Peer effects and externalities in technology adoption: Evidence from community reporting in Uganda*

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Abstract

Do social networks matter for the adoption of new political communication technologies? We collect complete social network data for sixteen Ugandan villages where an innovative reporting mobile platform was recently introduced, and show robust evidence of peer effects on technology adoption. However, peer effects were not observed in all networks. We develop a formal model showing that while peer effects facilitate adoption of technologies with minimal externalities (like agricultural practices), it can be more difficult for innovations with significant positive externalities to spread through a network. Early adopters might exaggerate benefits, leading others to discount information about the technology's value. Thus, peer effects are likely to emerge only where informal institutions support truthful communication. We show that the observable implications of our model are borne out in the data. These impediments to social diffusion might help explain the slow and varied uptake of new political communication technologies around the world.

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1 Introduction

Novel political communication technologies (PCTs) are facilitating new forms of political participation around the world. From New York City's NYC311 platform[1] to community monitoring text-messaging systems in Africa (Grossman, Platas and Rodden, 2017), new technologies are allowing for more frequent and cheaper forms of participation than traditional means of political engagement. These technologies have the potential to transform the relationship between citizens and their governments, offering opportunities to address some of the most intractable governance challenges. The potential benefits of PCTs are especially large when it comes to acute service delivery failures in the developing world. New programs allow citizens to report problems, such as teacher absenteeism, in a way that is immediate, inexpensive, and potentially anonymous (Peixoto and Sifry, 2017). However, recent studies have demonstrated that adoption of these promising new technologies has been variable from one context to another, and relatively disappointing overall in the developing world (Grossman, Humphreys and Sacramone-Lutz, 2016). These new technologies will not affect governance, or will only benefit a narrow group of users, if they are not broadly adopted. This paper asks a question of growing importance: what explains variation in the uptake of new political communication technologies?

We examine the role social factors, specifically *peer effects*, play in influencing the adoption of a new community reporting PCT platform in Uganda. Our starting point is past work on social diffusion, which explores how and why social learning from peers facilitates the adoption of new technologies (Golub and Sadler, 2017). In short, under conditions of uncertainty over the costs and benefits of the usage of new technologies, information is crucial to adoption decisions. Network ties are generally consequential because friends, family, neighbors and colleagues are often viewed as convenient and trustworthy sources of information.

Existing studies focus on the adoption of technologies that increase, for example, agriculture productivity (Bandiera and Rasul, 2006; Conley and Udry, 2010; Foster and Rosenzweig, 1995), health status (Kremer and Miguel, 2007; Dupas, 2014; Oster and Thornton, 2012), or access to financial services (Banerjee et al., 2013). Unlike past work, we explore the impact of social ties on the adoption of a (political communication) technological innovation that involves substantial

[1] `http://www1.nyc.gov/311/index.page`

positive externalities, and is thus more likely to involve strategic considerations. Existing theoretical and empirical studies are generally silent about whether and how peer effects might work in the presence of such externalities. An important concern is that diffusion of adoption of PCTs via peer effects might be undermined because of these externalities.

Exploring the effects of peers on *political* behavior is notoriously difficult (Jackson and Yariv, 2010). First, the set of neighbors that influence an individual's political actions is hard to define (Pietryka and DeBats, 2017). Second, even when networks are well-defined, data on inter-subject connectivity is typically unavailable to social scientists, causing them to rely heavily on simulation in social diffusion studies (Cranmer et al., 2017). We address these challenges by collecting original and complete social network data from sixteen Ugandan villages where a new political communication technology, U-Bridge, was introduced to facilitate the anonymous reporting of service delivery problems to local government officials.

We find that, on average, peer effects influence individuals' adoption of this PCT. A villager's decision to report a service delivery problem via U-Bridge is significantly affected by the adoption choices of social ties within the community's social network. Specifically, every additional neighbor that uses U-Bridge increases the likelihood of adoption of an individual by about 2.7 percentage points—a 61 percent increase relative to the base adoption rate. We demonstrate that this result is not likely a simple reflection of homophily, and is robust to other possible inferential threats we document below.

However, we also find considerable variation in the extent of peer effects across villages where the new political communication technology was introduced. While there is strong evidence of peer effects in some villages, others show little signs of such influence. Why do social networks sometimes fail to support the adoption of a new PCT? Moving from the individual to the network (i.e., village) level, in the second part of the paper we turn to adjudicate between several alternative explanations. We first explore and reject the possibility that the variation in the uptake of U-Bridge is due to (a) differences in *network structure* (Centola, 2015), or to (b) differences in the characteristics (personal and relational) of the initial seeders of the information that is to be diffused across the social network (Banerjee et al., 2013; Larson, Lewis and Rodrıguez, 2017).

We then turn to explain the puzzle of widely varying peer effects by introducing a simple formal model, demonstrating that whether or not networks support technology diffusion *depends* *on the nature of the technology itself.* Our model takes into account two features of PCTs. First, as with most new technologies, there is *uncertainty* about the costs and benefits of adoption. For example, "whistle-blowers" may face significant social costs if their identity is revealed, while potential benefits – teachers showing up to class, for example – depend on the responsiveness of public officials, which is not guaranteed in the many low-income countries (Kosack and Fung, 2014). Second, the benefits of this particular type of technology, like many crowdsourcing applications, are subjected to *positive externalities*–its effectiveness is increasing with the number of people who use it. In other words, PCTs belong to a class of goods for which the payoffs of one agent depends on the actions of other agents.

The model shows that while networks foster the diffusion of goods with minimal externalities, such as many consumer goods, they may play no role for goods that have significant positive externalities. We argue that under these conditions, early adopters of the new technology have strong incentives to exaggerate the benefits of adoption, in order to convince others to adopt. Recognizing this incentive, their neighbors have reason to discount information they receive from early adopters. Not all networks overcome the challenge of truthful communication about the new technology, without which social diffusion does not take place. Peer effects only support diffusion of new technologies with large positive externalities in networks where truthful communication is supported. We test the observable implications of the theory using network data, survey data and behavioral experiments, and find evidence consistent with the model's propositions.

Highlighting the importance of truthful communication for social learning situates our paper within a nascent literature that studies strategic communication in networks (Hagenbach and Koessler, 2010; Galeotti, Ghiglino and Squintani, 2013; Gieczewski, 2017). This literature considers situations where agents would like others to take an action that is close to the state of the world, but disagree on which action is optimal in a given state. Past studies focus on how these conflicts of interest hinder truthful communication. We consider situations that are somewhat different, and more specifically relevant for technology adoption with externalities. Namely, we consider instances in which all agents agree on the action that needs to be taken in "high" states, where the technology is useful, and are indifferent about the actions of other agents in low states, where the technology is useless. We show that such situations also hinder truthful communication.

Our study also contributes to a growing body of work on political communication technologies. Existing work has examined the efficacy of these technologies in improving service delivery (Grossman, Platas and Rodden, 2017), accountability (Grossman, Humphreys and Sacramone-Lutz, 2016), the accuracy of granular conflict data (Van der Windt and Humphreys, 2016), and corruption (Blair, Littman and Paluck, 2017). Recent work has also investigated determinants of PCT uptake. This work has focused on individual attributes (Grossman, Michelitch and Santamaria, 2016), neighborhood characteristics (Feigenbaum and Hall, 2016), and perceptions of government responsiveness (Sjoberg, Mellon and Peixoto, 2017). We expand this work by focusing on the role social networks play in adoption decisions.

Finally, we contribute to a literature exploring the effects of social networks on political behavior. Existing work focuses on traditional forms of political engagement (Rolfe, 2012). We investigate instead the role of social networks in the adoption of *new* forms of political engagement, where there is higher uncertainty over costs and benefits of participation and thus peer effects are potentially even more important. Further, with a few exceptions (Eubank et al., 2017), existing work on social networks and political behavior has relied almost exclusively on egocentric network data–reports by survey respondents on their friends, with no linking across respondents to create a full network (Abrams, Iversen and Soskice, 2011; Klofstad, Sokhey and McClurg, 2013). Though improving our understanding of the role social ties play in shaping political behavior, egocentric networks operate with incomplete network information, and are generally unable to correct for biases arising from homophily (Sinclair, 2012; Siegel, 2011). We address these concerns by constructing a relatively large number of independent whole networks and by implementing a set of robustness checks designed to minimize bias stemming from homophily. By situating our study in a low-income country, we also move beyond a narrow focus on peer effects on political behavior in a small number of industrial democracies.[2]

2 Context

The community reporting platform we study, U-Bridge, was implemented in a collaboration between the local government in Arua, a relatively poor district located in North-Western Uganda, and the Governance, Accountability, Participation, and Performance (GAPP) project, funded by the United

[2]See also Larson and Lewis (2017) that undertake a full network census in two Ugandan villages to study variation in the spread of information (rumors) as a function of ethnic diversity.

