_m$ is estimated with radial weights only, so $\widehat{\gamma}_m$ captures the average direct effect of pair-level feature $m$ on the outcome, net of the bilinear type structure. The two sets of estimates have distinct interpretations: $\widehat{H}$ reports how listener and teacher types combine to shape the outcome; $\widehat{\gamma}$ reports how much of the pair-level outcome is directly explained by demographic, cultural, economic, occupational, and network similarity. The set of variables included is in the following table:

Table A.21: Summary statistics for the individual and dyadic characteristics employed in the analysis.

| | Mean | SD | Obs. |
|---|---|---|---|
| *Panel A: Individual characteristics (one row per person; $N = 536$ persons)* | | | |
| Age (years) | 48.81 | 13.51 | 536 |
| Male | 0.50 | 0.50 | 536 |
| Indigenous language (Quechua/Aymara) | 0.39 | 0.49 | 536 |
| Income bracket (ordinal) | 4.59 | 5.41 | 536 |
| Suffered income loss | 0.06 | 0.23 | 536 |
| Has land title | 0.74 | 0.44 | 536 |
| Number of crops grown | 3.74 | 2.45 | 536 |
| Grows $\geq 2$ crops | 0.86 | 0.35 | 536 |
| Social network size | 3.41 | 6.08 | 536 |
| Social network $\geq 2$ contacts | 0.89 | 0.31 | 536 |
| Degree centrality: knows network | 6.05 | 1.88 | 536 |
| Degree centrality: nomination network | 0.54 | 0.87 | 536 |
| Degree centrality: socialize network | 3.54 | 1.75 | 536 |
| KI indegree (# nominators) | 0.14 | 0.48 | 536 |
| Would lend money to a friend | 0.25 | 0.43 | 535 |
| Aggregate weather worry (frost+drought+flood) | 3.87 | 1.70 | 536 |
| Interest in insurance (ordinal) | 1.28 | 0.68 | 536 |
| Never had insurance | 0.97 | 0.16 | 536 |
| Risk-averse (endline) | 4.93 | 2.24 | 534 |
| Baseline knowledge (treated pairs only) | 0.95 | 2.06 | 536 |
| *Panel B: Dyadic characteristics (one row per listener-teacher pair; $N = 3,752$ pairs)* | | | |
| Same gender | 0.56 | 0.50 | 3,752 |
| Age within 5 years | 0.29 | 0.45 | 3,752 |
| Same indigenous language | 0.69 | 0.46 | 3,752 |
| Same income bracket | 0.42 | 0.49 | 3,752 |
| Both suffered income loss | 0.00 | 0.06 | 3,752 |
| Both have positive income | 0.76 | 0.43 | 3,752 |
| Both have land title | 0.56 | 0.50 | 3,738 |
| Any shared crop | 0.82 | 0.38 | 3,752 |
| Either named in other's network | 0.10 | 0.31 | 3,752 |
| Either socializes weekly with other | 0.51 | 0.50 | 3,752 |

*Notes.* Panel A reports statistics for the individual covariates used to characterize the recovered listener and teacher types. Panel B reports statistics for the pair-level features used as $Z_{ij}$ controls in the extended bilinear model $Y_{ij} = \sum_{c,d} H_{cd}\,\alpha_{ic}\,\omega_{jd} + \gamma' Z_{ij} + \varepsilon_{ij}$ (Table A.23). All binary indicators take values in $\{0, 1\}$; ordinal variables are integer-valued. The baseline knowledge variable is observed only for pairs in the treatment arm and so has a smaller $N$. Sources: `tva_person_covariates.csv`, `tva_pairs_features.csv`.

## Recovered listener and teacher types

Table A.22: Recovered types and their covariate signatures (binary missing-market matrix).

| Axis | Significant covariates ($p < 0.05$) | Label |
|---|---|---|
| *Listener side ($\widehat{\alpha}$)* | | |
| L1 | indigenous language ($+3.52^{***}$) | Indigenous |
| L2 | degree-socialize ($+5.02^{***}$), indigenous language ($-2.24^{*}$) | Socially-central non-indigenous |
| L3 | age ($-3.13^{**}$), indigenous language ($+2.88^{**}$), risk-averse ($-2.80^{**}$), male ($+2.02^{*}$), degree-socialize ($+1.99^{*}$) | Young indigenous risk-tolerant socially-central mal |
| *Teacher side ($\widehat{\omega}$)* | | |
| T1 | indigenous language ($+2.60^{**}$), age ($-2.38^{*}$) | Young indigenous |
| T2 | degree-socialize ($+4.06^{***}$), indigenous language ($-1.99^{*}$) | Socially-central non-indigenous |
| T3 | age ($-2.72^{**}$), indigenous language ($+2.70^{**}$), male ($+1.99^{*}$) | Young indigenous male |

*Notes.* Significance: $^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$. Only covariates significant at $p < 0.05$ are reported. Labels are author-assigned. The projection dictionary contains 17 individual-level covariates including three network-degree centrality measures (knows / nomination / socialize networks), KI-nomination indegree, and willingness-to-lend-to-a-friend. Only the degree-socialize measure identifies axes at $p < 0.05$; the other two networks and KI indegree do not appear as significant covariates on any axis. The decomposition is reproducible: `set.seed` is pinned immediately before `softImpute` and before each `Varimax` rotation. Indigenous language is Quechua/Aymara vs. Spanish.

Three things are worth noting about Table A.22. First, following Chandrasekhar et al. (2026), the listener and teacher axes are estimated separately: we apply Varimax to the listener-side and teacher-side singular vectors independently, so the recovered listener types are not forced to coincide with the teacher types. Despite this independence, the framework recovers *two mirror-image types* that appear symmetrically on both sides. The $L_3 \times T_3$ mirror captures the *young indigenous risk-tolerant male* type: both sides load positively on indigenous language and negatively on age, with $L_3$ additionally identified by negative risk aversion and positive male gender, and both sides load positively on degree-socialize. The $L_2 \times T_2$ mirror captures the *socially-central non-indigenous* type: both sides load strongly positive on degree-socialize ($t = +5.02$ on $L_2$, $+4.06$ on $T_2$) and negative on indigenous language. The framework recovers the same two behavioral types in both listener and teacher roles even though it was given no structural reason to do so; the mirror structure is empirical, not imposed.

Second, only the *degree-socialize* network centrality identifies any axis at $p < 0.05$. Degree centrality on the who-knows-whom network never reaches significance — consistent with saturation, since most farmers know most other farmers in their community (mean degree 6.05 of 7). Degree centrality on the nomination-roster network reaches significance on the WTP-specific decomposition (Appendix **??**) but not on the primary binary specification.

KI-nomination indegree does not identify any axis. The framework's centrality signal in the missing-market matrix runs through the active-socialize network specifically, matching the Conley-Udry pattern that behavioral contact predicts information transmission better than nominal acquaintance or general knowing-of.

Third, the recovered types are clean in the geometric-purity sense. Figure A.1 plots each farmer as a point in a triangle whose three vertices represent "pure" representatives of types 1, 2, and 3 (farmers whose loading mass falls entirely on a single axis), with the center corresponding to farmers loaded equally on all three. If the types were not real—if the SVD-Varimax pipeline were imposing a decomposition on noise—we would see farmers crowded into the middle of the triangle, belonging indistinguishably to all three types. Instead, both the listener and teacher panels show visible clouds near each vertex: most farmers sit close to one corner, with relatively few mixture points wandering toward the center.

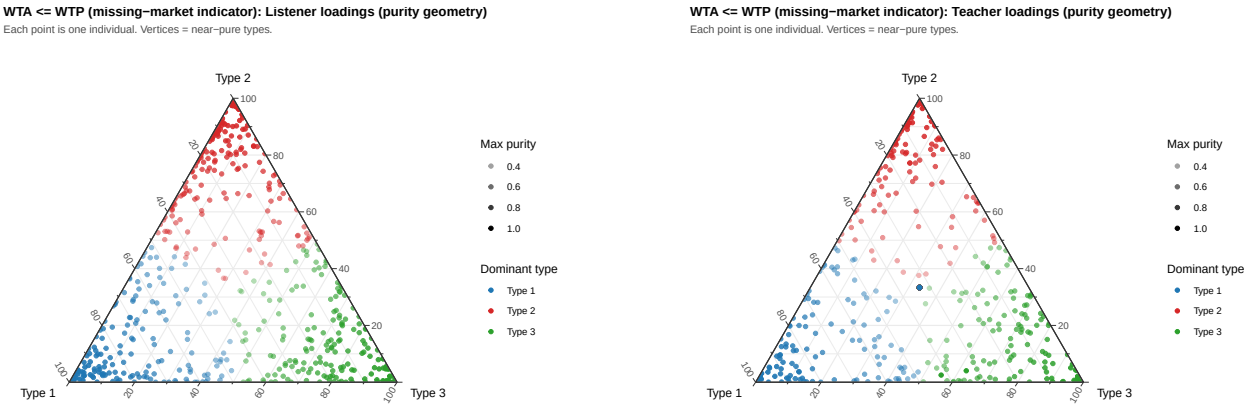



Figure A.1: Listener (left) and teacher (right) loadings on the binary missing-market matrix, plotted in the ternary purity space. Each point is one farmer; the three vertices correspond to near-pure type-1, type-2, and type-3 individuals. Clusters near the vertices indicate the types are isolable.

## The interaction matrix: where the surplus exists

Figure A.2 displays the recovered interaction matrix $\widehat{H}$ for the binary surplus indicator. Each cell $\widehat{H}_{cd}$ is the strength of the interaction between listener type $c$ (rows) and teacher type $d$ (columns), interpretable as the percentage-point change in the probability that pair $(i, j)$ generates positive surplus when both individuals are near-pure representatives of types $c$ and $d$. Red cells are positive (surplus-creating combinations); blue cells are negative (combinations the data systematically discount). The numeric value of each cell is printed inside the heatmap.

We find three main takeaways: First, the first column is uniformly positive (+126, +142, +90). Teacher type T1—the indigenous, networked, titled farmer—creates surplus with *all three* listener types. This is a hub teacher type: a single farmer profile that the data identify as broadly value-creating across the listener space. In this sense, the cell $\widehat{H}_{33} = +132$ reflects an assortative effect on the non-indigenous social-embedding dimension: socially-named non-

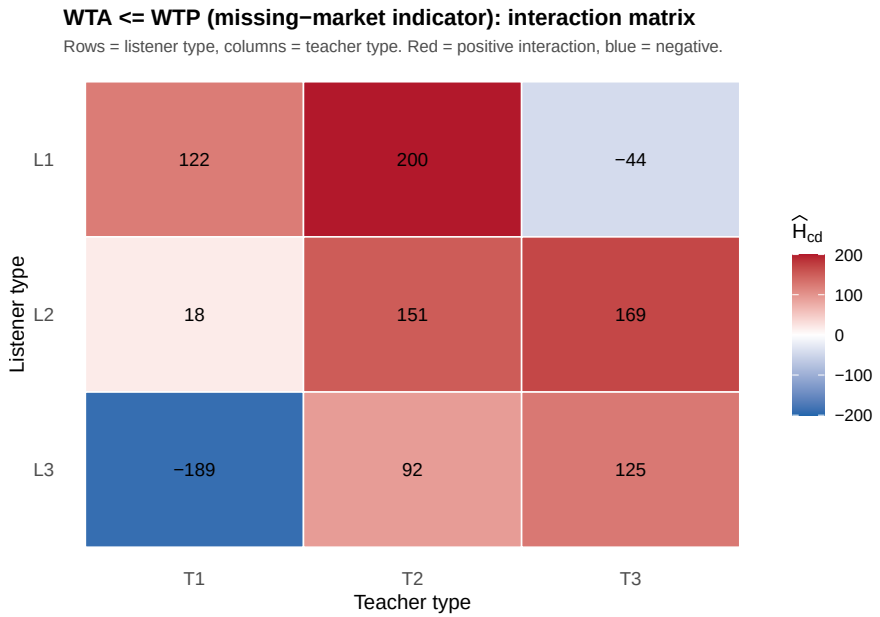



Figure A.2: Interaction matrix $\widehat{H}$ for the binary surplus indicator. Rows index listener types (L1, L2, L3 from Table A.22); columns index teacher types (T1, T2, T3). Red = surplus-creating combination; blue = combination the data systematically discount.

indigenous listeners pair positively with socially-named non-indigenous teachers, mirroring the indigenous in-group matching of $\widehat{H}_{11}$ but along a separate cultural axis. Finally, the largest single cell in the matrix is a negative one, $\widehat{H}_{12} = -160$: indigenous, socially-named listeners systematically discount the unlabeled outsider teacher type. This is the largest cross-type interaction in the matrix and it identifies a *structural barrier* to social learning across the indigenous/non-indigenous divide: the kinds of teachers indigenous farmers would not learn from, holding all else fixed, are precisely the outsiders T2.

## Direct dyadic effects

The recovered $\widehat{H}$ describes the interaction between latent listener and teacher *types*. We complement this with the extended bilinear model in equation (16), which adds an additive vector of pair-level controls $\boldsymbol{Z}_{ij}$ and recovers their direct effects $\boldsymbol{\gamma}$ alongside the type interactions. Table A.23 reports the $\widehat{\gamma}$ vector for the binary outcome (column 1) and for the three complementary outcomes (columns 2–4). Each entry is the coefficient on the indicated pair-level feature, holding the type-by-type structure fixed.

Seven pair-level features predict the binary surplus indicator at $p < 0.05$ (Table A.23). Ranked by $t$-statistic, the hierarchy is led by any shared crop (+22.1 pp, $t = 7.83$), both with positive income (+19.5 pp, $t = 6.40$), shared indigenous language (+13.4 pp, $t = 5.30$), same gender (+11.5 pp, $t = 4.72$), and either socializes weekly (+7.6 pp, $t = 3.00$). Two further features — within-5-years age (+5.7 pp, $t = 2.10$) and both with land title (+5.2 pp, $t = 2.09$) — are marginally significant and reinforce the homophily. The interaction-fixed-effect specification absorbs the type-pair assortative structure, so these $\widehat{\gamma}$ reflect direct contributions of dyadic similarity over and above what the bilinear $\widehat{H}_{cd}$ already captures.