States Agency for International Development (USAID). The demand for mobile-based political communication technologies such as U-Bridge stems from their potential for tackling persistent public service problems (Jahan et al., 2015), such as alarmingly high levels of absenteeism among government healthcare workers and teachers (Chaudhury et al., 2006). U-Bridge is one of many recent PCTs that are based on the simple idea that participatory grassroots programs need not circumvent government actors (Buntaine, Nielson and Skaggs, 2017). Instead, communities can be harnessed to better inform government officials of service delivery deficiencies (Grossman, Platas and Rodden, 2017).

Through U-Bridge, anyone can contact district officials by sending a text-message to a short-code number (8500). Messages sent through the U-Bridge platform are both *free* and *anonymous*, lowering the monetary and social costs for bottom-up reporting about service delivery problems. The back-end is an open-source software package that runs on a variety of mobile devices, including tablets and smartphones. The program provided district officials in both technical and political positions with 3G tablets and free Internet access that enabled them to access and respond to incoming messages.

U-Bridge was implemented using a field experimental research design, encouraging usage in 131 randomly selected villages across Arua district organized around 24 clusters.[3] Residents in treatment villages were invited to attend periodic community meetings, implemented and organized by GAPP. In these meetings, attendees received information about national service delivery standards, and were informed about ways to communicate with local officials. In addition, public officials provided attendees with an overview of government efforts in service delivery, especially in response to previous text messages. The first round of community meetings was held by GAPP in the last quarter of 2014 as part of the launch of the U-Bridge service. Subsequent meetings were held quarterly.

Usage of the new communication technology was further facilitated by registering a phone number, which involved texting “Join” to 8500, after which the sender would be asked to share basic demographic information, such as gender, age, and village of residence. Registration took

[3] We constructed 48 village-clusters in Arua district, defined as the group of nearby villages that are serviced by the same public health center. Half of Arua’s 48 clusters were randomly assigned to treatment (U-Bridge encouragement) and half to control. Villages within a cluster were all assigned to the same treatment. We study the effects of encouraging the usage of the new platform on service delivery outcomes in a companion paper.

place at community inception meetings, in a door-to-door registration drive, and by individuals who heard about the service by word of mouth. Registration did not compromise the anonymity of incoming text-messages, which are assigned a unique case ID such that phone numbers are never displayed on the U-Bridge dashboard.

Figure 1 shows the cumulative number of relevant and actionable incoming-messages between August 2014 and November 2015, demonstrating a relatively strong *demand* for a platform like U-Bridge, consistent with findings reported by Grossman, Humphreys and Sacramone-Lutz (2014). Nevertheless, it is evident that the vast majority of villagers have not used the platform, even as the quality of social services in Arua district is low compared to national benchmarks. Since the effectiveness of PCT platforms hinges critically on grassroots participation, and since platform adoption reflects whose voices (i.e., interests and priorities) are heard, it is imperative to further explore the determinants of differential uptake.

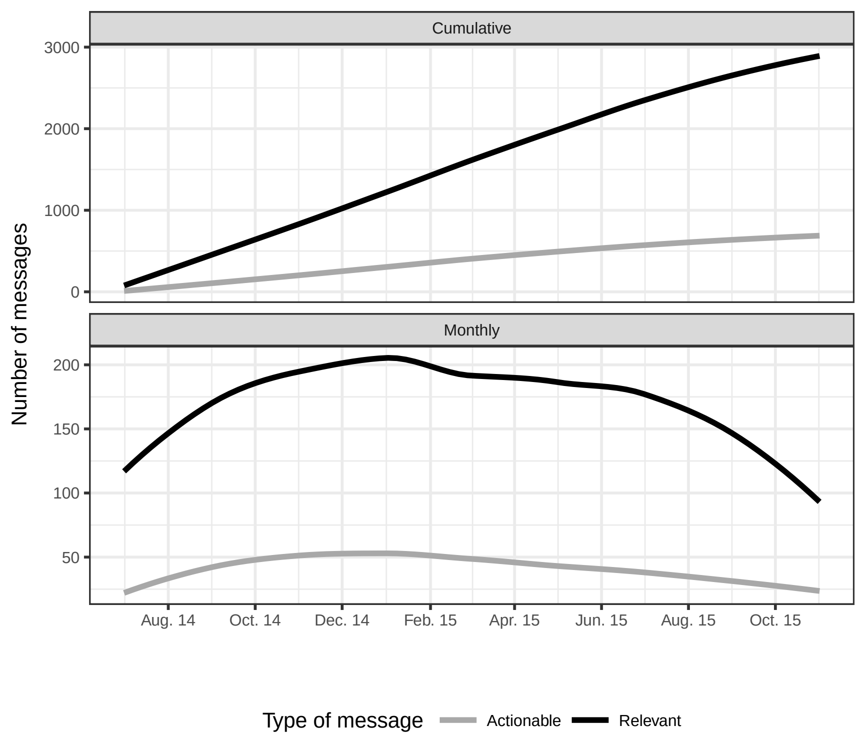

Figure 1: **Message intensity over time.** The monthly (bottom-panel) and cumulative (top-panel) number of relevant and actionable messages over time. Lines are derived from locally weighted regression (lowess).

3 Research design

We first discuss the process by which we selected villages to be included in the network survey, followed by a short description of how we constructed the social network data.

Village Selection

We collected complete network data in 16 villages—the number of villages determined by budget constraints. Half of the villages had a relatively high level of U-Bridge adoption given village characteristics, and half of which had low levels of adoption. In Table A.1 we report a set of OLS regressions in which two measures of adoption—the number of unique message senders and the number of messages sent via U-Bridge (normalized by village adult population)—are regressed on village predictors, derived from the 2014 census and from information assembled by the U-Bridge program. Using the regression model shown in column 6, we generate predicted values for the dependent variable ($\hat{y}$). We then calculated the difference between the predicted value and the actual value of the dependent variable; i.e., $\hat{\epsilon} = \hat{y} - y$. Using these residuals, we selected the 8 highest performing (largest positive $\hat{\epsilon}$) and the 8 lowest performing villages (largest negative $\hat{\epsilon}$). Figure A.1 maps the villages selected for data collection.

This design selects on the dependent variable, which is advantageous for a research agenda in its early stages. We construct a sample whose outcome is least explained by standard models of political participation, and thus more likely to be explained by potential network factors. Since half of our villages are high-performers and half are low-performers, our design also increases the likelihood of finding heterogeneous effects, allowing us to say more about when and why networks matter. Our design was also informed by the study's sample size, which was limited by the high cost of collecting complete real-world network data.

Data Collection

Data collection took place in April and May, 2016. Prior to enumeration, research team representatives met with the village chairperson to receive permission to undertake our activities and to conduct a listing exercise of all village households. On enumeration day, a short survey was conducted with every household in the village in which at least one adult was present, and with every available individual present in the household. The survey included a set of questions about basic demographics, respondents' social ties, and U-Bridge knowledge and usage. In total, we interviewed 3,184 individuals, covering about 75 percent of the adults residing in the surveyed villages.[4]

Network construction

We measured individuals' social networks using a standard name generator (Kolaczyk, 2009). We asked respondents to report four kinds of relationships in their village: (1) *family* ties, (2) *friendship* ties, (3) *lenders*: whom they would go to if they had to borrow money, and (4) *problem solvers*: whom they would go to in order to solve a problem regarding public services in the village. For each kind of relationship, respondents were asked to name up to five individuals. A common problem with network surveys is missing data. Since we were unable to interview every individual in the village, there are villagers for whom we only observe a fraction of their network: they were mentioned as ties by other respondents, but not interviewed in-person. About 30% of named individuals fall in this category. Following standard practice (e.g. Larson and Lewis, 2017), we exclude those nodes from the analysis.

Using survey responses, we first construct four different "undirected" village networks for the four different types of ties, by collapsing directed ties into undirected ones.[5] We further construct the union of those networks, by defining a tie between i and j if there is at least one tie between them in any of the above four networks. Respondents who were knowledgeable about the U-Bridge platform were further asked to name the individuals from whom they heard about the platform. This allows tracking the diffusion process of knowledge about the new political communication system. Figure 2 provides a graphical representation of the union network of two of the 16 villages: one high uptake (village P), and one low uptake (village G).

[4]In the Supplementary Information (SI), Table 1 we report the number of individuals we surveyed in each village, the number of individuals mentioned by at least one person (henceforth, "alters"), and the number of adults living in each village, according to 2014 census data. This information allows calculating the number of missing nodes.

[5]In other words, we say that i is friends with j if i mentioned j as a friend or j mentioned i as a friend. Our results are robust to treating constructing the family and friendship networks using reciprocated ties; that is, by saying that i is friends with j if i mentioned j as a friend and j mentioned i as a friend. All network concepts are defined informally in the main text. Formal definitions are available in the SI.

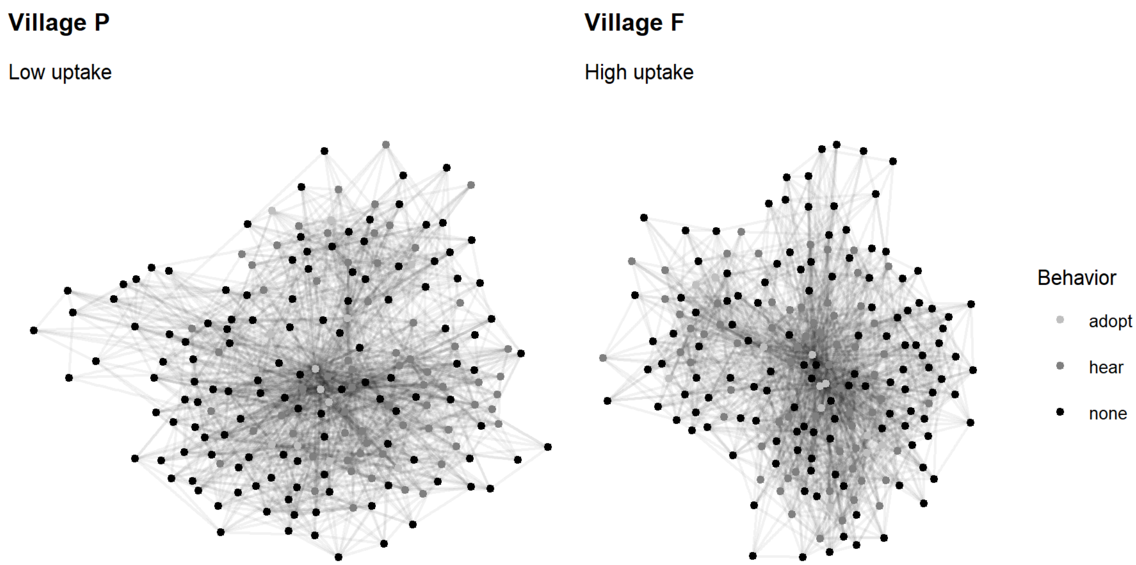

Figure 2: Graphical representation of the union network of two villages in the study area.

Variable description

Our core outcome measure is the adoption of U-Bridge, the new political communication platform. *Adopt* is a self-reported, binary variable that equals 1 if the respondent has used the platform at least once in the past 12 months. Similarly, *hear* is an indicator that gets the value of 1 if the respondent has heard about the U-Bridge service. By definition, U-Bridge adopters have a positive value for *hear*, but not vice versa. For those reporting that they have contacted Arua district local government via U-Bridge (i.e., "adopters") we also measure *satisfaction*: a rescaled binary variable that equals 1 if the respondent is at least somewhat satisfied with the platform (derived from a five-point Likert scale).

Our key explanatory variables are network characteristics that support diffusion. The empirical literature on social diffusion is large, and for tractability, we focus on two classes of diffusion models: (a) *fractional* threshold model, where an individual adopts a technological innovation if more than some *share* of her neighbors have adopted it (e.g., Acemoglu, Ozdaglar and Yildiz, 2011), and (b) *absolute* threshold model, where an individual adopts if more than some *number* of her neighbors have adopted (e.g., Centola and Macy, 2007). When examining *absolute* contagion processes, our key independent variable, *# adopting neighbors* counts, for each individual i, the number of social ties ('neighbors') in the union network that report using U-Bridge to contact district officials in the past 12 months. In some specifications, we also consider the variable *# hearing neighbors* that counts instead the number neighbors that have heard about U-Bridge. We also construct equivalent count measures for the four network types that make up the union network ('friends', 'family', 'lenders' and 'problem solvers'). When examining *fractional* threshold models, these variables are measured as the share of hearing / adopting neighbors among i's social ties.

While network ties account for *social* influence, we also account for *spatial* influence by using GIS information we collected on the location of each household. Specifically, the variable *geography* is a spatial lag that counts the number adopters within the village besides node i, and assigns less weight to those who reside farther away from that node.[6]

We collect a set of individual-level control variables that likely affect the usage of U-Bridge. These include the continuous measure of *age*; a *female* indicator variable; *secondary education*, which is a binary variable that equals 1 if the respondent attained at least secondary education; and *income*, a subjective wealth measure ranging from 1 (low) to 5 (high). The variable *use phone* is a binary variable that equals 1 if the respondent has used a mobile phone in the past 12 months to make a call or send a text message. *Leader* is a binary variable that equals 1 if the respondent occupies one of several formal public leadership positions within the village. *Political participation* is a summary index aggregating across recent political actions.[7] *Pro-sociality* is a behavioral proxy-measure of care for the community; it is measured as the level of contribution (i.e., number of monetary units) in a standard dictator game. Finally, *attend meeting* indicates whether the respondent attended any of GAPP's community meetings, in which the U-Bridge platform has been introduced or discussed.[8]

At the village level, we report network measures associated with social diffusion process—such as density, mean path length and clustering—in addition to several other standard predictors of political participation derived from the Ugandan 2014 census. Table 1 shows selected descriptive statistics for our 16 villages, split between high- and low-uptake.

[6] Let $y_i = 1$ if i adopted, and $y_i = 0$ otherwise. Let d_{ij} the distance between i and j. The spatial influence (*geography*) is then calculated as $\text{geo}_i = \sum_{j \neq i} \frac{y_j}{\log d_{ij}}$.

[7] We consider attending a village meeting, contributing money to a village project or a village member, contributing labor to a village project, reporting a problem to a village leader, and reporting a problem to the local government, in the past 12 months. The summary index is constructed following the method proposed by Anderson (2008), which gives more weight to more separating components of the index.

[8] All villagers attending GAPP meetings have heard of U-Bridge; thus we use this variable only when modeling adoption conditional on hearing about the platform.

A. Individuals

	Variable	Sample	High uptake	Low uptake	Δ	min	max
Outcome	% adopters	0.04	0.07	0.02	0.05***	0.00	1.00
	% heard	0.31	0.38	0.23	0.14***	0.00	1.00
	% satisfied	0.39	0.44	0.22	0.22**	0.00	1.00
Individual	age	37.39	37.55	37.22	0.33	18.00	101.00
	% females	0.58	0.56	0.59	-0.03**	0.00	1.00
	income	2.55	2.64	2.46	0.19*	1.00	5.00
	secondary education	0.23	0.28	0.18	0.09**	0.00	1.00
	% use phone	0.62	0.66	0.58	0.08*	0.00	1.00
	% leaders	0.14	0.16	0.12	0.04**	0.00	1.00
	political participation index	-0.00	0.06	-0.06	0.12***	-0.88	1.49
	% attend meeting	0.08	0.11	0.05	0.06***	0.00	1.00
	pro-sociality	0.20	0.20	0.20	0.01	0.00	1.00
Network	degree	16.07	16.77	15.36	1.42	1.00	227.00
	betweenness	143.86	150.79	136.91	13.89	0.00	16385.53
	clustering coefficient	0.39	0.38	0.40	-0.02	0.00	1.00
	N	3184	1595	1589	6		

B. Villages

	Variable	Sample	High uptake	Low uptake	Δ	min	max
Network	density	0.10	0.12	0.08	0.04	0.05	0.40
	path length	2.12	2.08	2.16	-0.08	1.60	2.33
	global clustering	0.25	0.27	0.24	0.03	0.17	0.55
Village	adult population	269.38	274.50	264.25	10.25	32.00	429.00
	ethnic fractionalization	0.04	0.07	0.02	0.05	0.00	0.41
	% employed	0.86	0.84	0.89	-0.05	0.68	1.00
	% non-agriculture	0.22	0.25	0.19	0.06	0.00	0.57
	poverty score	-0.07	-0.05	-0.09	0.03	-0.48	0.47
	N	16	8	8	0		

Table 1: Descriptive statistics. The table reports mean values for the full-sample, as well as for low- and high-uptake villages. Network characteristics are calculated from the union network. In panel A, difference in means are tested using a t-test, with standard errors clustered at the village level; *p<0.1; **p<0.05; ***p<0.01.

We find that villagers in high-uptake villages had somewhat higher socioeconomic status compared to individuals in low-uptake villages: they are slightly richer, more educated, more likely to use a phone, more likely to hold leadership positions, and more likely to attend GAPP meetings introducing U-Bridge. By contrast, small differences in individual-level networks characteristics – betweenness and degree centrality as well as clustering coefficient – fall below conventional significance levels. Similarly, high and low-uptake villages do not seem to differ in terms of network structure or community-level characteristics as culled from the 2014 census, including mean assets-based poverty score, share employed, ethnic diversity, distance to Arua town, and population size.

Altogether, Table 1 suggests that variation in technology adoption at the individual level may be better explained by differences in villagers' characteristics and processes of social influence (i.e., peer effects) than by differences in village characteristics commonly used in political economy studies. Our empirical strategy is designed to estimate the relative importance of these plausible determinants of the adoption of political communication technologies.