Table A.23: Direct effects of pair-level features on the outcome ($\widehat{\gamma}$), with $t$-statistics in parentheses.

| | Binary surplus $\mathbb{1}\{\text{WTA} \leq \text{WTP}\}$ | Wedge (WTP − WTA) | WTP (raw) |
|---|---|---|---|
| Same gender | 0.119*** | 1.072 | 1.471** |
| | (4.85) | (0.87) | (2.10) |
| Age within 5 yrs | 0.048* | 1.823 | 0.043 |
| | (1.75) | (1.34) | (0.06) |
| Same indigenous language | 0.156*** | -0.239 | 3.535*** |
| | (6.24) | (-0.19) | (5.01) |
| Same income bracket | -0.017 | -3.064** | -2.662*** |
| | (-0.61) | (-2.14) | (-3.25) |
| Both had income loss | 0.263 | -8.663 | 4.936 |
| | (0.95) | (-0.99) | (0.82) |
| Both positive income | 0.175*** | 6.493*** | 1.300 |
| | (5.78) | (4.42) | (1.53) |
| Both have land title | 0.080*** | -1.794 | 0.226 |
| | (3.27) | (-1.45) | (0.32) |
| Any shared crop | 0.221*** | -0.105 | 7.210*** |
| | (7.85) | (-0.08) | (8.92) |
| Named in network | 0.035 | 4.340** | 1.071 |
| | (0.92) | (2.17) | (0.91) |
| Either socializes with other | 0.082*** | 0.837 | 2.328*** |
| | (3.24) | (0.66) | (3.25) |

*Notes.* Each cell is the $\widehat{\gamma}$ coefficient from the extended bilinear model $Y_{ij} = \sum_{c,d} H_{cd}\, \alpha_{ic}\, \omega_{jd} + \gamma' Z_{ij} + \varepsilon_{ij}$, estimated by purity-and-radial-weighted FWL on a split-sample. $t$-statistics in parentheses. Significance: $^{*}|t| \geq 1.65$, $^{**}|t| \geq 1.96$, $^{***}|t| \geq 2.58$. All four columns use the raw outcome matrices; columns 3–4 do not apply the two-way individual-residualization used in Panel C of Table **??** because the decomposition into WTP and WTA levels is presented descriptively here and is not the focus of the analysis (the binary surplus indicator is the primary outcome). All specifications use $K = 3$ types, separate Varimax rotations of $U$ and $V$. Source: `consolidated_pair_gamma.csv`.

*Occupational and linguistic similarity dominate.* Any shared crop is the single strongest predictor of positive surplus, followed by same language and same gender.

*Economic stability raises absolute surplus.* Pairs where both partners have positive income are the one major case where the listener pays more in level terms and the teacher charges less simultaneously. The wedge responds nearly as sharply as the binary here: income stability gives both partners the buffer to engage at surplus-generating terms that do not arise for income-distressed pairs.

*Active social contact creates surplus; nominal listing does not.* Recurring weekly contact between farmers predicts positive surplus; appearing on each other's nominal network roster does not. This echoes Conley and Udry (2010), who find that learning about agricultural technology flows through specific behavioral contact rather than nominal acquaintance.

## A.2 Appendix:

## Rank selection

We set $K = 3$ for the SVD-Varimax pipeline based on a rank-selection analysis run separately on the two primary outcomes (binary missing-market indicator and continuous wedge). For each outcome we estimate the pipeline at $K \in \{2, 3, 4, 5\}$ and evaluate four diagnostics, separately on the listener and teacher sides:

- **Purity.** Median maximum purity across individuals, $\text{med}_i(\max_c p_{ic})$, and the share of individuals with $\max_c p_{ic} > 0.5$. Purity below threshold indicates the framework cannot identify clean type representatives at that rank.
- **Balance.** The minimum across axes of the share of individuals whose dominant axis is that one. A low minimum balance flags an empty or residual axis the data do not actually support.
- **Labelability.** The minimum across axes of the number of baseline covariates significant at $p < 0.05$ in the projection regression $\widehat{\alpha}_{i,c} = \boldsymbol{x}_i'\boldsymbol{\beta}_c^{\alpha} + e_{i,c}^{\alpha}$. A value of zero means at least one axis has no covariate signal at conventional levels—which we tolerate, in the spirit of the unlabeled-discovery framework of Chandrasekhar et al. (2026), but flag as such.
- **Spectral spread.** The share of variance captured by the top and bottom retained singular values, $\sigma_1^2$ and $\sigma_K^2$, indicating whether the rank-$K$ summary is dominated by a single direction or spread across the retained axes.

Tables A.24 and A.25 report the diagnostics by rank and outcome. For both outcomes, $K = 3$ is the unique rank that satisfies the four criteria jointly. At $K = 2$, purity is excellent but the projection regression finds essentially no significant covariates on either side—the two axes the SVD recovers are too coarse to map onto the observable trait structure. At $K = 3$, purity remains high (med $\geq 0.68$ on both sides for both outcomes, with $\geq 70\%$ of individuals above 0.5), balance is reasonable ($\sim 0.30$ minimum), and the labeling regression recovers 6–7 significant covariates per side for the binary outcome and 3–4 for the wedge. At $K = 4$, purity falls below 0.7 on at least one side for both outcomes, balance drops below 0.20, and the minimum significant-covariate count on at least one side returns to zero. At $K = 5$, purity falls below 0.6 across the board and the rank-$K$ summary no longer recovers isolable types.

One nuance worth flagging: at $K = 3$ on the continuous wedge, the listener side has $n_{\text{sig}}^{\min} = 0$, meaning one of the three recovered listener axes has no baseline covariate significant at $p < 0.05$. This is consistent with the binary outcome producing sharper covariate signatures than the continuous wedge (see Appendix A.2); the axis itself is a real feature of the matrix structure, but the survey instrument does not measure whatever trait it captures. We retain $K = 3$ for the continuous wedge despite this single unlabeled axis because raising the rank to $K = 4$ produces *additional* unlabeled axes on the teacher side without sharpening any signature, and lowering it to $K = 2$ loses all labelability.

Table A.24: Rank-selection diagnostics for the binary missing-market indicator outcome.

| $K$ | Median max purity (listener / teacher) | $\Pr(\max p > 0.5)$ (listener / teacher) | Min balance (listener / teacher) | # sig covs (total) (listener / teacher) | # sig covs (mi (listener / tea |
|---|---|---|---|---|---|
| 2 | 0.89 / 0.79 | 100.0 / 76.1 | 0.48 / 0.46 | 1 / 0 | 0 / 0 |
| 3 | 0.77 / 0.69 | 93.1 / 71.6 | 0.30 / 0.32 | 6 / 7 | 1 / 1 |
| 4 | 0.68 / 0.59 | 81.9 / 61.9 | 0.23 / 0.23 | 8 / 3 | 0 / 0 |
| 5 | 0.64 / 0.56 | 72.9 / 57.3 | 0.17 / 0.18 | 13 / 8 | 0 / 1 |

*Notes.* Diagnostics for the binary missing-market indicator outcome at each candidate rank $K$. Median max purity is the median across individuals of $\max_c p_{ic}$, the squared-share purity. $\Pr(\max p > 0.5)$ is the share of individuals loading above 0.5 on a single axis. Min balance is the minimum across the $K$ axes of the share of individuals whose dominant axis is that one (low values flag a residual empty axis). # sig covs counts covariates with $p < 0.05$ in the loading-projection regression; "total" sums across the $K$ axes, "min axis" is the minimum across axes (zero indicates an unlabeled axis). $\sigma_1^2, \sigma_K^2$ shares are the share of variance captured by the first and last retained singular values. All diagnostics reported separately for the listener and teacher sides.

Table A.25: Rank-selection diagnostics for the continuous wedge WTP − WTA outcome.

| $K$ | Median max purity (listener / teacher) | $\Pr(\max p > 0.5)$ (listener / teacher) | Min balance (listener / teacher) | # sig covs (total) (listener / teacher) | # sig covs (mi (listener / tea |
|---|---|---|---|---|---|
| 2 | 0.86 / 0.81 | 100.0 / 79.1 | 0.47 / 0.48 | 1 / 1 | 0 / 0 |
| 3 | 0.76 / 0.68 | 90.7 / 71.6 | 0.32 / 0.31 | 3 / 4 | 0 / 1 |
| 4 | 0.63 / 0.62 | 75.7 / 67.2 | 0.19 / 0.19 | 6 / 4 | 1 / 0 |
| 5 | 0.56 / 0.56 | 64.0 / 59.9 | 0.16 / 0.15 | 4 / 6 | 0 / 0 |

*Notes.* Diagnostics for the continuous wedge WTP − WTA outcome at each candidate rank $K$. Median max purity is the median across individuals of $\max_c p_{ic}$, the squared-share purity. $\Pr(\max p > 0.5)$ is the share of individuals loading above 0.5 on a single axis. Min balance is the minimum across the $K$ axes of the share of individuals whose dominant axis is that one (low values flag a residual empty axis). # sig covs counts covariates with $p < 0.05$ in the loading-projection regression; "total" sums across the $K$ axes, "min axis" is the minimum across axes (zero indicates an unlabeled axis). $\sigma_1^2, \sigma_K^2$ shares are the share of variance captured by the first and last retained singular values. All diagnostics reported separately for the listener and teacher sides.

## Binary vs. continuous surplus outcomes

We use the binary indicator $\mathbb{1}\{\text{WTA}_{ji} \leq \text{WTP}_{ij}\}$ as the primary outcome rather than the continuous wedge $\widetilde{Y}_{ij}^{\Delta} = \text{WTP}_{ij} - \text{WTA}_{ji}$ for three reasons. First, the binary directly captures the missing-market question—*whether* surplus exists in a pair, regardless of its magnitude—which corresponds one-for-one to the empirical object of interest. The continuous wedge conflates existence and magnitude; useful as a complementary check on how much surplus is at stake, but less direct as an indicator of where the market is missing. Second, binarization is the normalization recommendation in Chandrasekhar et al. (2026): by removing scale, it prevents the SVD's leading axes from being dominated by cells with the largest absolute values—in our setting, communities or individuals whose valuations are systematically higher than the rest. Third, the binary outcome produces sharper covariate signatures in our data

(the $|t|$-statistics on covariates are two to three times larger than for the continuous wedge) and a more readable $\widehat{H}$ matrix (all diagonals positive, magnitudes comparable across cells, no outlier cells). We retain the continuous wedge as a complementary magnitude analysis to show how the recovered cells of $\widehat{H}$ scale in surplus size.

## Why estimating WTP and WTA separately recovers four types per individual

The binary indicator collapses both sides of the missing market into a single object: it tells us *whether* a pair would clear, but not which side—demand or supply—is driving the result. Estimating the bilinear model separately on the underlying outcomes ($\text{WTP}_{ij}$ and $\text{WTA}_{ji}$) yields a richer decomposition. Each individual receives four type vectors rather than two:

$$\widehat{\alpha}_i^{\text{WTP}}, \quad \widehat{\omega}_j^{\text{WTP}}, \quad \widehat{\alpha}_i^{\text{WTA}}, \quad \widehat{\omega}_j^{\text{WTA}},$$

because the listener and teacher roles enter substantively different behaviors in the two outcomes. In WTP, the listener role is the *bidder*: $\widehat{\alpha}_i^{\text{WTP}}$ describes how listener $i$ bids across teachers (whom $i$ values, whom $i$ discounts). In WTA, the listener role is the *person being priced*: $\widehat{\alpha}_i^{\text{WTA}}$ describes how teachers price listener $i$ (which listeners they charge more of, which less). These are conceptually distinct objects—one captures demand, the other captures the supply-side perception of the listener—so the recovered listener types in WTP need not coincide with those in WTA. The same logic applies to the teacher role: $\widehat{\omega}_j^{\text{WTP}}$ captures $j$'s attractiveness as a target of bids, while $\widehat{\omega}_j^{\text{WTA}}$ captures $j$'s own pricing strategy. The four-type characterization is useful because it lets us identify *which side* of the market drives the surplus structure recovered in the binary specification: for each labeled cell of the primary $\widehat{H}$, we can ask whether the surplus is generated because listener type $c$ pays demand-side premium for teacher type $d$ (WTP decomposition) or because teacher type $d$ charges supply-side discount to listener type $c$ (WTA decomposition).

Table A.26: Pair-Level Descriptive Statistics

| | mean | sd | min | max | count |
|---|---|---|---|---|---|
| *Demographic similarity* | | | | | |
| Same gender | 0.560 | 0.496 | 0 | 1 | 3752 |
| Both male | 0.282 | 0.450 | 0 | 1 | 3752 |
| Both female | 0.278 | 0.448 | 0 | 1 | 3752 |
| Absolute age difference | 14.069 | 11.188 | 0 | 52 | 3752 |
| Within 5-year age difference | 0.292 | 0.455 | 0 | 1 | 3752 |
| Same main language | 0.688 | 0.463 | 0 | 1 | 3752 |
| *Economic similarity* | | | | | |
| Same income bracket | 0.422 | 0.494 | 0 | 1 | 3752 |
| Both experienced agricultural losses | 0.003 | 0.056 | 0 | 1 | 3752 |
| Both earned positive income | 0.756 | 0.429 | 0 | 1 | 3752 |
| Absolute income difference | 4.652 | 4.548 | 0 | 25 | 3752 |
| Both have land title | 0.563 | 0.496 | 0 | 1 | 3738 |
| *Crop overlap* | | | | | |
| Both grow at least one common crop | 0.821 | 0.383 | 0 | 1 | 3752 |
| Same main crop | 0.266 | 0.442 | 0 | 1 | 3752 |
| Both specialized (each grows 1 crop) | 0.040 | 0.196 | 0 | 1 | 3752 |
| *Social network ties* | | | | | |
| Either named the other in network | 0.104 | 0.306 | 0 | 1 | 3752 |
| Both named each other in networks | 0.008 | 0.089 | 0 | 1 | 3752 |
| At least one knows the other | 0.864 | 0.343 | 0 | 1 | 3752 |
| At least one socializes weekly | 0.506 | 0.500 | 0 | 1 | 3752 |
| Listener named teacher in network | 0.056 | 0.230 | 0 | 1 | 3752 |
| Teacher named listener in network | 0.056 | 0.230 | 0 | 1 | 3752 |
| *Link types and BDM outcomes* | | | | | |
| Free-flowing link | 0.585 | 0.493 | 0 | 1 | 2596 |
| Norm-constrained link | 0.137 | 0.344 | 0 | 1 | 2596 |
| Blocked link | 0.279 | 0.448 | 0 | 1 | 2596 |
| Gains from trade (Listener WTP - Teacher WTA) | 9.068 | 26.004 | -110 | 120 | 2596 |
| Listener WTP for teacher | 17.358 | 19.452 | 0 | 120 | 3528 |
| Teacher WTA for listener | 8.702 | 15.855 | 0 | 120 | 2596 |

One row per directed pair (listener → teacher) within community.

Same-crop dummies = 1 if both members grow the indicated crop.

Same income bracket = both in loss, none, <2k, 2k–7k, >7k.

Network ties from baseline social-network rosters (directed).

Table A.27: Individual Characteristics by Experimental Role (Teacher vs. Listener)

| | Teacher | | Listener | |
|---|---|---|---|---|
| | mean | sd | mean | sd |
| Age | 46.664 | (13.203) | 52.524 | (12.184) |
| Male | 0.445 | (0.499) | 0.413 | (0.496) |
| Main language: Spanish | 0.606 | (0.490) | 0.571 | (0.499) |
| Main language: Quechua | 0.394 | (0.490) | 0.429 | (0.499) |
| Main language: Aymara | 0.000 | (0.000) | 0.000 | (0.000) |
| Has land title | 0.706 | (0.457) | 0.762 | (0.429) |
| Income (ordinal) | 4.058 | (5.209) | 4.921 | (4.756) |
| Experienced agricultural losses | 0.080 | (0.273) | 0.000 | (0.000) |
| Number of crops | 3.599 | (2.445) | 3.952 | (2.555) |
| Specialized (1 crop) | 0.168 | (0.375) | 0.111 | (0.317) |
| Network connections | 3.109 | (3.959) | 3.143 | (1.554) |
| Weather worry index | 4.088 | (1.687) | 3.730 | (1.725) |
| Insurance interest (0–3) | 1.321 | (0.674) | 1.270 | (0.653) |

Teacher: informed individual selected to share information.