Estimation

We estimate peer effects using a standard Spatial Auto-Regressive (SAR) model, where the probability of adoption depends on some function of the adoption of one's neighbors. Consider individual i on network g, and let $N_i(g)$ be the set of her neighbors on g. Let y_i be i's outcome, equal to 1 if i adopts, and 0 otherwise, $y_{N_i(g)}$ be the vector of outcomes of her neighbors, x_i a vector of control variables, and ϵ_{ig} an error term. We estimate the following linear probability SAR model:

$$y_{ig} = \beta_0 + f(y_{N_i(g)})\beta_1 + x_i^T \beta_2 + \epsilon_{ig}$$

In particular, we examine both absolute, and fractional threshold models with and without controls. In the first case, $f(y_{N_i(g)}) = \sum_{j \in N_i(g)} y_j$ is the number of adopting neighbors. In the second case, $f(y_{N_i(g)}) = \frac{1}{|N_i(g)|} \sum_{j \in N_i(g)} y_j$ is the percentage of adopting neighbors.[9]

We use the most conservative approach: we account for village-level heterogeneity by adding village indicators, and use heteroskedastic robust standard errors. This is a conservative approach as we lumped into a village-level effect all factors that could not be explained by any other channel.

4 Results: Peer effects

In this section, we present our main results with respect to the role of peer effects on the adoption of U-Bridge, followed by a set of robustness checks, including an instrumental variable approach. We find that, whether using the *number* of adopting neighbors (absolute threshold, Table 2, columns 1-2), or the *share* of adopting neighbors (fractional threshold, Table 2, columns 4-5), adoption of the U-Bridge platform increases with the adoption decisions of one's social ties. Specifically, according to the baseline absolute threshold model (column 2), the likelihood of using U-Bridge increases by 2.7 percentage points for every adopting neighbor. Moving to the baseline 'fractional' threshold (column 5), we note that 32% of respondents have no ties to an adopter, and among those connected to at least one adopting neighbor, the mean *share* of adopting peers is 15%.

[9] Our results are robust to using a logistic regression instead.

Since the model fit for a absolute threshold contagion process (column 2) slightly outperforms modeling fractional threshold contagion (column 5)—using R^2 or the Akaike Information Criteria when fitting a logistic regression—we use the absolute threshold model when calculating marginal effects, reported below (Figure 3).

Robustness Checks

We report a host of robustness checks for our core finding on peer effects, reported in Table 2. We first test whether our results are sensitive to dropping village A, which has a smaller number of respondents (30) than other villages (mean number of respondents is 210). Results, reported in the SI, Table 5, show again a strong positive relationship between the number (or share) of adopting neighbors and one's adoption choice.

We next probe into mediating behavior: one can only adopt the innovation if she has heard about it. Building on recent work by Larson, Lewis and Rodrıguez (2017), we show that our results are robust to running a two-stage (logistic) selection model in which we model separately the social process of hearing about an innovation and that of adopting the new technology conditional on hearing about it. We find that peers affect both stages of the diffusion process (SI, Table 6). Figure 3 shows that the (total) average marginal effect of an adopting peer estimated using our two-stage model is comparable in magnitude to our baseline, reduced-form specification (Table 2, column 2) reestimated using a logistic regression.[10]

[10]The controls in Table 6 in the SI also reveal an important insight: if women are less likely to be U-Bridge users, this is only because they are less likely to hear about the existence of the program; they are not less likely to adopt, conditional on hearing. This finding on a traditionally politically marginalized category of individuals suggests that the role of social ties in the process of hearing about a new technology may be different than their role in the adoption phase (conditional on hearing).

	Dependent variable: adopt					
	Parsimonious	Baseline	Decomposition	Parsimonious	Baseline	Decomposition
	(1)	(2)	(3)	(4)	(5)	(6)
# adopting neighbors	0.035^{***}	0.027^{***}	0.019^{***}			
	(0.005)	(0.005)	(0.006)			
% adopting neighbors				0.325^{***}	0.218^{***}	0.157^{***}
				(0.052)	(0.048)	(0.057)
degree	0.002^{***}	0.001^{*}	0.0002	0.004^{***}	0.003^{***}	0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# neighbors who told me			0.062^{***}			
			(0.012)			
% neighbors who told me						0.871^{***}
						(0.198)
1+ satisfied neighbors			0.012			0.024^{**}
			(0.012)			(0.011)
Constant	0.061	0.125^{*}	0.124^{*}	0.052	0.109	0.093
	(0.073)	(0.076)	(0.075)	(0.073)	(0.075)	(0.075)
Controls	_	✓	✓	_	✓	✓
Observations	3,184	3,019	3,019	3,184	3,019	3,019
R^2	0.139	0.247	0.273	0.116	0.233	0.251
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

Table 2: **Adoption of U-Bridge.** OLS estimates with village-level fixed effects. Heteroskedastic standard errors in parentheses. Absolute threshold models (models 1-3) have weakly better fit than fractional threshold models (models 4-6). 1+ satisfied neighbors is an indicator variable that equals 1 if at least one neighbor is satisfied. Model 2 is our preferred specification.

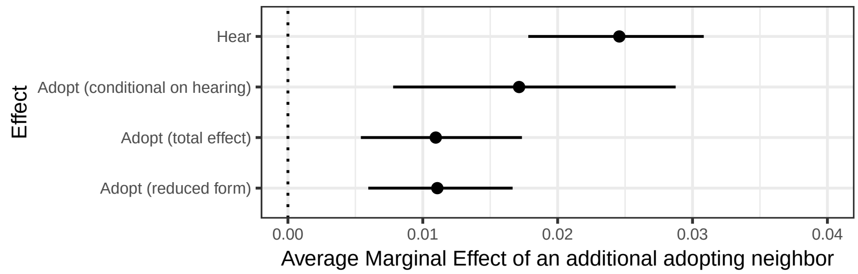

Figure 3: **Selection model with hearing.** Average marginal effect (AME) of an adopting neighbor on hearing (first stage) and of adopting conditional on hearing (second stage). The total effect of the selection model matches the estimate from a reduced form logistic regression. Bars represent heteroskedastic 95 percent confidence intervals.

Causally identifying peer effects

As with all social diffusion studies, the key empirical challenge we face is identifying peer effects; that is, the impact of an exogenous shock to the outcome of an agent on the outcome of one of her neighbors. We face two main endogeneity problems that we address with a variety of robustness checks. First, the initial encouragements to adopt the technology might be endogenous. Even in the absence of social learning and influence, two connected individuals may adopt similar behavior as a result of similar characteristics, due to homophily (Jackson, 2008), or because they are subject to related unobservable shocks (Conley and Udry, 2010). Second, exposure to peer influence is endogenous to one's network position (Aronow and Samii, n.d.). Indeed, individuals with more central network positions are more likely to be exposed to peer influence, since they have more neighbors, or neighbors who are themselves more central. In the limit, agents with no neighbors cannot be exposed to any influence.

To address the issue of endogenous encouragements, we use a generalization of An (2016) instrumental variable (IV) approach. To instrument for j's influence on i, the approach leverages covariates that directly affect j's outcome, and only affect i through j's influence. Our instrument is the distance from one's household to the location of the meeting introducing U-Bridge. Since meeting location was chosen as if randomly, being closer to the meeting represents an exogenous encouragement to adopt the technology. Indeed, the shorter the distance to the venue, the more likely a villager is to adopt U-Bridge, simply by increasing the likelihood that she attends the meeting and learns about the new technology. For the instrument to be valid, the exclusion restriction must be satisfied; i.e., we must assume that j's distance to the location of the meeting does not affect i's adoption via alternative channels than j's influence on i. This would be the case if contacts tended to cluster around locations that were more or less exposed to the meeting. Encouragingly, we find little (-.04) correlation between physical distance and having a social tie.[11] The results of our IV models, reported in SI, Table 7, confirms our basic adoption model.

We address the issue of endogenous exposure to peer influence owing to one's network position by comparing individuals who share similar network positions. While our main specification already did so by controlling for one's degree, we push such comparisons further by controlling for degree more flexibly, and for other attributes of network position. Our results are robust to controlling for degree non-parametrically with generalized additive modeling, as well as using a large number (10) of degree strata (SI, Table 10).

We further check the robustness of our core findings to endogenous exposure to peer influence by controlling for a host of other network centrality scores (SI, Table 11). Following recent contributions (Banerjee et al., 2013; Alatas et al., 2016), for each node i, we compute *betweenness* (the extent to which a node in the network needs to go through node i in order to reach some other network member), *closeness* (the mean distance between node i and any other node), *eigenvector* centrality (a measure that gives more weight to high degree nodes connected to other high degree nodes), *Bonacich* centrality (a measure that gives more weight to high degree nodes connected to low degree nodes), and clustering (the share of i's friends that are also friends with each other). We bin the continuous centrality measures into three equally sized bins (low, medium and high-centrality), and run separate model for each centrality measure. While confirming our main result, this robustness check also yields an insight that echoes previous findings from contagion studies: individuals in highly clustered neighborhoods are less likely to adopt (Centola and Macy, 2007).[12]

Finally, we use matching to address both problems simultaneously. Building on Aral, Muchnik and Sundararajan (2009) who show that matching allows eliminating most of the bias common in observational studies of peer effects, we match villagers that share similar individual and network

[11]We conduct additional checks for potential violations of the exclusion restriction by conducting several placebo tests (SI, Table 9). As expected, mean peer distance to the meeting location positively correlates with adoption. It does not correlate with other theoretically meaningful predictors of adoption, such as political participation, leadership status, or phone ownership.

[12]This is because nodes with lower clustering have ties to a more diverse set of contacts, and potentially exposed to more sources of contagion.

characteristics. Our matched sample alleviates the problem of endogenous encouragements to adopt the technology by comparing observations that are equally likely to be exposed to treatment, based on observable characteristics. We construct our matched sample using political participation, phone use, secondary education, and meeting attendance (individual-level covariates), as well as degree and eigenvector centrality (network covariates). Using network covariates alleviates the concern of endogenous exposure to treatment owing to network positions by explicitly matching on selected network covariates. Since centrality scores tend to be highly correlated, matching on those two network covariates constructs treatment and control groups that are also more likely to be comparable with respect to other centrality scores. We compared three matching procedures: nearest neighbor, coarsened exact, and full matching. We chose the latter matching because it achieved the highest distance reduction. We then estimated our main specification on the matched sample. Table 12 in the SI shows that our main result on peer effects is robust to such matching estimates.

5 Village-level variation in peer effects

Thus far, we have focused on the adoption choices of individuals pooling data from our sixteen villages. However, Table 2 above and Figure A.2 in the appendix suggest that there is likely important heterogeneity *across villages* with respect to the size (and significance) of peer effects. Exploring this more systematically, we reestimate our preferred regression model (Table 2, column 2) separately for each community. As shown in Figure 4, in about half of the villages in our sample, individuals' choice of U-Bridge adoption is *not* positively correlated with those of network peers. This finding suggests that the role that networks play in social diffusion processes is more nuanced than previously assumed.

What explains variation in the magnitude of peer effects across villages? Why are peer effects not universal in the adoption of a new PCT? To answer this question, one approach is to compare villages with large peer effects to villages with small peer effects. We will compare instead high- and low-uptake villages for two reasons. First, our estimates of peer effects come with uncertainty, which makes the makeup of high- and low-peer-effect groups uncertain. Second, figure 4 shows that save for one pair of villages (M and F), high-peer effect villages are also high-uptake villages.

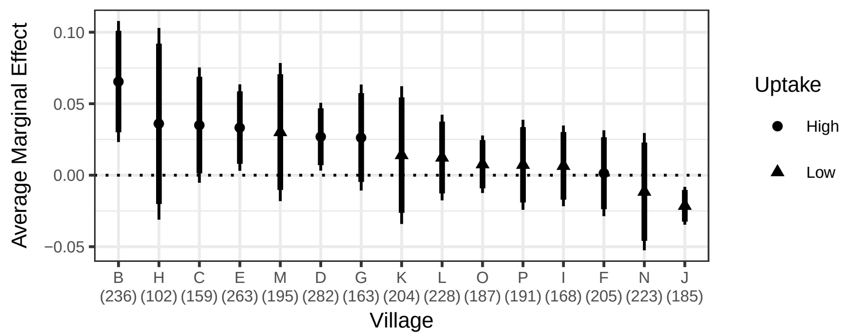

Figure 4: **Average marginal effect of one adopting neighbor on adoption by village.** Estimates from our main specification when run separately for each village; sample sizes in parenthesis. High uptake villages have large, generally significant peer effects. Low uptake villages have small, statistically insignificant peer effects. Village A is omitted because its sample size is too small. Bars represent heteroskedastic 90 and 95 percent confidence intervals.

Past work points toward two possible network-level explanations for which we find little support in our data. First, it might be that some networks do not facilitate processes of social diffusion due to "inadequate" structure. For example, Centola (2015) argues that social diffusion processes are highly dependent of network properties—clustering, path length and bridge width.[13] Comparing core network-level properties, such as density, clustering, path length and size, we find minuscule differences between high and low-uptake villages (Table 1).

Second, past work has highlighted the importance – for diffusion of information across networks – of the identity (Banerjee et al., 2013) and network position (Larson, Lewis and Rodrıguez, 2017) of initial 'seeders'. In Table 3, we compare the individual attributes as well as network characteristics of the those attending GAPP's inception meetings and find small and insignificant differences in seeders' characteristics in high- and low-uptake villages.[14]

Next, in order to better account for the observed variability in peer effects, we present a new theory that is grounded in an intuition gleaned from focus group discussions and open-ended interviews with villagers in the study area.

[13]Similarly, network density is thought to support public goods provision in ethnically homogenous communities by allowing information on defectors' behavior to spread fast and wide (Miguel and Gugerty, 2005).

[14]Those villages differ, however, in the number of seeders. While this may account for differences in uptake, it cannot explain differences in the magnitude of peer effects, especially since our main specification controls for meeting attendance.

	Variable	Sample	High uptake	Low uptake	Δ	min	max
Outcome	% adopters	0.29	0.33	0.21	0.12***	0.00	1.00
	% heard	1.00	1.00	1.00	0	1.00	1.00
	% satisfied	0.36	0.40	0.26	0.13	0.00	1.00
Individual	age	40.06	39.99	40.21	-0.22	18.00	88.00
	% females	0.28	0.30	0.24	0.06	0.00	1.00
	income	2.79	2.81	2.74	0.07	1.00	5.00
	secondary education	0.47	0.49	0.42	0.07	0.00	1.00
	% use phone	0.81	0.82	0.78	0.04	0.00	1.00
	% leaders	0.28	0.29	0.27	0.02	0.00	1.00
	political participation index	0.36	0.36	0.36	0	-0.88	1.49
	pro-sociality	0.20	0.19	0.21	-0.02	0.00	1.00
Network	degree	29.43	27.66	33.11	-5.44	3.00	227.00
	betweenness	666.04	596.48	810.88	-214.4	0.00	16385.53
	clustering coefficient	0.33	0.34	0.32	0.02	0.05	0.84
	N	262.00	177.00	85.00	92		

Table 3: Descriptive statistics meeting of attendees in the 16 villages sampled. The table reports mean values for the sample, as well as for low- and high-uptake villages. Network characteristics are calculated from the union network. Difference in means are tested using a t-test, with standard errors clustered at the village level; *p<0.1; **p<0.05; ***p<0.01.

6 Model: networks and (political) technology adoption

In this section, we present a model of social networks and technology adoption. The starting point of our theory is a simple intuition: that the importance of peers (network ties) in supporting social learning and facilitating technology adoption depends crucially on the extent to which the newly introduced good produces positive externalities. Unlike new technologies examined by recent studies of diffusion, political communication technologies have significant positive externalities. These externalities may affect the extent to which communication, particularly by early adopters, conveys accurate information.

In classic models of technology adoption, innovations spread through social ties (Coleman et al., 1966). Adopting an innovation is risky due to uncertainty over perceived costs and benefits. Social ties facilitate diffusion because they allow agents to learn about the new innovation not only from their own experience, but also from the experience of their peers (Rogers, 1962). As such, agents with more neighbors (i.e. larger number of social ties) learn faster, because they benefit from the experiences of a greater number of people. The adoption outcomes of neighbors also tend to be more correlated, as peers update their priors from the same events.

Yet to date, models of social learning primarily consider goods that produce minimal externalities; that is, goods for the payoff derived from adoption does not depend on the adoption decision of other agents. For example, the benefits of adopting a new fertilizer depend almost exclusively on an individual farmer's actions. A farmer can learn from her neighbor about how effective a new fertilizer is, but the neighbor's use of fertilizer on his crop does not affect the farmer's own crop yield.[15] Importantly, this leads past theories to implicitly assume that neighbors will share accurate information about their experience with the good. The assumption of truthful communication may be warranted for a good with no externalities, where the payoff of an agent does not depend on the payoff of other agents.

New (political communication) technologies that feature positive externalities–i.e., goods for which the benefits from adoption increase with the number of adopters—may hinder truthful communication which, in turn, may annihilate peer effects. With positive externalities, early adopters must convince others to adopt, and therefore have an incentive to exaggerate benefits. Their neighbors, recognizing this incentive, may discount information they receive from early adopters. Communities can address the problem of truthful communication by employing a variety of informal institutions. For example, early adopters who are embedded in communities with high levels of social cohesion, or where local leaders can coordinate social sanctions for sharing inaccurate information, may be more likely to provide an honest assessment about the program's efficacy. In these cases, communication about the new technology is truthful. Being truthful, communication is most useful, and displays the same benefits as for goods with no externalities. However, communities may vary in their ability to enforce truthful communication. Thus, compared to goods without externalities, goods with externalities will exhibit greater variation in the extent to which social networks facilitate adoption of the good. Some communities, perhaps due to pre-existing but largely unobservable informal institutions and norms, are able to enforce truthful communication while others are not. The role of peer effects on adoption will be lower in communities where truthful communication is not enforced.