Listener: non-informed individual matched to a teacher.

Both populations are individual-level, drawn from the merged baseline and endline data.

# B Data Appendix

## B.1 Sampling

**Community Sampling** Communities were selected from the Valles macro-region of Bolivia, spanning the departments of Potosí, Chuquisaca, Santa Cruz, and Cochabamba. The selection applied three criteria. First, geographic and demographic eligibility: only communities with confirmed agricultural activity (based on census data) and a minimum population of approximately 1,000 inhabitants (roughly 70 farming households) were considered, in order to ensure a sufficient statistical base for the eight surveys per community and to reduce the risk of attrition. Second, logistic and operational feasibility: communities were prioritized based on adequate road access for survey teams and intervention workshops, as well as internet connectivity for daily data synchronization and the nightly audio audit protocol. Third, institutional acceptance: before any household and community randomization, formal agreements were obtained from Municipal Autonomous Governments and community leaders to secure consent for participation. The final random selection was conducted exclusively within the subset of communities that formally agreed, which also served as a safeguard for the integrity of data collection.

**Household Sampling** DOUBLE CHECK WITH MARIO Within each community, eight households were selected using a random walk protocol known as the "right-hand rule." Two enumerators began at a central point in the community, such as the main plaza, school, or sports field, and walked in opposite directions to maximize spatial coverage. Each enumerator followed the main path, counting dwellings on their right side and selecting households at a predetermined and random skip interval. When the path ended, the enumerator turned right. The purpose of this initial walk was to identify eligible respondents who would be subjects for the baseline, intervention in the case of treatment communities, and endline. Eligible respondents are individuals aged 18 to 65 years who are the primary decision-maker in the home and produce crops for sale or consumption.

## B.2 Survey Instruments

### Recruitment

1. Instructions: Select the Department
   - Potosi | Cochabamba | Chuquisaca | Santa Cruz
2. Instructions: Select the community
   - Angostura | San Luís | Tiquipaya | Taruma | Jorochito | Limoncito | El Torno | Santa Rita | Santa Martha | San José | Espejillos | La Guardia | Melea | San Carlos | San Juan | Segunda Línea | Villa del Rosario | Iscaypata | Combuyo | Buena vista | Chinchilla | La Palma | Chaupi Molino | Mojotoro | Curima | Abra | Tuero Chico | Tasa Pampa | Yotalilla | El Molino | La Palca | Santa Lucia | Cayara | Santa Rosalia | Pulqui | Puente Sucre | Totacoa | Chacarilla | Media Luna | Chaquito | Mayu Tambo | Chaco | Mosoj Llajta | Samasa Baja | Samasa Alta | Leche Huira | Chulchucani | Chili Mocko | Anocaraire | Pairumani | Vinto

chico | Chocaya | Violomilla | Thiomoco | Curima | Abra | Lica Lica | Koa Koa | Pacaja Alta | Suticollo | Valle Hermoso | Chacapaya | Hamiraya | Collpa Pampa | Caviloma | Sijlla K'asa | Canarias | Collpa central | Pirhuas | Mallco chapi | Chahuarani | Vila vila sud | Siqui siquia | Safiri | Yurubamba | Chulpas | Ravelo | Aruni | Vuela Grande | Llinfi | Barranca | Bermejo | Laja | Cuevas | Rancho Chico | Agua Rica | Vila Vila Norte | Parotani | Sauce Rancho | Chulla | Caltrancani

3. Instructions: Select your name
   - Jimena Romero | Fabio Calvimontes | Roxana Reinaga | Fabiola Rojas | Mayte Salas | Mario Gonzalez | Maribel Murillo Vera | Cinthia Espinoza Vargas | Paola Cordova | Mirian Mundocorre Canaviri | Henrry Manuel Vargas | Silvana Cabellero Flores | Angeles Joana Llave | Vicenta Patricia Chocllu | Miguel Flores | Jimena Teresa Beltrán Perez | CRISTINA BRAVO MAMANI | JIMENA BRAVO MAMANI | ALEX DAZA SALAS | ZULMA LIZBETH ISLA LEON | CARLA ISLA LEON | CLAUDIA ANDREA SALAS REYNAGA | PAMELA ELIZABETH FUERTES CAMPOS | Yorbelis Yonaly Goitia Ventura | Gladys Yessenia Pedraza | Nayeli Maite Galindo Nacimiento | Estefania Rosales Candia | Karina Choque Flores | Paula Andrea Huebe Cambara | Leidy Flores Padilla | Julio Melan | Mariana Mamani Diaz | Grover Merida Castellon | Alejandra Concepcion Choque Lizarazu | Cinthia Elena Guerrero Mejia | Maria Alejandra Carvajal Peñaranda | Andrea Valentina Villarreal Carvajal | michelle Isabella Rojas Valencia | Claudia Mendez Escobar | Bladimir Quispe Gutierrez | Rodrigo Iporre Reynaga | Luís Soria Galvarro | Alicia Lucano Alba para Santa Cruz | Wilber Victoria
4. Instructions: You and your partner enumerator should divide the community into eight sections with approximately the same number of households in each section. Each of you should be assigned one section. Please enter the number of the section you are working in.
   - 1.0 | 2.0 | 3.0 | 4.0 | 5.0 | 6.0 | 7.0 | 8.0
5. Is this the first household you are approaching in section [SECTION], or have you already approached a household and been told no?
   - First household | Already been told no
6. Instructions: How many households are in this section? Please use your best guess.
7. Instructions: Start at the left-most edge of the section. Go [RANDOM NUMBER] houses to your right from where you are now.
8. Instructions: Go to the right one house from the last house that you tried.
9. Instructions: Take GPS reading
10. Instructions: Knock on the household door. Is anyone home?
    - Yes | No
11. *[If yes:]* Good day. We would like to speak with the adult in this household who is primarily responsible for agricultural decisions. We are hoping to talk to the main decision-maker regarding agricultural activities. They must be over 18 years old. Are you that person?
    - Yes | No | Household does not practice agriculture
12. *[If no:]* Is the main agricultural decision-maker available? If yes, please go talk to them.

- Yes, that person is available | No, that person is not available | Household does not practice agriculture

13. *[If yes:]* Hello, my name is [ENUMERATOR NAME], and I am working with a research team from Cornell University and Harvard University. We are conducting a study to learn more about how farmers like you think about agricultural decisions and the weather. We are inviting a group of farmers in this area to participate in a series of short surveys. You were randomly selected to be part of this study. Your participation is completely voluntary, and your answers will be kept confidential. You can skip any question or stop at any time.
14. The process consist on having a survey today, and in four days approximately. There is a possiblity that we need to meet with you in two days for a short time. There will be compensation for participating from 30 bolivars to 60 bolivars. Will you be available to meet these days?
    - Yes | No
15. I will come back later today to complete a 30 minute survey with you. What times today are you NOT available?
    Instructions: please record when the respondent is unavailable in your notebook. Tell them when you think you will likely try to be back.
16. Can you read?
    - Yes | No
17. Instructions:
    Give copy of consent form.
18. I am giving you this copy of the consent form.
    Your participation is completely voluntary. You may choose to participate or not, and you may withdraw at any time without any problem.
    Participation lasts up to 4 days and includes two surveys of approximately 20 to 25 minutes each, and possibly a meeting with another farmer, which will be assigned at random.
    All the information you provide will be confidential and anonymous. No one will be able to identify you based on your responses.
    For your participation, you will receive a monetary compensation of 15 bolivianos, and you may receive an additional payment of 10 bolivianos if you participate in the meeting."
19. Who can I talk to?
    If you have questions, concerns, or complaints, or think the research has hurt you, talk to the research team at Jimena Romero Pinto at Cornell University (mjr456@cornell.edu) and Dev Patel at Harvard University (devpatel@fas.harvard.edu).
    This research has been reviewed and approved by the Harvard University Area Institutional Review Board ("IRB"). You may contact the IRB at (617) 496-2847 or cuhs@harvard.edu
20. *[If no:]* Instructions: Read CONSENT
    Thank you.
    Key Information
    The following is a short summary of this study to help you decide whether to be a part

of this study. More detailed information is listed later in this form.

21. Why am I being invited to take part in a research study?
    We invite you to take part in a research study because you are an agricultural household.
    What should I know about a research study?
    • Someone will explain this research study to you.
    • Whether or not you take part is up to you.
    • Your participation is completely voluntary.
    • You can choose not to take part.
    • You can agree to take part and later change your mind.
    • Your decision will not be held against you.
    • Your refusal to participate will not result in any consequences or any loss of benefits that you are otherwise entitled to receive.
    • You can ask all the questions you want before you decide.
    Why is this research being done?
    We want to understand how crop insurance and early warnings about extreme weather could benefit agricultural outcomes, and how farmers like you learn information from others in your village about this type of technology.
    How long will the research last and what will I need to do?
    We expect that you will be in this research study for about one week. You will be asked to do one survey later today that lasts about 20-25 minutes. You may be randomly chosen to be given information about these products. You will have the chance to be matched with another person in the village to exchange information during a conversation and to pay to increase your chances of that happening. You may earn additional payment for participating in these conversations. If possible, we will record the audio of that meeting to make sure that we are accurately capturing what information is exchanged. Then you will be asked to do another survey a 2-3 days later that will also last about 20-25 minutes. In the first survey, you will also be asked if you have any agricultural advice for others in your community, and anonymized versions of this advice, along with anonymized information about your age and your yield last year may be shared with others in your community. At the end of this process, you will receive a small payment as a bonus as a thank you.
    Is there any way being in this study could be bad for me?
    We don't believe there are any risks from participating in this research.
    Will being in this study help me in any way?
    We cannot promise any benefits to you or others from your taking part in this research. However, possible benefits include the chance to learn about a new crop insurance and weather warning system that is being deployed soon in areas like yours.
    What happens if I do not want to be in this research?
    Participation in research is completely voluntary. You can decide to participate, not participate, or discontinue participation at any time without penalty or loss of benefits to which you are otherwise entitled.
    Your alternative to participating in this research study is to not participate.
22. Detailed Information
    The following is more detailed information about this study in addition to the infor-

mation listed above.
What happens if I say yes, but I change my mind later?
You can leave the research at any time; it will not be held against you.
If I take part in this research, how will my privacy be protected? What happens to the information you collect?
Efforts will be made to limit the use and disclosure of your Personal Information. Your answers about who you would like to exchange information with in the village may be shared in the context of arranging the meetings. GPS measurements will be taken to understand the environmental conditions you face and help us locate your household in a future visit. If identifiers are removed from your identifiable private information or identifiable samples that are collected during this research, that information or those samples could be used for future research studies or distributed to another investigator for future research studies without your additional informed consent.

23. Who can I talk to?
    If you have questions, concerns, or complaints, or think the research has hurt you, talk to the research team at Jimena Romero Pinto at Cornell University (mjr456@cornell.edu) and Dev Patel at Harvard University (devpatel@fas.harvard.edu).
    This research has been reviewed and approved by the Harvard University Area Institutional Review Board ("IRB"). You may contact the IRB at (617) 496-2847 or cuhs@harvard.edu if:
    • Your questions, concerns, or complaints are not being answered by the research team.
    • You cannot reach the research team.
    • You want to talk to someone besides the research team.
    • You have questions about your rights as a research subject.
    • You want to get information or provide input about this research.
24. Do you understand this consent form?
    Instructions: Please answer any clarifying questions.
25. *[If yes:]* Are you interested in participating in this research?
    • Yes | No
26. What is your name?
27. I'm now going to ask you some basic questions so that I can identify you to other people in your village. I'm asking because we will be asking about spreading information, and so we will be referring to you.
28. How old are you?
29. What is your gender?
    • Female | Male | Otro
30. How many people are in your household?
31. How much land do you cultivate right now? In hectares
32. What is your phone number?
33. What is a back-up phone number of someone close to you that we can call if we have trouble getting ahold of you?
    Instructions: Please enter -999 if they don't know or refuse
34. What is that person's name?
35. Thank you for your time. I'll come back later today, probably around [estimated time]

36. Instructions: Take a photo of your surroundings
37. *[If no:]* Instructions: Thank you for your time.
38. Instructions: Close this survey. Go one door to your right and start a new survey with that household.
39. Did you face any technical issues or any other problems in taking this survey?
    - Yes | No
40. *[If yes:]* Please describe the issues you faced

## Baseline

1. Instructions: Select the Department
    - Potosi | Cochabamba | Chuquisaca | Santa Cruz
2. Instructions: Select the community
    - Angostura | San Luís | Tiquipaya | Taruma | Jorochito | Limoncito | El Torno | Santa Rita | Santa Martha | San José | Espejillos | La Guardia | Melea | San Carlos | San Juan | Segunda Línea | Villa del Rosario | Iscaypata | Combuyo | Buena vista | Chinchilla | La Palma | Chaupi Molino | Mojotoro | Curima | Abra | Tuero Chico | Tasa Pampa | Yotalilla | El Molino | La Palca | Santa Lucia | Cayara | Santa Rosalia | Pulqui | Puente Sucre | Totacoa | Chacarilla | Media Luna | Chaquito | Mayu Tambo | Chaco | Mosoj Llajta | Samasa Baja | Samasa Alta | Leche Huira | Chulchucani | Chili Mocko | Anocaraire | Pairumani | Vinto chico | Chocaya | Violomilla | Thiomoco | Curima | Abra | Lica Lica | Koa Koa | Pacaja Alta | Suticollo | Valle Hermoso | Chacapaya | Hamiraya | Collpa Pampa | Caviloma | Sijlla K'asa | Canarias | Collpa central | Pirhuas | Mallco chapi | Chahuarani | Vila vila sud | Siqui siquia | Safiri | Yurubamba | Chulpas | Ravelo | Aruni | Vuela Grande | Llinfi | Barranca | Bermejo | Laja | Cuevas | Rancho Chico | Agua Rica | Vila Vila Norte | Parotani | Sauce Rancho | Chulla | Caltrancani
3. Instructions: Select your name
    - Jimena Romero | Fabio Calvimontes | Roxana Reinaga | Fabiola Rojas | Mayte Salas | Mario Gonzalez | Maribel Murillo Vera | Cinthia Espinoza Vargas | Paola Cordova | Mirian Mundocorre Canaviri | Henrry Manuel Vargas | Silvana Caballero Flores | Angeles Joana Llave | Vicenta Patricia Chocllu | Miguel Flores | Jimena Teresa Beltrán Perez | CRISTINA BRAVO MAMANI | JIMENA BRAVO MAMANI | ALEX DAZA SALAS | ZULMA LIZBETH ISLA LEON | CARLA ISLA LEON | CLAUDIA ANDREA SALAS REYNAGA | PAMELA ELIZABETH FUERTES CAMPOS | Yorbelis Yonaly Goitia Ventura | Gladys Yessenia Pedraza | Nayeli Maite Galindo Nacimiento | Estefania Rosales Candia | Karina Choque Flores | Paula Andrea Huebe Cambara | Leidy Flores Padilla | Julio Melan | Mariana Mamani Diaz | Grover Merida Castellon | Alejandra Concepcion Choque Lizarazu | Cinthia Elena Guerrero Mejia | Maria Alejandra Carvajal Peñaranda | Andrea Valentina Villarreal Carvajal | michelle Isabella Rojas Valencia | Claudia Mendez Escobar | Bladimir Quispe Gutierrez | Rodrigo Iporre Reynaga | Luís Soria Galvarro | Alicia Lucano Alba para Santa Cruz | Wilber Victoria
4. Instructions: Type the Code of the Person you are interviewing

5. Instructions: Type the Name of the Person you are interviewing
6. Instructions: Type the Gender you are interviewing
    - Male | Female | Other
7. Instructions: Type the Age of the Person you are interviewing
8. Instructions: Take GPS reading
9. Thank you for your time! We will now begin the survey, which will take about 20-25 minutes.
10. What is the main language that you speak at home?
    - Spanish | Aymara | Quechua | Guarani
11. What crops do you cultivate? Select all that apply
    - Soybean | Sugarcane | Potato | Banana | Corn | Sorghum | Rice | Sunflowers | Wheat | Barley | Cotton | Cassava | Tangerine | Orange | Chirimoya | Mango | Palto | Onion | Other fruits | Other Vegetables | Other
12. What crop is the most important for your household earnings?
    - Soybean | Sugarcane | Potato | Banana | Corn | Sorghum | Rice | Sunflowers | Wheat | Barley | Cotton | Cassava | Tangerine | Orange | Chirimoya | Mango | Palto | Onion | Other fruits | Other Vegetables | Other
13. How much total money did you earn from all of your agricultural activities in the last year?
    - Lost more than 2000 bolivars | Lost 1500-2000 bolivars | Lost 1000-1500 bolivars | Lost 500-1000 bolivars | Lost 1-500 bolivars | Nothing | 1 - 500 bolivars | 500-1000 bolivars | 1000-1500 bolivars | 1500-2000 bolivars | 2000-2500 bolivars | 2500-3000 bolivars | 3000-3500 bolivars | 3500-4000 bolivars | 4000 - 4500 bolivars | 4500 - 5000 bolivars | 5000 - 5500 bolivars | 5500 - 6000 bolivars | 6000 - 6500 bolivars | 6500 - 7000 bolivars | 7000 - 7500 bolivars | 7500 - 8000 bolivars | 8000 +
14. Do you have or had you had an insurance contract against bad weather or natural disasters?
    - Never had | Had government insurance in the past but not now | Currently have government insurance | Had private insurance in the past but not now | Currently have private insurance
15. How interested are you in climate insurance?
    - Not at all interested | Somewhat interested | Very interested | Extremely interested
16. How worried are you about frost or cold spells?
    - Not at all worried | Somewhat worried | Very worried | Extremely worried
17. How worried are you about drought?
    - Not at all worried | Somewhat worried | Very worried | Extremely worried
18. How worried are you about floods?
    - Not at all worried | Somewhat worried | Very worried | Extremely worried
19. What is a piece of agricultural advice you would share with others in this community?
20. We want to get a sense of your social connections in this community. We are asking this because we are trying to understand how information about crop insurance might spread.
21. If we wanted to spread information about a new crop insurance product to everyone in your village, to whom do you suggest we speak? Please tell me their name and your best estimate of their age. (Format: Name, Age)

22. Besides this person, with how many other people in this community do you regularly share or receive important information (for example, advice about health issues, work or agricultural work, savings, or financial problems)?
23. Please tell us the names of people in this community with whom you regularly share or receive important information, such as advice on health problems, work, agricultural work, savings, or financial problems.
    Instructions: Separate each name by a comma: e.g., FIRST NAME 1 FIRST LAST NAME 1 SECOND LAST NAME 1, FIRST NAME 2 FIRST LAST NAME 2 SECOND LAST NAME 2, FIRST NAME 3 FIRST LAST NAME 3 SECOND LAST NAME 3, ...
24. Please tell us the names of the 5 people in this community with whom you most regularly share or receive important information, such as advice on health problems, work, agricultural work, savings, or financial problems.
    Instructions: Separate each name by a comma: e.g., FIRST NAME 1 LAST NAME 1, FIRST NAME 2 LAST NAME 2, FIRST NAME 3 LAST NAME 3, ...
25. What is the complete name and age of the person you share or receive important information with? (Format: Name, Age)
26. You said that there are [N] people in this community with whom you regularly share or receive important information. Are you sure there aren't any others?
    - There aren't any others | There are others
27. How many more people?
28. What is the complete name and age of the person you share or receive important information with? (Format: Name, Age)
29. Is there another person?
    - Yes | No
30. A company wants to introduce two new products in communities like yours.
    One is crop insurance. The other is a warning system that sends an alert if frost is coming.
    Some people in this community will receive information about these products. You might be chosen, or another person might be chosen.
    Some people may also be randomly chosen to meet and learn about these products from each other.
31. In this part of the survey, we would like to learn how much you would value receiving information about these products from others and how much you value giving information about these products to others to understand how people learn about this type of technology.
32. The way we will measure how much you value giving this information and receiving it from a specific person is a little complicated, so I will explain the whole process to you. If you have any questions about anything you can ask me, and I will try to explain to you as best I can.
33. To show how this works, we will first do a practice example. This is only for practice. Imagine a friend of your is the only person in this community who knows about these services. We want to know how much you would be willing to pay to receive this information from that person.
    I will start with a low amount and slowly increase it until you say that you would not

pay that amount.
After that, the phone will choose a random price. If this price is less than or equal to the maximum amount you said, you will have to buy the information. If the price is higher than what you said, you will not buy it.
Once the price is shown, you cannot change your answer.
This is just an example. After this, we will ask you how much you would be willing to pay to receive information from other people in your community.
It is important that you answer honestly, because after the survey the price will be drawn and we will check whether you can or cannot get the information.

34. Please, tell me the name of a person you know in this community
35. Imagine that [NAME] is given information about the crop insurance and weather forecast system products.
36. Would you be willing to pay to meet with [NAME] to learn about this information for 10 bolivars?
    - Yes | No, too high | No, too low
37. *[Repeat, increasing the offered amount by 10 bolivianos each time, until the respondent declines.]*
38. *[If no:]* Would you be willing to meet with [NAME] to learn about this information for 0 bolivares? It would be free.
    - Yes | No
39. Would you be willing to meet with [NAME] to learn about this information if you are paid 10 bolivares?
    - Yes | Not for that amount | Not, for any amount
40. Just to confirm, you said that you would pay at most [WTP] bolivianos to receive information from [NAME].
    If the tablet shows a price higher than [WTP], you would not pay to meet with [NAME].
    If it shows a price equal to or lower than [WTP], you would have to pay that price to receive the information.
    Is that correct?
    Instructions: If the respondent does not agree, go back and ask the questions again.
41. Just to make sure, you said that you would not want to meet with [NAME], even if it were free. That means that no matter what price the phone shows, you would not be willing to pay for the information. Is that what you mean?
    Instructions: If the respondent does not agree, go back and ask the questions again.

PRICE bolivianos
Because this price is higher than what you said you would be willing to pay, you would not be able to meet and pay to receive the information from [NAME].

PRICE bolivianos
Earlier, you said that you would be willing to pay up to [WTP] bolivianos.
Because this price is lower than what you said you would be willing to pay, you should meet and pay [PRICE] bolivianos to receive the information from [NAME].

42. Do you have any questions about this process?
    Instructions: Respond the questions.
    - Yes | No
43. Now that we have practiced with an example, you will next be asked questions about

7 people.
First, you will be asked how much you would be willing to pay to receive information from each person, if that person had information about the new early warning system and insurance.
Then, you will be asked how much you would be willing to receive if you were the one sharing that information.
At the end, you will be asked some questions about your relationship with each person. Please remember to answer honestly, as a price will be determined that will define whether or not you can pay for the information. In this case, the final price will be determined at the end of the day.

44. Do you have any questions about this process?
    Instructions: Respond the questions.
    - Yes | No
45. How confusing do you find this procedure? Please answer truthfully.
    - Not at all confusing | A little confusing | Somewhat confusing | Very confusing | Extremely confusing
46. Instructions: How well do you think the respondent understood the procedure?
    - Did not understand at all | Understood a little | Understood somewhat | Understood well | Understood completely
47. *[The following blocks loop over each of the other community members, in a random order.]*
48. Write down the complete name corresponding to person number [NUMBER] in the paper form.
49. Write down the age corresponding to person number [NUMBER]
50. I will ask you about [NAME], who is [AGE] years old.
    Do you know who I am referring to?
    - Yes | No
51. Imagine that [NAME] is given information about the crop insurance and weather forecast system products.
52. Would you be willing to pay to meet with [NAME] to learn about this information for 10 bolivars?
    - Yes | No, too high | No, too low
53. *[Repeat, increasing the offered amount by 10 bolivianos each time, until the respondent declines.]*
54. *[If no:]* Would you be willing to meet with [NAME] to learn about this information for 0 bolivares? It would be free.
    - Yes | No
55. Would you be willing to meet with [NAME] to learn about this information if you are paid 10 bolivares?
    - Yes | Not for that amount | Not, for any amount
56. Just to make sure, you said you would pay [WTP] bolivares to meet with [NAME] to receive information, but no higher.
    Is this what you mean?
    Instructions: If the respondent does not agree, go back and ask the questions again.
57. Now, imagine that [NAME] is given information about the crop insurance and weather

forecast system products, and they are given a flyer that contains information about these products, which they can hand to you.

58. Would your answer change?
    - No, it would be the same | Yes, it would increase | Yes, it would decrease
59. How much would you pay?
60. How much would you pay?
61. How much would you pay?
62. WTR

    Now we are going to ask you about the value of your knowledge. Imagine that you have been given information about the new crop insurance product and the weather forecasting product.
63. Would you be willing to meet with [NAME] to share this information if you were paid 5 bolivares?
    - Yes | Not for that amount | Not, for any amount
64. *[Repeat, increasing the offered amount by 10 bolivianos each time, until the respondent declines.]*
65. *[If yes:]* Would you be willing to meet with [NAME] to share this information for 0 bolivares? It would be free.
    - Yes | No
66. Would you be willing to meet with [NAME] to share this information if you pay 10 bolivares?
    - Yes | No
67. Just to make sure, you said you would be willing to share information with [NAME] if you were paid [WTR] bolivares, but no less. Is this what you mean?

    Instructions: If the respondent does not agree, go back and ask the questions again.
68. Now, imagine that you are given the information about crop insurance and weather forecast system products, and the opportunity to meet with [NAME]. Imagine you are also given a flyer that contains information about these products which you can hand to [NAME].
69. Would your answer change?
    - No, it would be the same | Yes, it would increase | Yes, it would decrease
70. How much would you want to receive?
71. How much would you want to receive?
72. How much would you want to receive?
73. I'm now going to ask you abou your relationship with [NAME].
74. How similar do you think you are to [NAME]?
    - Not at all similar | A little bit similar | Somewhat similar | Very similar | Extremely similar
75. What best describes your relationship with [NAME]?
    - Family member | Close friend | Friend | Acquaintance | Don't know them well
76. I'm now going to ask you abou your relationships in the community
77. Select the person(s) with whom, in the last 12 months, you have lent or borrowed money, goods, or favors.
78. *[Asked separately for each of the other community members. Response for each: Yes | No.]*

79. Select which person you think could be a good entrepeneur within the community
80. *[Asked separately for each of the other community members. Response for each: Yes | No.]*
81. Select which person would be a good communicator of the insurance and eaerly warning system services
82. *[Asked separately for each of the other community members. Response for each: Yes | No.]*
83. Select which person you enjoy their company a lot.
84. *[Asked separately for each of the other community members. Response for each: Yes | No.]*
85. Select which person you think is highly respected in the community.
86. *[Asked separately for each of the other community members. Response for each: Yes | No.]*
87. Select which person you would take advice about agriculture.
88. *[Asked separately for each of the other community members. Response for each: Yes | No.]*
89. Select which person you socialize with at least once a week.
90. *[Asked separately for each of the other community members. Response for each: Yes | No.]*
91. *[If control:]* Thank you for your time. We will be returning to your community in the next couple of days to do another survey, and the computer will also let us know if you have been selected to participate in a meeting. At that time, you will receive your bonus payment for your participation.
92. *[If treatment:]* You have been randomly selected to receive the information. I am now going to share information about two tools offered by the company Suyana that may help farmers manage climate risks: (1) a drought insurance product and (2) an early warning system that sends forecasts to help plan for extreme weather events. The goal of this section is only to explain how each product works. You are free to ask any questions. This is not a sales pitch, and these products are not available right now, though hopefully they will be soon in areas including yours.
93. Agricultural Drought Insurance
    Suyana, together with Cidre, is developing an agricultural insurance product that covers all crops, such as rice, wheat, potatoes, tomatoes, onions, and others.
    This insurance is only available to people who have a loan with Cidre, and enrollment is done through Cidre.
    How does the insurance work?
    • You pay only once at the beginning of the agricultural season.
    • The cost is 5% of the value of the harvest you want to insure.
    For example, if you expect to earn 1,000 Bolivianos, you pay 50 Bolivianos.
    • There are no additional payments during the season.
    When does the insurance pay?
    Suyana uses satellite information to measure soil moisture. If satellites show that the soil is much drier than normal, this is considered a drought. If the soil is much wetter than normal, that can also cause the crops to suffer, and the insurance project will cover that too.