Thus, we introduce a model to highlight the key role that externalities play in social learning processes, and especially how externalities condition the role social networks play in technology adoption. In our setting, agents decide whether to adopt a new technology (also referred to as a good). Adoption is costly, and their decision depends on an unobserved state of the world that

[15] In practice, all goods feature a minimal amount of externalities, for if no other agent invests in the new technology, then the company producing it may go bust, thereby affecting the focal agent's ability to invest in it. Yet, this sort of externality is negligible, compared to goods characterized by joint production and diffuse benefits.

conditions how useful the technology is. Agents are connected on a network, and learn about the state of the world from their neighbor's experience with the good.

We depart from standard models (eg. DeGroot, 1974; Bala and Goyal, 1998) in two ways. First, we consider not only goods without externalities, but also goods that feature positive externalities. Second, we make communication strategic; instead of simply observing their neighbors, agents hear reports about their experience with the good. Using this simple setup, we show that the standard result that networks foster learning and adoption hinges on whether agents maintain *truthful communication*; that is, they convey accurate information to their neighbors about their experience. We then show that goods without externalities support truthful communication, reproducing the main comparative statics of the canonical models. However, goods with externalities do not necessarily support truthful communication and thus do not necessarily enjoy the benefits of social learning.

Formally, consider a society of N agents connected by the undirected graph $g = (G, N)$, where G is a set of ties. Agents decide whether to adopt a technological innovation or not. There is an unobserved, binary state of the world: $\theta \in \{H, L\}$. In the high state H, the technology is useful, while it is not in the low state L. Thinking of a good with positive externalities, this captures, for example, whether the government is responsive to or ignores incoming messages from constituents. At $t = 0$, nature randomly draws the state of the world θ. Agents have a prior belief $\pi_i = \Pr(\theta = H)$ of being in the high state, and each gets an independent signal about the state, $s_i \in \{H, L\}$. The signal is informative: it matches the true state with probability $p_i = \Pr(s_i = \theta) > 1/2$. The probability p_i differs across agents, to capture varying degrees of *expertise*: agents with a higher p_i have more expertise in the sense that they observe correct signals more often. At $t = 1$, each agent i sends a message $m_{ij} \in \{H, L\}$ to each of their neighbors $j \in N_i(g)$ to inform them about the signal they observed.[16] At $t = 2$, each agent decides whether to adopt the innovation ($y_i = 1$) or not ($y_i = 0$) and her payoff $u_i(., \theta)$ accrues.

Using different payoff functions, we consider a good without externalities, and a good with externalities. In both cases, adopting incurs cost $c_i \in (0, 1)$. In the high state, adopting generates a benefit B (normalized to 1) with some probability. It generates a benefit of 0 in the low state. The cases differ in that without externalities, one's payoff depends only on her action; $u_i = u_i(y_i, \theta)$.

[16] Recall that $N_i(g)$ is the set of neighbors of agent i on graph g.

Specifically:

$$u_i(y_i, \theta) = q_\theta(y_i) - y_i c_i \tag{1}$$

where $q_\theta : \{0,1\} \to [0,1]$ is the probability of reaping benefit $B = 1$ in state θ. We assume that irrespective of the state, not adopting gives a benefit of 0: $q_\theta(0) = 0$. Adopting allows reaping benefit $B = 1$ with positive probability in the high state, but with probability 0 in the low state: $q_H(1) > q_L(1) = 0$. If the technology is a good with significant externalities, as is the case with political communication technologies, i's payoff crucially depends on the actions of other agents: $u_i = u_i(y_i, y_{-i}, \theta)$, where $y_{-i} = (y_j)_{j \neq i}$ the vector of actions taken by all other agents. We use:

$$u_i(y_i, y_{-i}, \theta) = q_\theta\left(y_i + \sum_{j \neq i} y_j\right) - y_i c_i \tag{2}$$

With positive externalities, the probability of reaping the benefit also depends on the actions of others, with $q_\theta : \{0, ..., N\} \to [0,1]$. As is the case without externalities, if no one adopts there is a benefit of 0 in all states, with $q_\theta(0) = 0$. In the high state, the probability of reaping benefit B increases with the number of adoptions: $q_H(n) < q_H(n+1)$. In the low state, adoption gives no benefits: $q_L(n) = 0$ for any n.

The benefits of truthful communication

We start by examining what drives the adoption decision both with and without externalities, and then examine behavior under the assumption that agents enforce truthful communication, to show that our model reproduces a set of standard results.

We first show that in equilibrium, agents have threshold strategies: they adopt the new technology if they are sufficiently certain that they are in the high state. In equilibrium, agent i chooses the action that maximizes her expected payoff, using her available information $S_{ig} \in \mathcal{I}_{ig}$ to update her prior about the state. This information is a vector containing her signal and messages she received from her neighbors on network g; that is, $S_{ig} = (s_i, (m_{ji})_{j \in N_i(g)})$. The set $\mathcal{I}_{ig} = \{0,1\}^{|N_i(g)|+1}$ contains all possible realizations of such vector. In equilibrium, i's action $y^*_{ig}(S_{ig})$ solves $\max_{y_i} \mathbb{E}_\theta[u_i(y_i, ., \theta)|S_{ig}]$. She adopts and sets $y^*_{ig}(S_{ig}) = 1$ if S_i contains enough evidence favoring the high state against the low state, as captured by a higher (log) likelihood ratio

$l(S_{ig}) = \log \frac{\Pr(\theta=H|S_{ig})}{\Pr(\theta=L|S_{ig})}$. How much evidence is necessary depends on an individual threshold a_i. Agents that have a higher cost of adoption, or were originally too pessimistic about the state have a higher threshold. Formally:

Proposition 1 (Threshold strategy) *In any perfect Bayesian equilibrium, agents have a threshold strategy such that* $y^*_{ig}(S_{ig}) = 1 \iff l(S_{ig}) \geq a_i$.

Under truthful communication, agents send messages that match their observed signal: $m_{ij} = s_i$. Truthful communication is important, because this is when messages are most informative. The value V_{ig} of i's information on graph g under truthful communication is her expected payoff from all potential information she could receive $\mathcal{I}_{ig}$, given that neighbors communicate truthfully and that she responds optimally to that information. Formally, $V_{ig} = \sum_{S_i \in \mathcal{I}_i} \mathbb{E}_\theta[u_i(y^*_i(S_i), ., \theta)|S_i] \Pr(S_i)$. In a perfect Bayesian equilibrium where communication is not truthful, agents lie with some probability about their signal. Intuitively, i's information is most valuable under truthful communication, because lies introduce additional noise that make her inferences about the state less precise. Formally:

Proposition 2 (Truthful communication is most valuable) *Let* $\tilde{V}_{ig}$ *be the value of information in an equilibrium profile where some* $j \in N_i(g)$ *misrepresents her signal to* i *with some probability. We have*

$$\tilde{V}_{ig} \leq V_{ig}$$

Truthful communication has three important implications. First, agents with larger neighborhoods learn at a faster rate, because they observe more signals, allowing them to make better inferences about the state of the world. In other words, the value of i's information increases with the size of her neighborhood. We show that i's information is more valuable when she has an additional neighbor:

Proposition 3 (Larger neighborhoods are conducive to better learning) *Consider graphs* g *and* g'*, constructed by adding a tie between* i *and* j *on* g*. We have*

$$V_{ig} \leq V_{ig'}$$

Because neighbors share their experiences, they learn from the same sources of information and make more similar inferences. Note that such peer effect gets stronger the more neighbors a dyad has in common, because the two neighbors acquire more similar information. Formally, this means that connecting two agents increases the correlation of their (log) likelihood ratios:

Proposition 4 (With peer influence, the posteriors of neighbors are more correlated) *Consider graphs g and g', constructed by adding a tie between i and j to g. Let $\rho(x,y)$ the correlation coefficient between x and y. Under truthful communication, we have*

$$\rho\left[l(S_{ig}),l(S_{jg})\right] \leq \rho\left[l(S_{ig'}),l(S_{jg'})\right]$$

Experts are more likely to observe correct signals.[17] As such, agents place a higher weight on the messages of experts when making inferences about the state. By the same reasoning, experts are less susceptible to peer influence, because they place a higher weight on their own signal. Formally, we show that the impact of j observing the high versus low signal on i's posterior grows with j's expertise.

Proposition 5 (Experts have more influence) *Consider the vectors of messages S_{ig}^H and S_{ig}^L that differ only in that one message $m_{ki} = H$ in S_{ig}^H and $m_{ki} = L$ in S_{ig}^H. Under truthful communication, we have*

$$\frac{\partial}{\partial p_j}\left[l(S_{ig}^H) - l(S_{ig}^L)\right] > 0.$$

When communication is not truthful, agents put less weight on the messages sent by their neighbors to make their inferences about the state of the world. In the limit, the messages they receive are uninformative, and agents only use their own signal when deriving their posterior: $\mathcal{I}_i = \{s_i\}$. When this is the case, propositions 3, 4 and 5 do not hold anymore: agents with larger neighborhoods do not necessarily learn faster, the posteriors of neighbors are not more correlated than those that are not connected, and expert neighbors do not wield more influence.