There are three levels of drought:
• Very severe drought (occurs about once every 20 years): the insurance pays approximately 6 times what you paid.
• Severe drought (occurs about once every 10 years): the insurance pays approximately 5 times what you paid.
• Moderate drought (occurs about once every 5 years): the insurance pays approximately 3 times what you paid.
If there is no drought, there is no payment, but you keep whatever harvest you get.
The payment is made automatically and is deposited into your Cidre account, reducing your outstanding loan balance.
Important information about the insurance
• The insurance pays only once per agricultural season
• It does not cover pests, hail, frost, or price changes
• It does not guarantee that all losses will be covered
Climate Alert System
In addition, Suyana is working with CIDRE to develop a Climate Early Warning System, which will likely be free of charge.
This system:
• Sends alerts via WhatsApp
• Warns about heavy rainfall and cold spells
• Sends alerts up to 5 days in advance
The alerts are not perfect:
• For heavy rainfall, they are accurate about 1 out of 2 times
• For cold spells, they are accurate about 3 out of 5 times

94. This concludes the information about the insurance and the Early Warning System. Do you have any questions before we continue?
    - Yes | No
95. Now I will make some questions to understand how clearly the information was shares and what do you remember.
96. What kind of shock does the crop insurance product cover?
    - Drought | Hail | Floods | Excess rain | Wind | Other
97. *[If other:]* Please, specify
98. Which crops are covered by the insurance product?
    - corn | potatos | fruits | onion | Other | All crops | Don't know
99. *[If other:]* Please, specify
100. How much does the insurance cost?
    - 10 bolivars per 2500 metros | 100 bolivars per 2500 metros | 5% of harvest value | 10% of harvest value | Don't know
101. When do you pay for the insurance?
    - At the beginning of the season | After a drought happens | At harvest time | Don't know
102. When do Suyana and Cidre decide when to trigger the insurance payout?
    Instructions: Do not read the options aloud.
    - When satellite data shows soil moisture is far below (or above) normal | When the farmer files a claim at the office | When crop damage is seen during visits |

When government declares a drought | Don't know

103. What types of climate shocks will be alerted in the Early Warning System? Instructions: Do not read the options aloud.
    - Drought | Hail | Floods | Excess rain | Wind | Other | Don't know
104. How far in advance can warnings be issued?
    - 1-5 Days | 6-10 Days | 10 Days to 1 month | 1 - 2 Months | Don't know
105. How often are these forecasts correct? For instance, out of six forecasts, how many do you think will be accurate?
    - They are almost always correct | They are correct about 5 out of 6 times | They are correct about 4 out of 6 times | They are correct about 3 out of 6 times | They are correct about 2 out of 6 times | They are correct about 1 out of 6 times | They are almost never correct | Don't know
106. *[If control:]* Thank you for your time. We will be returning to your community in the next couple of days to do another survey, and the computer will also let us know if you have been selected to participate in a meeting. At that time, you will receive your bonus payment for your participation.
107. Instructions: Has it rained at all today in this community so far?
    - Yes | No | Don't know
108. Instructions: Did you face any technical issues or any other problems in taking this survey?
    - Yes | No
109. *[If yes:]* Instructions: Please describe

## Conversation Scheduling

1. Instructions: Take a GPS reading
2. Instructions: Select the Department
    - Potosi | Cochabamba | Chuquisaca | Santa Cruz
3. Instructions: Select a community
    - Angostura | San Luís | Tiquipaya | Taruma | Jorochito | Limoncito | El Torno | Santa Rita | Santa Martha | San José | Espejillos | La Guardia | Melea | San Carlos | San Juan | Segunda Línea | Villa del Rosario | Iscaypata | Combuyo | Buena vista | Chinchilla | La Palma | Chaupi Molino | Mojotoro | Curima | Abra | Tuero Chico | Tasa Pampa | Yotalilla | El Molino | La Palca | Santa Lucia | Cayara | Santa Rosalia | Pulqui | Puente Sucre | Totacoa | Chacarilla | Media Luna | Chaquito | Mayu Tambo | Chaco | Mosoj Llajta | Samasa Baja | Samasa Alta | Leche Huira | Chulchucani | Chili Mocko | Anocaraire | Pairumani | Vinto chico | Chocaya | Violomilla | Thiomoco | Curima | Abra | Lica Lica | Koa Koa | Pacaja Alta | Suticollo | Valle Hermoso | Chacapaya | Hamiraya | Collpa Pampa | Caviloma | Sijlla K'asa | Canarias | Collpa central | Pirhuas | Mallco chapi | Chahuarani | Vila vila sud | Siqui siquia | Safiri | Yurubamba | Chulpas | Ravelo | Aruni | Vuela Grande | Llinfi | Barranca | Bermejo | Laja | Cuevas | Rancho Chico | Agua Rica | Vila Vila Norte | Parotani | Sauce Rancho | Chulla | Caltrancani
4. Select your name
    - Jimena Romero | Fabio Calvimontes | Roxana Reinaga | Fabiola Rojas | Mayte

Salas | Mario Gonzalez | Maribel Murillo Vera | Cinthia Espinoza Vargas | Paola Cordova | Mirian Mundocorre Canaviri | Henrry Manuel Vargas | Silvana Cabellero Flores | Angeles Joana Llave | Vicenta Patricia Chocllu | Miguel Flores | Jimena Teresa Beltrán Perez | CRISTINA BRAVO MAMANI | JIMENA BRAVO MAMANI | ALEX DAZA SALAS | ZULMA LIZBETH ISLA LEON | CARLA ISLA LEON | CLAUDIA ANDREA SALAS REYNAGA | PAMELA ELIZABETH FUERTES CAMPOS | Yorbelis Yonaly Goitia Ventura | Gladys Yessenia Pedraza | Nayeli Maite Galindo Nacimiento | Estefania Rosales Candia | Karina Choque Flores | Paula Andrea Huebe Cambara | Leidy Flores Padilla | Julio Melan | Mariana Mamani Diaz | Grover Merida Castellon | Alejandra Concepcion Choque Lizarazu | Cinthia Elena Guerrero Mejia | Maria Alejandra Carvajal Peñaranda | Andrea Valentina Villarreal Carvajal | michelle Isabella Rojas Valencia | Claudia Mendez Escobar | Bladimir Quispe Gutierrez | Rodrigo Iporre Reynaga | Luís Soria Galvarro | Alicia Lucano Alba para Santa Cruz | Wilber Victoria

5. Instructions: Select the name of the person that will be teaching the information TEACHER 1 | [TEACHER 2]
6. Is the person who will receive the information (listener) [LISTENER]?
    - No | Yes
7. *[If no:]* Instructions: Please confirm the community and select the teacher again.

## Conversation

1. Thank you both for joining!
   The purpose of this survey is for you two to discuss the new insurance and forecast products that may be introduced into your village soon. [TEACHER] has been informed about hese products and can share information with [LISTENER], who hasn't received the informacion. I will not speak any more for the rest of this conversation–the point is just for you two to discuss together. Before we begin, I just want to check one thing. Are you two okay if I record this conversation? This is just for research purposes–nothing will be shared with anyone else, and it's just to make sure we understand what happened during the conversation.
    - No, at least one person does not consent | Yes, both consent
2. Instructions: Press record if consent was given. Record the entire conversation until people leave. It's okay if they discuss other things than the climate products–do not stop the recording.
3. How clear did the meeting seem overall?
    - Very unclear | Somewhat unclear | Clear | Very clear
4. Approximately how many minutes of walking is the conversation location from [TEACHER]'s house?
5. Approximately how many minutes of walking is the conversation location from [LISTENER]'s house?
6. Based on your observation, how happy or positive did [TEACHER] seem during the meeting?
    - Unhapy | Slightly unhappy | Happy | Very happy

7. Based on your observation, how happy or positive did [LISTENER] seem during the meeting?
    - Unhapy | Slightly unhappy | Happy | Very happy
8. Did either participant seem confused about the information being shared?
    - Not confused at all | Slightly confused | Moderately confused | Very confused | Extremely confused
9. In your opinion, did the meeting go well?
    - Not very well | Somewhat well | Very well | Extremely well
10. Did you face any technical issues or any other problems in administering this survey?
    - No | Yes
11. *[If yes:]* Please describe

## Endline

1. Select the department
    - Potosi | Cochabamba | Chuquisaca | Santa Cruz
2. Select the community
    - Angostura | San Luís | Tiquipaya | Taruma | Jorochito | Limoncito | El Torno | Santa Rita | Santa Martha | San José | Espejillos | La Guardia | Melea | San Carlos | San Juan | Segunda Línea | Villa del Rosario | Iscaypata | Combuyo | Buena vista | Chinchilla | La Palma | Chaupi Molino | Mojotoro | Curima | Abra | Tuero Chico | Tasa Pampa | Yotalilla | El Molino | La Palca | Santa Lucia | Cayara | Santa Rosalia | Pulqui | Puente Sucre | Totacoa | Chacarilla | Media Luna | Chaquito | Mayu Tambo | Chaco | Mosoj Llajta | Samasa Baja | Samasa Alta | Leche Huira | Chulchucani | Chili Mocko | Anocaraire | Pairumani | Vinto chico | Chocaya | Violomilla | Thiomoco | Curima | Abra | Lica Lica | Koa Koa | Pacaja Alta | Suticollo | Valle Hermoso | Chacapaya | Hamiraya | Collpa Pampa | Caviloma | Sijlla K'asa | Canarias | Collpa central | Pirhuas | Mallco chapi | Chahuarani | Vila vila sud | Siqui siquia | Safiri | Yurubamba | Chulpas | Ravelo | Aruni | Vuela Grande | Llinfi | Barranca | Bermejo | Laja | Cuevas | Rancho Chico | Agua Rica | Vila Vila Norte | Parotani | Sauce Rancho | Chulla | Caltrancani
3. Select your name
    - Jimena Romero | Fabio Calvimontes | Roxana Reinaga | Fabiola Rojas | Mayte Salas | Mario Gonzalez | Maribel Murillo Vera | Cinthia Espinoza Vargas | Paola Cordova | Mirian Mundocorre Canaviri | Henrry Manuel Vargas | Silvana Cabellero Flores | Angeles Joana Llave | Vicenta Patricia Chocllu | Miguel Flores | Jimena Teresa Beltrán Perez | CRISTINA BRAVO MAMANI | JIMENA BRAVO MAMANI | ALEX DAZA SALAS | ZULMA LIZBETH ISLA LEON | CARLA ISLA LEON | CLAUDIA ANDREA SALAS REYNAGA | PAMELA ELIZABETH FUERTES CAMPOS | Yorbelis Yonaly Goitia Ventura | Gladys Yessenia Pedraza | Nayeli Maite Galindo Nacimiento | Estefania Rosales Candia | Karina Choque Flores | Paula Andrea Huebe Cambara | Leidy Flores Padilla | Julio Melan | Mariana Mamani Diaz | Grover Merida Castellon | Alejandra Concepcion Choque Lizarazu | Cinthia Elena Guerrero Mejia | Maria Alejandra Carvajal Peñaranda | Andrea Valentina Villarreal Carvajal | michelle Isabella Rojas Va-

lencia | Claudia Mendez Escobar | Bladimir Quispe Gutierrez | Rodrigo Iporre Reynaga | Luís Soria Galvarro | Alicia Lucano Alba para Santa Cruz | Wilber Victoria

4. Select the respondent

NAME 1 | [NAME 2] | [NAME 3] | [NAME 4] | [NAME 5] | [NAME 6] | [NAME 7] | [NAME 8]

5. Take GPS reading
6. Thank you for time! This survey will take about 25 minutes.
   We would like to ask you a few questions about a crop insurance product and a forecast product that might be introduced in your village soon. Some people in your village were given information about these products, and you may have heard about them being discussed. In this next section, we will ask some simple questions about the basic features of these products.
   We only want to understand how clearly the information was communicated and what people remember. Your answers will not affect your participation in the study or any of your payments.
7. What kind of shock does the crop insurance product cover?
   - Drought | Hail | Floods | Excess rain | Wind | Other
8. *[If other:]* Please, specify
9. Which crops are covered by the insurance product?
   - corn | potatos | fruits | onion | Other | All crops | Don't know
10. *[If other:]* Please, specify
11. How much does the insurance cost?
    - 10 bolivars per 2500 metros | 100 bolivars per 2500 metros | 5% of harvest value | 10% of harvest value | Don't know
12. When do you pay for the insurance?
    - At the beginning of the season | After a drought happens | At harvest time | Don't know
13. When do Suyana and Cidre decide when to trigger the insurance payout?
    Instructions: Do not read the options aloud.
    - When satellite data shows soil moisture is far below (or above) normal | When the farmer files a claim at the office | When crop damage is seen during visits | When government declares a drought | Don't know
14. What types of climate shocks will be alerted in the Early Warning System?
    Instructions: Do not read the options aloud.
    - Drought | Hail | Floods | Excess rain | Wind | Other | Don't know
15. How far in advance can warnings be issued?
    - 1-5 Days | 6-10 Days | 10 Days to 1 month | 1 - 2 Months | Don't know
16. How often are these forecasts correct? For instance, out of six forecasts, how many do you think will be accurate?
    - They are almost always correct | They are correct about 5 out of 6 times | They are correct about 4 out of 6 times | They are correct about 3 out of 6 times | They are correct about 2 out of 6 times | They are correct about 1 out of 6 times | They are almost never correct | Don't know
17. Would you like us to give your contact information to Suyana so that they can contact

you if this insurance product becomes available in your community?
   - No | Yes

18. What is the maximum amount you would be willing to pay for Suyana's insurance product? Instructions: Please enter -99 for don't know and -10 if the respondent says they don't want it even if it is free.
19. I will now read you the names of seven people we asked you about earlier. Please tell me if you met with them to talk about the drought insurance or early warning system. Instructions: Select who they talked with

NAME 1 | [NAME 2] | [NAME 3] | [NAME 4] | [NAME 5] | [NAME 6] | [NAME 7] | [NAME 8]

20. How many conversations have you had with these people about the drought insurance or the early warning system?
21. What did you mainly talk about?
    - Insurance | Early warning system | Both | Something else
22. Did your meeting with [MATCHED PERSON] actually take place?
    - No | Yes
23. *[If yes:]* How long did the meeting last? (minutes)
24. How clearly did the other person explain the information?
    - Not clearly at all | A little clearly | Clearly | Very clearly
25. How comfortable did you feel during the meeting?
    - Not comfortable | Somewhat comfortable | Comfortable | Very comfortable
26. Since the beginning of this study, how many conversations have you had with other people about the drought insurance product or the early warning system?
27. Today, we would like to ask you questions to understand your perceptions, and your willingness to pay for these types of products. At the end of this interview, we will provide you with the same full information that was given to the other farmers. You will not be asked to pay anything today, and your answers will not affect any bonus or payment in this study. We ask these questions only to learn how much farmers in your community value these tools.
28. Instructions:
    Take out the crop damage image and the ten buttons.
    This image shows two scenarios that might happen to you. In the example on the left, there is a drought that damages at least some of your crops this season.
    Instructions:
    : point to the picture on the left.
    In the example on the right, there is no drought.
    Instructions:
    point to the picture on the right.
    Please take these peanuts, and move them onto the picture that you think is more likely. If you think there is no chance there would be a drought, you should move all of the peanuts onto the picture on the right. If you think there is definitely going to be a drought, you should move all of the peanuts onto the picture on the left. If you think there is some chance of both, you would put some peanuts on each picture. Put more peanuts on the scenario that you think is more relevant. Does this question make sense to you?

Instructions:
: answer any questions they have.

29. Please place all 10 peanuts now.
    Instructions:
    enter how many peanuts they put on the drought picture.
30. Instructions:
    Take out the crop damage image and the ten buttons.
    This insurance product will pay you 100 pesos if your land shows a drought according to satellites. Using this picture, please tell me how likely you think it will be that the insurance company agrees with you that you have experienced a drought when you think you have. Assume you experience a drought based on what you consider a drought. Now move buttons based on what you think the insurance company would say. If every time you say there is a drought, the insurance company also says there is a drought, then you would put all of the buttons on the picture of a drought. If every time you say there is a drought, the insurance company says there is no drought, then you would put all of the buttons on this picture. Please put buttons according to how likely you think it is that the insurance company agrees with you that there is a drought.
    Instructions:
    please enter how many buttons they placed on the drought picture
31. Now, please tell me how likely you think it will be that the insurance company agrees with you that you have not experienced a drought when you think you have also not experienced a drought. Assume you have not experienced a drought based on what you consider a drought. Now move buttons based on what you think the insurance company would say. If every time you say there is not a drought, the insurance company also says there is not a drought, then you would put all of the buttons on the picture of no drought. If every time you say there is not a drought, the insurance company says there is a drought, then you would put all of the buttons on this picture. Please put buttons according to how likely you think it is that the insurance company agrees with you that there is not a drought.
    Instructions:
    please enter how many buttons they placed on the drought picture on the left.
32. How much are you willing to pay for this insurance per hectare and year?
33. Imagine that you had insurance for a drought, and it paid out at the end of the season if you had a drought. What would you do differently on your farm, if anything?
    - Change crops | Change seeds | Cultivate more land | Use more fertilizer | Use less fertilizer | Spend more on agricultural inputs | Spend less on agricultural inputs | No change | Other
34. *[If other:]* Please, specify
35. Which crops would you cultivate?
    - Corn | Potato | Onion | Citrics | Other fruits | Hortalizas | Other
36. *[If other:]* Please, specify
37. Imagine that you had insurance for a drought, and it paid out as soon as the satellites predicted there would be a drought . What would you do differently on your farm, if anything?

- Install irrigation system | Change crops | Change seeds | Cultivate more land | Use more fertilizer | Use less fertilizer | Spend more on agricultural inputs | Spend less on agricultural inputs | Install irrigation system | No change | Other

38. *[If other:]* Please, specify
39. Which crops would you cultivate?
    - Corn | Potato | Onion | Citrics | Other fruits | Hortalizas | Other
40. *[If other:]* Please, specify
41. Now imagine that you were offered access to an early warning system that uses satellite and weather station data to predict whether a frost is arriving three days in advance. Imagine that you are told a frost is coming three days in advance. What are the steps you would take, if any?
    - Protect my crops physically | Harvest early | Irrigate | Create bonfires | Pray to the land | No steps | Other
42. *[If other:]* Please, specify
43. Instructions: Take out the crop damage image and the ten buttons. Using this picture, please tell me how likely you think it would be that the early warning system tells you that a frost is coming and it actually comes? Assume that the warning system tells you a frost is coming. If every time it tells you that frost is coming, frost actually comes, then move all of the buttons to this side.
    Instructions: Point to the crop damage picture. If every time it tells you that frost is coming, frost does not actually comes, then move all of the buttons to this side.
    Instructions: Point to the no crop damage picture. Move more buttons to the scenario that you think is more likely to occur if the EWS tells you a frost is coming.
    Instructions: please enter how many buttons they placed on the crop damage picture on the left.
44. Now, using this same picture, tell me how likely do you think it will be that the early warning system tells you a frost is not coming and it does actually come. Assume that the warning system tells you a frost is not coming. If every time it tells you that frost is not coming, frost actually comes, then move all of the buttons to this side.
    Instructions: Point to the crop damage picture. If every time it tells you that frost is not coming, frost does not actually come, then move all of the buttons to this side.
    Instructions: Point to the no crop damage picture. Move more buttons to the scenario that you think is more likely to occur if the EWS tells you a frost is not coming.
    Instructions: please enter how many buttons they placed on the crop damage picture on the left.
45. Sometimes, the early warning system may predict a frost is not coming when actually it does happen. If you were told that no frost is coming but actually a frost does occur, how much would the frost cost you? Please give an estimate of the total cost to your household in pesos.
46. Sometimes, the early warning system may accurately predict a frost is coming three days in advanced, giving time for mitigation actions. If you were told that a frost is coming and a frost actually occurs, how much do you think that experience would cost you? Please give an estimate of the total costs to your household in pesos.
47. Sometimes, researchers may predict a frost is coming when it is not coming. If you were told that a frost is coming but no frost actually occurs, how much would that cost

you? Please give an estimate of the total cost to your household in pesos, taking into account any preparations you might have done when you thought a frost might arrive.

48. How much would you be willing to pay for this early warning system service?
49. Now, imagine that you are given the insurance for free. How much would you be willing to pay for the early warning system service?
50. Now, imagine that you are given the early warning system for free. How much would you be willing to pay for the insurance?
51. Now, imagine that you could buy both the early warning system and the insurance. How much would you be willing to pay for both of them together?
52. How easy or difficult did you find these questions to answer?
    - Extremely easy | A little bit easy | Neither easy nor difficult | A little bit difficult | Extremely difficult
53. In general, how willing or unwilling are you to take risks on a scale of 0 to 10, where 0 means you are not willing to take risks at all and 10 means you have no problem taking risks? You can choose any number from 1, 2, 3, 4, 5, 6, 7, 8, 9 or 10.
54. Do you prefer to eat crops that you have grown yourself?
    - No | Yes | Don't remember
55. *[If yes:]* What are the reasons?
    - It tastes better | I take pride in my own crops | It is cheaper | I have more control over the fertilizer and pesticide used | Other
56. *[If other:]* Please, specify
57. *[If yes:]* Imagine that you are not allowed to eat any of the crops that you harvest. Would you make the following different decisions?
    - Would change how much land I cultivate | Would change which crops I cultivate | Would change which seeds I cultivate | Would change the amount of fertilizer or pesticides I use | Would change something else | Would not change anything | Don't know
58. Do you have individual land title?
    - No | Yes
59. In which month do you expect to harvest your main crop?
    - January | February | March | April | May | June | July | August | September | October | November | December
60. Do you sell your harvest?
    - No | Yes
61. *[If yes:]* How do you sell your products?
    - I sell them directly to recurrent clientes | I sell them in a market | I sell them to agro dealers or intermediaries | Other
62. Please, specify
63. What are the reasons you don't sell to agrodealers?
    - Because they don't reach this area | Because I don't trust them | Because they take a big margin from profits | Other
64. Please, specify
65. Now we will ask you about your welleness. In the last month,
66. "... how often have you felt that you were unable to control the important things in your life?"

- Never | Sometimes | Often | Very often

67. "...how often have you felt confident about your ability to handle your personal problems?"
    - Never | Sometimes | Often | Very often
68. Would you ever consider paying a friend for useful agricultural information or advice they might have?
    - Yes, definitely | Maybe / It depends | No, never | Not sure
69. why would you not consider paying a friend for advice?
    - It feels strange / uncomfortable | Friends should help each other for free | I don't trust the information | I don't have extra money for that | I don't think information is worth paying for
70. We interviewed other farmers in your village. One of them earned [INCOME] in agricultural profits last year. What do you think is the chance that this farmer is under the age of 45? Move more corn kernels over to the left side of the sheet if you think there is a higher chance they are under the age of 45, and more to the right if you think there is a higher chance they are above the age of 45.
71. Number of corn kernels on below 45 side
72. *[If treatment:]* The farmer we spoke to said they were [SIMILARITY] to you.
73. How useful do you think this farmer's advice is to you?
    - Not at all useful | Somewhat useful | Very useful | Extremely useful | Don't know
74. The survey is almost over. But if you would like, we can add some more time to tell you what the agricultural advice was that this farmer who earned [INCOME] shared. Would you like to hear the advice?
    - No | Yes
75. *[If yes:]* The farmer's advice was: [ADVICE]
76. Do you prefer to learn agricultural information from farmers who are more similar to you or more different?
    - More similar | More different | Equal | Don't know
77. Why?
    - They have more relevant information to me | I communicate better with them | I see them more/easier to ask | They know things I don't | They have different experiences which can be valuable | Other
78. Please specify:
79. Instructions:: Before ending the survey, share the information about the insurance and early warning system
80. Agricultural Drought Insurance

    In some places, there is an insurance that helps when the weather is very bad. The insurance is paid before the harvest and pays automatically if a drought occurs (see diagram).

    Suyana, together with Cidre, is developing an agricultural insurance product that covers all crops, such as rice, wheat, potatoes, tomatoes, onions, and others.

    This insurance is only available to people who have a loan with Cidre, and enrollment is done through Cidre.

    How does the insurance work?

    • You pay only once at the beginning of the agricultural season.

• The cost is 5% of the value of the harvest you want to insure.
For example, if you expect to earn 1,000 Bolivianos, you pay 50 Bolivianos.
• There are no additional payments during the season.
When does the insurance pay?
Suyana uses satellite information to measure soil moisture. If satellites show that the soil is much drier than normal, this is considered a drought.
There are three levels of drought:
• Very severe drought (occurs about once every 20 years): the insurance pays 6 times what you paid.
• Severe drought (occurs about once every 10 years): the insurance pays 5 times what you paid.
• Moderate drought (occurs about once every 5 years): the insurance pays 3 times what you paid.
If there is no drought, there is no payment, but you keep your harvest.
The payment is made automatically and is deposited into your Cidre account, reducing your outstanding loan balance.
Important information about the insurance
• The insurance pays only once per agricultural season
• It does not cover pests, hail, frost, or price changes
• It does not guarantee that all losses will be covered
Climate Alert System
In addition, Suyana is developing a Climate Early Warning System, which will likely be free of charge.
This system:
• Sends alerts via WhatsApp
• Warns about heavy rainfall and cold spells
• Sends alerts up to 5 days in advance
The alerts are not perfect:
• For heavy rainfall, they are accurate about 1 out of 2 times
• For cold spells, they are accurate about 2 out of 3 times

81. If these products (the insurance and/or the early warning system) become available in your area, are you interested in putting your name down so that the insurance company can contact you?
    - No | Yes
82. Which of the two products would you be interested in hearing more about?
    - Drought insurance | Early warning system | Both | Neither | Not sure
83. Section for interviewer only
84. Instructions:In your opinion as the interviewer, how easy or difficult did you think the respondent found these questions?
    - Extremely easy | A little bit easy | Neither easy nor difficult | A little bit difficult | Extremely difficult
85. Has it rained at all today in this community so far?
    - Yes | No | Don't know
86. Did you face any technical issues or any other problems in taking this survey?
    - No | Yes

87. Please, describe

# C Model Appendix

"'latex

# D Theory Appendix: Derivations and Proofs

This appendix provides full derivations for the model in Section **??**.

## D.1 Willingness to pay and willingness to accept

Consider a potential learning relationship in which $j$ is informed and $i$ is uninformed.

Conditional on an interaction, information is transmitted with probability $\theta_{ij}$. If information is successfully transmitted, learner $i$ obtains instrumental benefit $B_i$. Therefore the expected instrumental benefit of the interaction is

$$\begin{aligned}\mathbb{E}[\text{instrumental benefit}] &= \Pr(\text{successful transmission}) \times B_i \\ &= \theta_{ij} B_i. \end{aligned} \tag{17}$$

Learner $i$ additionally receives non-instrumental social utility $s_{ij}$ from interacting with $j$. If $x$ denotes a generalized transfer from $i$ to $j$, the learner's expected utility is therefore

$$u_{ij}^L(x) = \theta_{ij} B_i + s_{ij} - x. \tag{18}$$

The learner is willing to participate whenever

$$\begin{aligned} u_{ij}^L(x) &\geq 0, \\ \theta_{ij} B_i + s_{ij} - x &\geq 0. \end{aligned} \tag{19}$$

Adding $x$ to both sides gives

$$\theta_{ij} B_i + s_{ij} \geq x. \tag{20}$$

Equivalently,

$$x \leq \theta_{ij} B_i + s_{ij}. \tag{21}$$

Hence the maximum transfer the learner is willing to make is

$$W_{ij} = \theta_{ij} B_i + s_{ij}. \tag{22}$$

Now consider the teacher. Teacher $j$ incurs cost $c_{ji}$ from teaching $i$ and receives non-

instrumental social utility $r_{ji}$. Her utility from the interaction is

$$u_{ji}^{T}(x) = x + r_{ji} - c_{ji}. \tag{23}$$

The teacher is willing to participate whenever

$$\begin{aligned} u_{ji}^{T}(x) &\geq 0, \\ x + r_{ji} - c_{ji} &\geq 0. \end{aligned} \tag{24}$$

Adding $c_{ji}$ to both sides gives

$$x + r_{ji} \geq c_{ji}. \tag{25}$$

Subtracting $r_{ji}$ from both sides yields

$$x \geq c_{ji} - r_{ji}. \tag{26}$$

Hence the minimum transfer required by the teacher is

$$A_{ji} = c_{ji} - r_{ji}. \tag{27}$$

The objects elicited in the experiment therefore satisfy

$$W_{ij} = B_i\theta_{ij} + s_{ij}, \tag{28}$$

$$A_{ji} = c_{ji} - r_{ji}. \tag{29}$$

Notice that both objects can contain non-instrumental utility. A learner can have high WTP for a low-$\theta$ teacher when $s_{ij}$ is sufficiently large. A teacher can have low WTA even when teaching is costly if $r_{ji}$ is sufficiently large.

## D.2 The endogenous interaction condition

Let $\kappa_{ij} \geq 0$ denote the cost of searching for, coordinating with, and arranging an interaction with $j$. For simplicity, assign this cost to the learner. The learner therefore participates if

$$B_i\theta_{ij} + s_{ij} - x - \kappa_{ij} \geq 0. \tag{30}$$

Using

$$W_{ij} = B_i\theta_{ij} + s_{ij},$$

this condition becomes

$$W_{ij} - x - \kappa_{ij} \geq 0. \tag{31}$$

Rearranging,

$$x \leq W_{ij} - \kappa_{ij}. \tag{32}$$

The teacher participates if

$$x + r_{ji} - c_{ji} \geq 0. \tag{33}$$

From the derivation above, this is equivalent to

$$x \geq A_{ji}. \tag{34}$$

Thus, an interaction can take place if there exists some $x$ satisfying both

$$x \leq W_{ij} - \kappa_{ij}, \tag{35}$$
$$x \geq A_{ji}. \tag{36}$$

Such an $x$ exists if and only if the lower bound does not exceed the upper bound:

$$A_{ji} \leq W_{ij} - \kappa_{ij}. \tag{37}$$

Adding $\kappa_{ij}$ to both sides,

$$A_{ji} + \kappa_{ij} \leq W_{ij}. \tag{38}$$

Subtracting $A_{ji} + \kappa_{ij}$ from both sides,

$$W_{ij} - A_{ji} - \kappa_{ij} \geq 0. \tag{39}$$

Define

$$X_{ij} \equiv W_{ij} - A_{ji} - \kappa_{ij}. \tag{40}$$

Substituting for WTP and WTA,

$$X_{ij} = (B_i\theta_{ij} + s_{ij}) - (c_{ji} - r_{ji}) - \kappa_{ij}, \tag{41}$$
$$= B_i\theta_{ij} + s_{ij} - c_{ji} + r_{ji} - \kappa_{ij}, \tag{42}$$
$$= B_i\theta_{ij} + s_{ij} + r_{ji} - c_{ji} - \kappa_{ij}. \tag{43}$$

Hence the endogenous interaction rule is

$$M_{ij}^0 = \mathbf{1}\{X_{ij} \geq 0\}. \tag{44}$$

## D.3 Proof of Proposition 1

Consider two potential teachers $j$ and $k$ for learner $i$.