[17]By definition, expertise is having a higher p_i, which is probability of observing correct signals.

Comparing goods with and without externalities

While goods without externalities always support truthful communication, goods with externalities may not. To shed more light onto this, we introduce a cost of lying. This may represent a moral cost, or a reduced form for social sanctions enforced by the community to foster cooperation. Specifically, we assume that agent i incurs a cost $\kappa \geq 0$ for every message m_{ij} different from the signal s_i she observed. Payoff functions become:[18]

$$u_i(y_i, m_i, \theta) = q_\theta(y_i) - y_i c_i - \kappa \sum_{j \in N_i(g)} 1\{m_{ij} \neq s_i\}$$

$$u_i(y_i, y_{-i}, m_i, \theta) = q_\theta\left(y_i + \sum_{j \neq i} y_j\right) - y_i c_i - \kappa \sum_{j \in N_i(g)} 1\{m_{ij} \neq s_i\},$$

with $1\{.\}$ the indicator function.

Without externalities, agents have no incentive to lie: lying brings no benefits, and creates costs. In such case, we have the following proposition:

Proposition 6 *Without externalities, truthful communication is a perfect Bayesian equilibrium for any $\kappa \geq 0$. It is the unique equilibrium for any $\kappa > 0$.*

With externalities, however, truthful communication may not be an equilibrium, because i has an incentive to announce state H, increase j's posterior, to encourage j to adopt. A high enough cost of lying deters such behavior and establishes truthful communication. Formally:

Proposition 7 *With externalities, there are thresholds $\bar{\kappa}_1, \bar{\kappa}_2$ with $0 \leq \bar{\kappa}_1 \leq \bar{\kappa}_2 \leq 1$ such that truthful communication is a perfect Bayesian equilibrium if and only if $\kappa \geq \bar{\kappa}_1$ and is the unique perfect Bayseian equilibrium for any $\kappa > \bar{\kappa}_2$.*

7 Empirical implications of the model

Our theoretical findings qualify the range of goods for which social networks facilitate diffusion. Specifically, for goods with no (or minimal) externalities, agents with larger neighborhoods learn

[18]Note that under truthful communication, the cost κ is never incurred, and payoff functions reduce to the expressions in 1 and 2.

faster, and outcomes of neighbors are more highly correlated because such technological innovations are compatible with truthful communication. However, for goods with significant externalities, truthful communication can break down, in which case social ties do not provide additional advantage.

Yet, truthful communication need not always break down within communities. Truthful communication increases the more that agents are concerned about possible social costs of 'defection', κ (Habyarimana et al., 2009). Should a community manage to impose truthful communication ($\kappa \geq \bar{\kappa}_1$), the diffusion process of goods with positive externalities with respect to peer effects will behave as goods without externalities.

There are several observable implications of the model.

1. *Variation* across networks in the support of diffusion of goods with externalities, above and beyond what can be explained by variation in hearing rates.
2. *Discounting* of positive signals (peers' recommendations) when truthful communication is not enforced.
3. *Strong ties* will be more effective than weak ties in supporting truthful communication, and therefore, in supporting diffusion.
4. *Experts* will have a stronger peer effect than novices when a network supports diffusion, as their signal carries greater weight.

We test these implications in turn. First, as shown above, there is *variation* in our core result on peer effects: these effects do not necessarily hold when running the model separately for each community (Figure 4). The model shows why not all communities necessarily solve the problem of truthful communication (proposition 7). For goods that have large externalities, social networks may not support the process of technology diffusion if nodes do not trust the signal that their neighbors emit.

Villages differ in the extent to which peer effects foster adoption above and beyond what can be explained by diffusion of information about the existence of the platform. The model emphasizes that differential effects owe to agents processing differently the information they obtain from their peers about the technology. An important alternative explanation would be that agents simply vary in the extent to which they communicate about the technology, for which we find little support. First, our explanation and the alternative are not completely distinct, since hearing may be endogenous to the enforcement of truthful communication: seeds in low-uptake villages may choose not to discuss the platform with neighbors, internalizing the fact that their input is likely to be down-weighted. Second, although high-uptake villages hear about and adopt the platform at higher rates, the magnitudes are very different (Table 1). High-uptake villages hear about the U-Bridge platform 65% more than low-uptake villages, but adopt it 250% more, suggesting that other factors are at play.

Since the dimensions explaining differences in hearing and uptake need not be related to social influence (Larson, Lewis and Rodrıguez, 2017), we investigate influence more specifically by comparing peer effects in adoption and peer effects in hearing across villages. We estimate peer effects in hearing for each village using the same procedure as for peer effects in adoption: for each village, we regress hearing on the number of hearing neighbors, using a similar set of controls. We then compare high- and low-uptake villages. The effect of a peer adopting is 3.2 percentage points higher in high-uptake villages than in low-uptake ones. The effect of a peer hearing is only 1.0 percentage point higher in high-uptake villages than in low-uptake ones.[19]

Second, we find evidence of *discounting* signals about the technology from peers. In villages that do not support the diffusion of technologies with externalities, agents should not trust the messages sent by their neighbors. We test this by decomposing peer effects into three components: (1) whether i's neighbors adopted the technology, (2) whether they discussed the technology with agent i, and (3) whether at least one of them reports being satisfied with the technology (Table 2, columns 3 and 6). Our theoretical expectation is that while neighbors' satisfaction should significantly increase the likelihood of adoption in high-uptake villages, it should have no discernible effect in low-uptake villages.

Figure 5 confirms the model's prediction. Reestimating the model reported in Table 2 (column 3) separately for high- and low-uptake villages reveals that the marginal effect of having at least one satisfied neighbor is 1.9 percentage points in high-uptake villages, it is effectively zero in low-uptake villages. Figure 5 also underscores another important finding: social diffusion processes are a function of the nature of the information being communicated, above and beyond the mere existence of a social tie (Larson and Lewis, 2017). While the effect of communication in high uptake

[19] Regressing estimates from a model in an auxiliary model introduces heteroscedasticity (Lewis and Linzer, 2005). We thus follow Shalizi (2018), and estimate weighted least square regressions, whereby the weights are calculated as the inverse variance of the dependent variable. We account for any remaining heteroscedasticity by using heteroscedastic-robust standard errors. The difference in peer effects on adoption is significant at the 10 percent level (p-value = .053). The difference in peer effects on hearing is not statistically significant (p-value = .37).

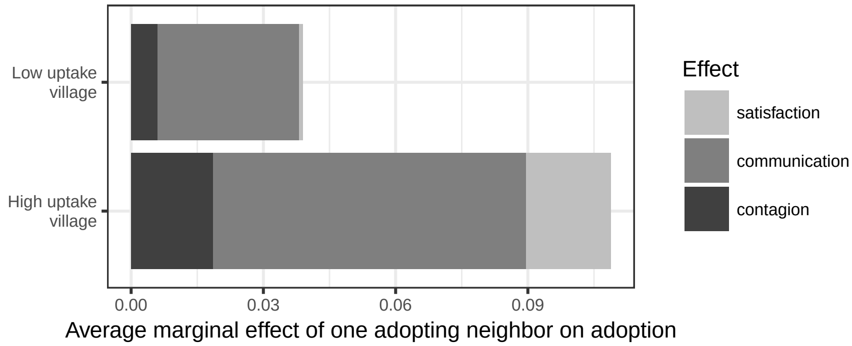

Figure 5: **Components of social influence in high and low uptake villages.** Marginal effect of one adopting neighbor (contagion) on the probability of adoption, with the additional effects of interpersonal communication with the neighbor (communication), and of that neighbor being satisfied (satisfaction). Communication most fosters adoption. High-uptake villages have larger effect sizes. Satisfaction has almost no effect in low uptake villages.

villages is 7.1 percentage points, in low-uptake villages it is 3.2 percentage points.

A third implication is that some types of networks are more likely to facilitate truthful communication than others. We have argued that *strong ties* are better positioned to enforce truthful communication, given the higher social cost of mischaracterizing the costs and benefits of the new technology. To test this argument, we disaggregate all network relations into simple ties (i shares a single type of relationship with j), and complex ties (i's relationship with j is based on more than one of four types of ties). We then reestimate our absolute threshold model, first comparing the effect of a complex tie to that of any simple tie, then to that of each kind of simple tie. Consistent with our expectation, we find that peer effects are stronger for complex ties than for simple ties (Table 4, column 1), and that, among simple ties, friendship and family ties are most influential (column 2).