Their WTP values are

$$W_{ij} = B_i\theta_{ij} + s_{ij}, \tag{45}$$
$$W_{ik} = B_i\theta_{ik} + s_{ik}. \tag{46}$$

We want to characterize when

$$W_{ij} > W_{ik}. \tag{47}$$

Substituting (45) and (46),

$$B_i\theta_{ij} + s_{ij} > B_i\theta_{ik} + s_{ik}. \tag{48}$$

Subtract $B_i\theta_{ij}$ from both sides:

$$s_{ij} > B_i\theta_{ik} - B_i\theta_{ij} + s_{ik}. \tag{49}$$

Subtract $s_{ik}$ from both sides:

$$s_{ij} - s_{ik} > B_i\theta_{ik} - B_i\theta_{ij}. \tag{50}$$

Factor $B_i$ on the right-hand side:

$$s_{ij} - s_{ik} > B_i\left(\theta_{ik} - \theta_{ij}\right). \tag{51}$$

Therefore, even when

$$\theta_{ij} < \theta_{ik},$$

the learner has greater willingness to pay for $j$ whenever

$$s_{ij} - s_{ik} > B_i\left(\theta_{ik} - \theta_{ij}\right).$$

This proves the first statement.
We next derive the covariance expression. Holding learner $i$ fixed,

$$W_{ij} = B_i\theta_{ij} + s_{ij}. \tag{52}$$

Take the covariance with $\theta_{ij}$:

$$\left(W_{ij}, \theta_{ij} \mid i\right) = \left(B_i\theta_{ij} + s_{ij}, \theta_{ij} \mid i\right). \tag{53}$$

Using the linearity of covariance,

$$\left(W_{ij}, \theta_{ij} \mid i\right) = \left(B_i\theta_{ij}, \theta_{ij} \mid i\right) + \left(s_{ij}, \theta_{ij} \mid i\right). \tag{54}$$

Since $B_i$ is constant when conditioning on learner $i$,

$$\left(B_i\theta_{ij}, \theta_{ij} \mid i\right) = B_i\left(\theta_{ij}, \theta_{ij} \mid i\right). \tag{55}$$

By definition,

$$(\theta_{ij}, \theta_{ij} \mid i) = (\theta_{ij} \mid i). \tag{56}$$

Therefore

$$(W_{ij}, \theta_{ij} \mid i) = B_i(\theta_{ij} \mid i) + (s_{ij}, \theta_{ij} \mid i). \tag{57}$$

Consequently,

$$(W_{ij}, \theta_{ij} \mid i) < 0 \tag{58}$$

if and only if

$$B_i(\theta_{ij} \mid i) + (s_{ij}, \theta_{ij} \mid i) < 0. \tag{59}$$

Subtracting the first term from both sides gives

$$(s_{ij}, \theta_{ij} \mid i) < -B_i(\theta_{ij} \mid i). \tag{60}$$

Thus sufficiently negative covariance between social value and transmission quality can make observed WTP negatively correlated with information quality. □

## D.4 A popularity example

Suppose the social value of interacting with $j$ is

$$s_{ij} = \alpha_i P_j, \tag{61}$$

where $P_j$ denotes the popularity or social status of $j$ and $\alpha_i > 0$ measures how much $i$ values popularity.

Then

$$W_{ij} = B_i \theta_{ij} + \alpha_i P_j. \tag{62}$$

Consider teachers $j$ and $k$, and suppose that

$$P_j > P_k, \tag{63}$$
$$\theta_{ij} < \theta_{ik}. \tag{64}$$

Learner $i$ nevertheless prefers $j$ according to WTP if

$$W_{ij} > W_{ik}. \tag{65}$$

Substituting,

$$B_i \theta_{ij} + \alpha_i P_j > B_i \theta_{ik} + \alpha_i P_k. \tag{66}$$

Collecting popularity terms on the left and transmission terms on the right,

$$\alpha_i P_j - \alpha_i P_k > B_i \theta_{ik} - B_i \theta_{ij}. \tag{67}$$

Factoring,

$$\alpha_i \left( P_j - P_k \right) > B_i \left( \theta_{ik} - \theta_{ij} \right). \tag{68}$$

Hence the popularity advantage of $j$ can outweigh the information-quality advantage of $k$.

## D.5 Experimental matching

The baseline interaction indicator is

$$M_{ij}^0 = \mathbf{1}\{X_{ij} \geq 0\}. \tag{69}$$

Suppose experimental assignment raises the surplus from an assigned interaction by $\lambda \geq 0$. The treatment interaction indicator is

$$M_{ij}^T = \mathbf{1}\{X_{ij} + \lambda \geq 0\}. \tag{70}$$

The treatment changes whether the interaction occurs by

$$M_{ij}^T - M_{ij}^0 = \mathbf{1}\{X_{ij} + \lambda \geq 0\} - \mathbf{1}\{X_{ij} \geq 0\}. \tag{71}$$

We consider the possible values of $X_{ij}$.

First, suppose

$$X_{ij} \geq 0. \tag{72}$$

Because $\lambda \geq 0$,

$$X_{ij} + \lambda \geq X_{ij} \geq 0. \tag{73}$$

Thus

$$M_{ij}^T = 1, \tag{74}$$

$$M_{ij}^0 = 1, \tag{75}$$

and therefore

$$M_{ij}^T - M_{ij}^0 = 0. \tag{76}$$

Second, suppose

$$X_{ij} < -\lambda. \tag{77}$$

Adding $\lambda$ to both sides gives

$$X_{ij} + \lambda < 0. \tag{78}$$

Since $X_{ij} < -\lambda \leq 0$, we also have

$$X_{ij} < 0. \tag{79}$$

Hence

$$M_{ij}^T = 0, \tag{80}$$
$$M_{ij}^0 = 0, \tag{81}$$

so

$$M_{ij}^T - M_{ij}^0 = 0. \tag{82}$$

Finally, suppose

$$-\lambda \leq X_{ij} < 0. \tag{83}$$

The right inequality implies

$$M_{ij}^0 = 0. \tag{84}$$

The left inequality implies

$$X_{ij} + \lambda \geq 0, \tag{85}$$

so

$$M_{ij}^T = 1. \tag{86}$$

Therefore

$$M_{ij}^T - M_{ij}^0 = 1. \tag{87}$$

Combining all three cases,

$$M_{ij}^T - M_{ij}^0 = \mathbf{1}\left\{-\lambda \leq X_{ij} < 0\right\}. \tag{88}$$

## D.6 Proof of Proposition 2

Conditional on an interaction, information passes from $j$ to $i$ with probability $\theta_{ij}$.

In the baseline,

$$p_{ij}^0 = \Pr(i \text{ learns directly from } j) \tag{89}$$
$$= \Pr(\text{interaction}) \Pr(\text{transmission} \mid \text{interaction}) \tag{90}$$
$$= M_{ij}^0 \theta_{ij} \tag{91}$$
$$= \theta_{ij} \mathbf{1}\{X_{ij} \geq 0\}. \tag{92}$$

Under treatment,

$$p_{ij}^T = M_{ij}^T \theta_{ij} \tag{93}$$
$$= \theta_{ij} \mathbf{1}\{X_{ij} + \lambda \geq 0\}. \tag{94}$$

The direct treatment effect is therefore

$$\Delta_{ij}^{\text{direct}} = p_{ij}^T - p_{ij}^0 \tag{95}$$
$$= \theta_{ij} M_{ij}^T - \theta_{ij} M_{ij}^0 \tag{96}$$
$$= \theta_{ij} \left( M_{ij}^T - M_{ij}^0 \right). \tag{97}$$

Substituting (88),

$$\Delta_{ij}^{\text{direct}} = \theta_{ij} \mathbf{1}\left\{ -\lambda \leq X_{ij} < 0 \right\}. \tag{98}$$

This proves (10).

Now consider an intervention that guarantees interaction for the assigned pair. Then

$$M_{ij}^T = 1. \tag{99}$$

Hence

$$M_{ij}^T - M_{ij}^0 = 1 - \mathbf{1}\{X_{ij} \geq 0\}. \tag{100}$$

For any scalar $X_{ij}$,

$$1 - \mathbf{1}\{X_{ij} \geq 0\} = \mathbf{1}\{X_{ij} < 0\}. \tag{101}$$

Thus

$$\Delta_{ij}^{\text{direct}} = \theta_{ij} \mathbf{1}\{X_{ij} < 0\}. \tag{102}$$

This proves (11). □

## D.7 Why treatment effects tend to be larger for low-WTP dyads

Recall

$$X_{ij} = W_{ij} - A_{ji} - \kappa_{ij}. \tag{103}$$

Holding $A_{ji}$ and $\kappa_{ij}$ fixed,

$$\frac{\partial X_{ij}}{\partial W_{ij}} = 1. \tag{104}$$

Thus a one-unit increase in WTP increases match surplus by exactly one unit.
Similarly, holding $W_{ij}$ and $\kappa_{ij}$ fixed,

$$\frac{\partial X_{ij}}{\partial A_{ji}} = -1. \tag{105}$$

Thus a one-unit increase in WTA reduces match surplus by exactly one unit.
The treatment affects interaction when

$$-\lambda \leq X_{ij} < 0. \tag{106}$$

Substituting for $X_{ij}$,

$$-\lambda \leq W_{ij} - A_{ji} - \kappa_{ij} < 0. \tag{107}$$

Consider the right-hand inequality:

$$W_{ij} - A_{ji} - \kappa_{ij} < 0. \tag{108}$$

Adding $A_{ji} + \kappa_{ij}$ to both sides,

$$W_{ij} < A_{ji} + \kappa_{ij}. \tag{109}$$

Now consider the left-hand inequality:

$$-\lambda \leq W_{ij} - A_{ji} - \kappa_{ij}. \tag{110}$$

Adding $A_{ji} + \kappa_{ij}$ to both sides,

$$A_{ji} + \kappa_{ij} - \lambda \leq W_{ij}. \tag{111}$$

Combining (109) and (111), treatment changes interaction precisely when

$$A_{ji} + \kappa_{ij} - \lambda \leq W_{ij} < A_{ji} + \kappa_{ij}. \tag{112}$$

Thus randomized matching primarily affects WTP values lying below the endogenous interaction threshold.

Importantly, however, this result alone does not imply that low-WTP dyads have greater diffusion productivity. Conditional on the intervention changing interaction, the direct treatment effect is

$$\Delta_{ij}^{\text{direct}} = \theta_{ij}. \tag{113}$$

Therefore the treatment-effect heterogeneity combines

1. the effect of WTP and WTA on whether the experimental match changes behavior; and
2. heterogeneity in $\theta_{ij}$ among the dyads whose interactions are changed.

## D.8 Network diffusion and the live-edge representation

For every directed pair $j \to i$, define a Bernoulli random variable

$$L_{ij} \in \{0, 1\} \tag{114}$$

indicating whether the edge is "live."

Under baseline behavior,

$$\Pr(L_{ij} = 1) = p_{ij}^0 \tag{115}$$

$$= \theta_{ij} \mathbf{1}\{X_{ij} \geq 0\}. \tag{116}$$

Suppose an individual becomes informed. She receives one opportunity to transmit information along each active outgoing relationship. If the corresponding edge is live, transmission succeeds.

For any realization of the collection

$$\{L_{ij}\},$$

an individual $k$ is eventually informed if and only if there exists a directed path

$$s \to \cdots \to k$$

from some seed $s \in S$ such that every edge on the path is live.

Thus the dynamic diffusion process can be represented as a static reachability problem on the random live-edge graph.

## D.9 Proof of Proposition 3

Consider a single experimentally manipulated edge

$$e = (j \to i),$$

where $j$ is an initial seed.

Hold fixed the realization of every edge other than $e$.

Let

$$H_{-e}$$

denote this realized graph with edge $e$ excluded.

Define

$$R_S(H_{-e})$$

as the set of individuals reachable from the initial seeds in $H_{-e}$.

Define

$$R_i(H_{-e})$$

as the set of individuals reachable from $i$ in $H_{-e}$, including $i$ itself.

If edge $e$ fails to transmit, the final informed set is

$$R_S(H_{-e}).$$

If edge $e$ succeeds, then because $j$ is already an initial seed, $i$ becomes informed. The final informed set becomes

$$R_S(H_{-e}) \cup R_i(H_{-e}). \tag{117}$$

Hence the number of additional individuals informed as a consequence of successful transmission along edge $e$ is

$$G_{ij}(H_{-e}) = \left| R_i(H_{-e}) \setminus R_S(H_{-e}) \right|. \tag{118}$$

Take expectations over the realization of all other edges:

$$\Gamma_{ij} \equiv \mathbb{E}\left[ G_{ij}(H_{-e}) \right]. \tag{119}$$

This is the diffusion multiplier used in the main text.

The probability that edge $e$ successfully transmits in the baseline is

$$p_{ij}^0 = \theta_{ij} M_{ij}^0. \tag{120}$$

Under treatment,

$$p_{ij}^T = \theta_{ij} M_{ij}^T. \tag{121}$$

Hence the increase in the probability that the edge successfully transmits is

$$p_{ij}^T - p_{ij}^0 = \theta_{ij} \left( M_{ij}^T - M_{ij}^0 \right). \tag{122}$$

Every additional successful transmission along the edge produces, in expectation, $\Gamma_{ij}$ additional informed individuals. Therefore

$$\Delta_{ij}^{\text{total}} = \left( p_{ij}^T - p_{ij}^0 \right) \Gamma_{ij}. \tag{123}$$

Substituting,

$$\Delta_{ij}^{\text{total}} = \theta_{ij} \left( M_{ij}^T - M_{ij}^0 \right) \Gamma_{ij}. \tag{124}$$

Using

$$M_{ij}^T - M_{ij}^0 = \mathbf{1}\left\{ -\lambda \leq X_{ij} < 0 \right\}, \tag{125}$$

we obtain

$$\Delta_{ij}^{\text{total}} = \theta_{ij}\mathbf{1}\left\{-\lambda \leq X_{ij} < 0\right\}\Gamma_{ij}. \tag{126}$$

This proves (12).

If assignment guarantees interaction, then

$$M_{ij}^{T} - M_{ij}^{0} = \mathbf{1}\{X_{ij} < 0\}, \tag{127}$$

and hence

$$\Delta_{ij}^{\text{total}} = \theta_{ij}\mathbf{1}\{X_{ij} < 0\}\Gamma_{ij}. \tag{128}$$

This proves (13). □

## D.10 A tree as a special case

The multiplier $\Gamma_{ij}$ has a particularly simple interpretation on a tree.

Suppose $i$ has descendants

$$\mathcal{D}(i)$$

and that there is a unique path from the initial seeds to every node.

If $i$ is not informed through edge $j \to i$, none of the descendants whose unique path runs through $i$ can be informed through that branch.

If $i$ is informed, the expected number of individuals ultimately reached through $i$ can be written recursively as

$$\Gamma_i = 1 + \sum_{k \in C(i)} p_{ki}^{0}\Gamma_k, \tag{129}$$

where $C(i)$ denotes the children of $i$.

To see this, the first term equals one because $i$ herself becomes informed. For each child $k$, information reaches $k$ with probability $p_{ki}^{0}$. Conditional on reaching $k$, the expected subsequent number informed through that branch is $\Gamma_k$. Thus the expected contribution from child $k$ is

$$p_{ki}^{0}\Gamma_k. \tag{130}$$

Summing over children produces (129).

For a leaf $i$,

$$C(i) = \varnothing,$$

and therefore

$$\Gamma_i = 1. \tag{131}$$

## D.11 Capacity constraints and endogenous choice of learning partner

We now impose the minimal additional assumption required for social preferences to crowd out more productive learning opportunities.

Suppose learner $i$ can undertake only one learning interaction in a period.

Let

$$\mathcal{J}_i$$

denote the set of currently informed potential teachers.

For any $j \in \mathcal{J}_i$, total match surplus is

$$X_{ij} = B_i\theta_{ij} + s_{ij} + r_{ji} - c_{ji} - \kappa_{ij}. \tag{132}$$

Suppose decentralized interaction allocates the learner's single opportunity to a teacher maximizing social surplus:

$$j_i^S \in \arg\max_{j\in\mathcal{J}_i} X_{ij}. \tag{133}$$

The expected amount of eventual diffusion generated by choosing $j$ is proportional to

$$D_{ij} \equiv \theta_{ij}\Gamma_{ij}. \tag{134}$$

The diffusion-maximizing teacher is therefore

$$j_i^D \in \arg\max_{j\in\mathcal{J}_i} D_{ij} \tag{135}$$

$$= \arg\max_{j\in\mathcal{J}_i} \left\{\theta_{ij}\Gamma_{ij}\right\}. \tag{136}$$

## D.12 Proof of Proposition ??

By definition,

$$j_i^D \in \arg\max_{j} \left\{\theta_{ij}\Gamma_{ij}\right\}. \tag{137}$$

Therefore,

$$\theta_{ij_i^D}\Gamma_{ij_i^D} = \max_{j} \left\{\theta_{ij}\Gamma_{ij}\right\}. \tag{138}$$

The decentralized process instead chooses

$$j_i^S \in \arg\max_{j} X_{ij}. \tag{139}$$

The amount of diffusion associated with this choice is

$$\theta_{ij_i^S}\Gamma_{ij_i^S}. \tag{140}$$

Define the diffusion loss as the difference between the maximum feasible diffusion productivity and the diffusion productivity of the socially chosen teacher:

$$L_i \equiv \theta_{ij_i^D}\Gamma_{ij_i^D} - \theta_{ij_i^S}\Gamma_{ij_i^S}. \tag{141}$$

Using (138),

$$L_i = \max_j \{\theta_{ij}\Gamma_{ij}\} - \theta_{ij_i^S}\Gamma_{ij_i^S}. \tag{142}$$

Because the first term is the maximum over all feasible teachers, it must be at least as large as its value at $j_i^S$:

$$\max_j \{\theta_{ij}\Gamma_{ij}\} \geq \theta_{ij_i^S}\Gamma_{ij_i^S}. \tag{143}$$

Subtracting the right-hand side from both sides yields

$$\max_j \{\theta_{ij}\Gamma_{ij}\} - \theta_{ij_i^S}\Gamma_{ij_i^S} \geq 0. \tag{144}$$

Hence

$$L_i \geq 0. \tag{145}$$

Equality holds if and only if $j_i^S$ is itself a maximizer of diffusion productivity. That is,

$$L_i = 0 \tag{146}$$

if and only if

$$j_i^S \in \arg\max_j \{\theta_{ij}\Gamma_{ij}\}. \tag{147}$$

Thus decentralized social learning is diffusion-maximizing if and only if the social-surplus ranking selects a diffusion-maximizing teacher. □

## D.13 How non-instrumental utility generates crowd-out

To make the mechanism transparent, consider two teachers $j$ and $k$.
Suppose teacher $k$ has higher diffusion productivity:

$$\theta_{ik}\Gamma_{ik} > \theta_{ij}\Gamma_{ij}. \tag{148}$$

Nevertheless, the social-learning process selects $j$ when

$$X_{ij} > X_{ik}. \tag{149}$$

Substituting for $X$,

$$B_i\theta_{ij} + s_{ij} + r_{ji} - c_{ji} - \kappa_{ij} > B_i\theta_{ik} + s_{ik} + r_{ki} - c_{ki} - \kappa_{ik}. \tag{150}$$

Move the instrumental terms to the right:

$$s_{ij} + r_{ji} - c_{ji} - \kappa_{ij} - s_{ik} - r_{ki} + c_{ki} + \kappa_{ik} > B_i\left(\theta_{ik} - \theta_{ij}\right). \tag{151}$$

Hence even when $k$ is the better transmitter, $j$ will be selected if the difference in non-informational match value is sufficiently large.

In the special case in which teacher costs, teacher social utility, and coordination costs are identical across the two dyads,

$$r_{ji} = r_{ki}, \tag{152}$$
$$c_{ji} = c_{ki}, \tag{153}$$
$$\kappa_{ij} = \kappa_{ik}, \tag{154}$$

condition (151) reduces to

$$s_{ij} - s_{ik} > B_i\left(\theta_{ik} - \theta_{ij}\right). \tag{155}$$

This is precisely the WTP rank-reversal condition from Proposition 1.

## D.14 What the experimental heterogeneity does and does not identify

The model distinguishes two reasons why experimentally arranged matches can have particularly large effects among low-WTP dyads.

First, low WTP reduces endogenous interaction. Since

$$X_{ij} = W_{ij} - A_{ji} - \kappa_{ij}, \tag{156}$$

low values of $W_{ij}$ make

$$X_{ij} < 0 \tag{157}$$

more likely. Such dyads therefore have greater scope to be moved by random matching from

$$M_{ij}^0 = 0 \tag{158}$$

to

$$M_{ij}^T = 1. \tag{159}$$

This is an extensive-margin selection effect.

Second, conditional on treatment inducing an interaction, the effect on diffusion equals

$$\theta_{ij}\Gamma_{ij}. \tag{160}$$

Hence the stronger hypothesis that WTP is negatively aligned with diffusion productivity concerns the relationship

$$(W_{ij}, \theta_{ij}\Gamma_{ij}). \tag{161}$$

If randomized matching permits the researcher to construct a measure $Y_{ij}$ whose conditional expectation is proportional to diffusion productivity,

$$\mathbb{E}\left[Y_{ij} \mid (i,j) \text{ experimentally matched}\right] = \theta_{ij}\Gamma_{ij}, \tag{162}$$

then the relationship between $Y_{ij}$ and $W_{ij}$ identifies whether individuals' willingness to learn ranks dyads in the same way as their realized capacity to diffuse information.

To see why this is informative about non-instrumental motives, abstract temporarily from variation in $\Gamma_{ij}$ and suppose

$$\Gamma_{ij} = \Gamma_i \tag{163}$$

for all potential teachers $j$ of learner $i$.

Then

$$W_{ij} = B_i\theta_{ij} + s_{ij}. \tag{164}$$

If WTP contained only informational value, then

$$s_{ij} = 0 \tag{165}$$

for every $j$, implying

$$W_{ij} = B_i\theta_{ij}. \tag{166}$$

Since $B_i > 0$, for any two teachers $j$ and $k$,

$$\theta_{ij} > \theta_{ik} \iff B_i\theta_{ij} > B_i\theta_{ik} \tag{167}$$

$$\iff W_{ij} > W_{ik}. \tag{168}$$

Thus a purely instrumental model implies that WTP must preserve the ranking of transmission quality within learner.

If, instead, the data show

$$W_{ij} > W_{ik} \tag{169}$$

but

$$\theta_{ij} < \theta_{ik}, \tag{170}$$

then substituting

$$W_{ij} = B_i\theta_{ij} + s_{ij}, \tag{171}$$
$$W_{ik} = B_i\theta_{ik} + s_{ik} \tag{172}$$

implies

$$B_i\theta_{ij} + s_{ij} > B_i\theta_{ik} + s_{ik}, \tag{173}$$

which, by the steps in Section D.3, requires

$$s_{ij} - s_{ik} > B_i\left(\theta_{ik} - \theta_{ij}\right) > 0. \tag{174}$$

The rank reversal therefore directly reveals a component of willingness to learn that is not explained by information-transmission quality.

When downstream position $\Gamma_{ij}$ also varies across dyads, the same logic applies to the distinction between private information value and social diffusion, but one must distinguish the probability that $i$ learns,

$$\theta_{ij},$$

from the amount of aggregate diffusion generated after $i$ learns,

$$\theta_{ij}\Gamma_{ij}.$$

The randomized seed and matching design permits these objects to be studied separately.

# E Ethics Appendix

**1. Policy Equipoise** *Is there policy equipoise? That is, is there uncertainty regarding participants' net benefits from each arm of the study relative to the other arms and to the best possible policy to which participants could have access? If not, ethical randomization requires two conditions related to scarcity: (1) Was there scarcity, i.e., did the inclusion of multiple arms change the expected aggregate value of the programs delivered? (2) Do all ex-ante identifiable participants have equal moral or legal claims to the scarce programs? If there is no reasonable expectation that one arm of the study produces more benefits to participants than any other arm or than the best possible alternative policy, then randomization is ethically unproblematic. If not, then excluding some participants from the superior treatment arm can only be justified by scarcity. Scarcity conditions are two-fold: (1) resources are not sufficient, given constraints, to include all participants in the superior treatment arm; (2) no ex-ante identifiable participants are excluded from the superior arm and have a greater claim to those resources than any participant assigned to the superior arm. See MacKay 2018, 2020 for more complete discussions of policy equipoise.*

In our setting, there is no scarcity, but there is equipoise about the best way to diffuse information. However, to ensure that everyone ultimately had equal benefit regardless of randomization status, we provided the information directly to all respondents in the endline survey, so everyone received equal access to the information about the climate adaptation products.

**2. Role of researchers with respect to implementation** *Are researchers "active" researchers, i.e. did the researchers have direct decision making power over whether and how to implement the program? If YES, what was the disclosure to participants and informed consent process for participation in the program? Providing IRB approval details may be sufficient but further clarification of any important issues should be discussed here. If NO, i.e., implementation was separate, explain the separation. A researcher should be considered "active" if, for example, the implementing staff are employed by an institution at which the PI is employed, and the staff report either directly or indirectly to the PI at this institution with regard to this project. Or if researchers control funding for implementation, or have direct decision-making power over key implementation decisions. Some key factors that help illuminate whether the researchers are "active" or not (here "researchers" are defined as the PIs and the staff that report directly or indirectly to the PIs): Did researchers directly provide any of the interventions, or parts thereof, to participants? Did researchers interact directly with participants and implicitly endorse one or more of the interventions?*

Yes, the researchers were active in this implementation. All participants were informed at the consent stage about the randomization procedures. In the willingness-to-pay and willingness-to-accept elicitations, the details provided to respondents were deliberately vague relative to the actual procedures that were implemented. See below for more details.

**3. Potential harms to participants or nonparticipants from the interventions or policies** Does the intervention, policy or product being studied pose potential harm to participants or non-participants? Related, are participants or likely affected non-participants particularly vulnerable? Also related, are participants' access to future services or policies changed because of participation in the study? If yes to any of the above, what is being done to mitigate such risks? It may be important to consider whether the researchers are "active" (see above) or not for this discussion. If the researchers are "active", then they are responsible for the potential harms, and thus a robust discussion is appropriate. If the researchers are not "active", then while they may not be responsible for potential harms, a discussion of this would be appropriate here. There will almost always be some potential harms, if nothing else because of complementary investments such as time that participants in an intervention necessarily redirect from one activity to another. Quantifying these risks and complementary investments may be difficult ex-ante, but a discussion of what they are here would help the reader assess their likely importance relative to the potential benefits of the tested intervention. Also note that measuring any harms ex-post may be the exact reason for the study, particularly when the intervention is common. If risks to nonparticipants exist, discuss the mechanisms through which the risk arises from the study and provide an estimate of the magnitude of the risk and the probability of harm.

We were concerned about two potential issues: first, giving people info and encouraging

them to give it to specific other people may interfere with the normal way that information is diffused in the village. This could create implicit feelings of reciprocity to the giver from the receiver that are different than normal. Second, by paying people to give information, we may be introducing a transactional culture in a place where that norm did not exist.

We designed our experiment to mitigate these risks while attempting to preserve external validity to the natural setting of information diffusion processes in two ways. First, when the conversations are actually arranged in the treatments, we frame them very explicitly as a job in which the giver of information is being paid to give this info to someone else. That emphasis is not placed at the BDM stage in an attempt to try to preserve that portion as a realistic elicitation of who people want to learn from/share with, but it makes it clear in both.

**4. Potential harms to research participants or research staff from data collection (e.g., surveying, privacy, data management) or research protocols (e.g., random assignment)** Are data collection and/or research procedures adherent to privacy, confidentiality, risk-management, and informed consent protocols with regard to human subjects? Are they respectful of community norms, e.g., community consent not merely individual consent, when appropriate? Are there potential harms to research staff from conducting the data collection that are beyond "normal" risks? Example of sub-questions to consider as part of the broad question: Are there any risks that could ensue because of the data collection process or storage, e.g. discomfort to being asked certain questions or breach of confidentiality? If so, what are the mitigation strategies? Are there costs to the participant for the data collection process, such as their time, and if so, what is the strategy or rationale for offsetting this cost? Because these are all issues covered by most IRB processes, a sufficient explanation for a "yes" response may be to provide the IRB approval numbers for all IRBs that have approved the project. However, if there are particular issues that are important to discuss, please do so here. Harms to research staff could include, e.g., exposure to political violence, exposure to unusual levels of a communicable disease, mistrust due to lack of perceived lack of community consent, or emotional wellbeing from surveying about difficult subject matters. This would not include, e.g., traffic accidents. None.

**5. Financial and reputational conflicts of interest** *Do any of the researchers have financial conflicts of interest with regard to the results of the research? Do any of the researchers have potential reputational conflicts of interest? We define financial conflicts of interest as that used by the researcher's institutional (e.g., their university) guidelines. We define a reputational conflict of interest as one in which prior writing or advocacy could be contradicted by specific results pursued in this study, and such contradiction would pose reputational risks to the author.* None.

**6. Intellectual freedom** *Were there any contractual limitations on the ability of the researchers to report the results of the study? If so, what were those restrictions, and who were they from? This could include, for example, approval of release of the paper and restrictions on data release, but does not include things such as a "comment period" during which interested parties have a right to review and provide comments prior to release but not to control*

*the outputs of the study.* None.

**7. Feedback to participants or communities** *Is there a plan for providing feedback on research results to participants or communities? If yes, what is the plan? If not, why not? Engaging in post-study feedback is a way of acknowledging the agency of participants and communities, and is thus a desired practice. However, it may be impractical due to costs, timing, challenges communicating the results, or potential harms if such communication may itself change behavior in undesirable ways.* No.

**8. Foreseeable misuse of research results** *Is there a foreseeable and plausible risk that the results of the research will be misused and/or deliberately misinterpreted by interested parties to the detriment of other interested parties? If yes, please explain any efforts to mitigate such risk. In settings with strong imbalances of power between interested parties, there may be foreseeable risks that a powerful party could use deliberately selected research findings to their advantage and to the harm of participants or non-participants, including for general public policy. For example, if the research might reveal the vulnerability of some that can be exploited for the gain of the more powerful party, what steps does the researcher plan to mitigate this risk?* No.

**9. Other Ethics Issues to Discuss** *Are there any other issues to discuss?*
None.