Finally, in our model, agents learn from their neighbors' signal about the state of the world: $\theta \in \{H, L\}$. Proposition 5 predicts that agents put more weight on the signals emitted from political *experts* (e.g., community leaders) who are knowledgeable abut the responsiveness of district officials as compared to the average non-elite villager. This yields a simple testable implication: the marginal effect of a neighboring leader on adoption should be higher than that of an "ordinary" neighbor.[20] To test this proposition, we modify our main specification by disaggregating our core explanatory variable – the number of adopting neighbors – into two separate variables measuring the number

[20]Being a leader is a binary variable that equals 1 for respondents who self-reported that they occupy one of several formal leadership positions within the village.

	Dependent variable: adopt	
	Simple vs. complex ties	Types of relationships
	(1)	(2)
# adopting simple ties, β_s	0.024***	
	(0.005)	
# adopting simple family		0.015*
		(0.008)
# adopting simple friends		0.032***
		(0.011)
# adopting simple lender		0.018
		(0.011)
# adopting simple solver		0.010
		(0.010)
# adopting complex ties, β_c	0.039***	0.038***
	(0.010)	(0.010)
degree	0.001*	0.001*
	(0.001)	(0.001)
Constant	0.119	0.114
	(0.077)	(0.079)
$\beta_c - \beta_s \neq 0$, F statistic	2.21	—
Controls	✓	✓
Observations	3,019	3,019
R^2	0.248	0.254
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4: **Network types.** OLS estimates with village-level fixed effects. Heteroskedastic standard errors in parentheses. Model 1 reports the effect of one adopting neighbor with whom i shares a single type of relationship (simple tie) and more than one type of relationship (complex tie). Models 2 breaks down simple ties into family, friends, leader, and solver. Complex ties are weakly more influential than simple ties (F-test not significant). Friendship and family ties are the most influential simple ties.

of adopting *peers* and the number of adopting *leaders*, and estimate this model on the set of peers. Results, reported in Table 5 suggest that the probability of adoption is somewhat higher for connections to leaders as compared to peers, whether using the entire pooled sample (column 1), or subsetting to only high-uptake villages where networks support social diffusion (column 2). Note, however, that these differences are not statistically significant.

	Dependent variable: adopt		
	Leader: all	Leader: high	Leader: low
	(1)	(2)	(3)
# adopting peers, β_p	0.021^{***}	0.020^{**}	0.008
	(0.007)	(0.009)	(0.008)
# adopting leaders, β_l	0.032^{***}	0.029^{***}	0.012
	(0.008)	(0.010)	(0.008)
degree (peers)	0.003^{**}	0.004^{**}	0.003^{*}
	(0.001)	(0.002)	(0.002)
degree (leaders)	0.002	0.003	0.002
	(0.003)	(0.004)	(0.004)
Constant	0.094	0.076	0.152^{***}
	(0.081)	(0.085)	(0.047)
$\beta_p - \beta_l \neq 0$, F statistic	0.97	0.42	0.1
Controls	✓	✓	✓
Observations	2,585	1,202	1,383
R^2	0.233	0.251	0.180
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 5: **Leader vs. peer effects.** OLS estimates with village-level fixed effects. Heteroskedastic standard errors in parentheses. Models 1-3 are estimated on the sample of citizens for all villages (model 1), then separately for high and low-uptake villages (models 2 and 3). Leader and peer effects are significant on average and in high-uptake villages. Leaders' influence is weakly higher than peer's influence (F statistic not significant). Models 4: although not significant, leaders are less sensitive to peer influence.

What kind of communities support peer effects?

Our model suggests that networks that support peer effects do so because some (informal or formal) institutions manage to enforce truthful communication. While we are unable to identify what these institutions may be, we test three classes of explanations that past research has advanced as means to overcome collective action problems arising from externalities: (a) pro-sociality; (b) leadership structure, and especially leadership concentration; (c) and ethnic (and religious) homogeneity. In practice, we run separate models in which we regress our estimates of village-level peer effects (Figure 4) on a range of proxy variables:[21]

Pro-sociality: is measure as village mean contributions in two lab-in-field experiments: (a) *public good* game and (b) *dictator game*. While dictator games measure the extent to which nodes internalize the payoffs of other co-villagers, public goods game measure how villagers balance their private interests against the interests of their group. Both measures—which have been shown to be correlated with communities' outcomes outside the laboratory setting (Grossman and Baldassarri, 2012)—should support an equilibrium of truthful communication.[22]

Leadership structure: is proxied by *Leadership concentration*, calculated as a Herfindahl concentration index of ties to informal leaders in a village network.[23] Concentrated leadership allows coordinating communities around shared goals (Rojo, Jha and Wibbels, 2014), as well as coordinating punishment of (potential) defectors (Grossman and Baldassarri, 2012) in the face of externalities.

Homogeneity: is measured using Herfindahl concentration indices for both (a) *Ethnicity* and (b) *Religion* derived from the 2014 Ugandan census. Homogeneity helps overcoming externalities due to potential defectors' fear that information on their behavior would be transmitted widely (Habyarimana et al., 2009).

Figure 6 shows the effect of village-level features on the village-level peer effect.[24] Both measures

[21]See footnote 19 for details about estimation.

[22]A detailed description of the games can be found in the SI.

[23]Survey respondents were asked to report whom they considered to be the most effective leader in their community. We defined as an informal leader any such individual that was named by at least five respondents.

[24]Figure 3 in the SI shows scatter plots of the data used to construct this figure.

of pro-sociality have a large positive and significant association with peer effect. This finding is consistent with the idea that the more individuals care about the utility of their neighbors, the more likely it is that communication of information about new technology is accurate and truthful communication an equilibrium. In addition, we find evidence that leadership concentration supports truthful communication in the face of externalities. These findings are consistent with our theoretical framework.

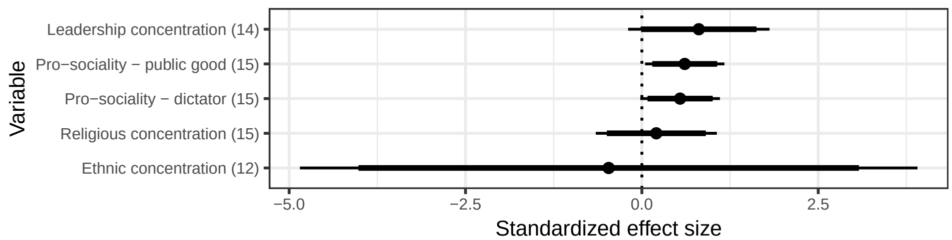

Figure 6: **Determinants of village-level peer effects**. Each row reports separate weighted least square estimates of village-level peer effect (figure 4) on the row covariate controlling for village satisfaction, weighted by inverse variance of the DV. Bars represent heteroskedastic 90 and 95 percent confidence intervals. Outliers with high leverage excluded (sample sizes in parenthesis).

8 Conclusion

What explains variation in the uptake of new political communication technologies? In this paper, we have shown that the adoption of political communication technologies—an increasingly common form of political participation—is powerfully influenced by peer effects. Across the sixteen Ugandan villages we studied, the likelihood of an individual adopting the new technology is a function of the number of her neighbors who had adopted the technology. This finding contributes to a growing body of work examining the determinants of uptake for PCT, looking beyond the role of individual attributes, neighborhood characteristics, and perceptions of government responsiveness to investigate the role of social networks in adoption choices. As such, it contributes to a literature that investigates the adoption of new technologies, particularly in the context of low income countries.

However, while we find robust evidence of peer effects on technology adoption in the aggregate, this finding masks variation in the role of peer effects across villages. Indeed, peer effects were only observed in a subset of villages, suggesting that diffusion processes of PCT may differ importantly from those of more commonly studied agricultural technologies. We develop a model motivated by the intuition that the information sharing process within a network may differ for goods that have minimal externalities, as in the case of a good like a fertilizer, or positive externalities, as in the case of PCT. The model serves to highlight differences in the diffusion process across these two types of technologies.

There are several features of political communication technologies that are relevant to understanding processes of diffusion. First, adoption of PCTs can involve personal risks and public benefits. Second, the newness of the technology means that there is uncertainty about the extent and natures of the costs and benefits of adoption. Third, there are externalities in adoption—the technology is only effective if a substantial number of people use it. These factors give us reason to believe that peer effects are likely to affect adoption, but also that early adopters have incentives to exaggerate the benefits of adoption. It then follows that individuals may discount the information they receive from initial adopters. When a community is able to enforce truthful communication—for example through informal institutions—the diffusion of innovations with externalities looks similar to the diffusion process of goods without externalities: individuals with larger networks learn faster and are more likely to adopt, and the adoption choices of network 'neighbors' are more correlated than the adoption choices of unconnected nodes. However, if a community is unable to enforce truthful communication, individuals do not learn from their neighbors and adoption rates of the new technology remain low.

Our study qualifies the long-standing argument that peer effects are ubiquitous in the process of technology adoption. We show that while peer effects do facilitate the adoption of goods where the benefit one derives from using the good does not depend on others' adoption, peer effects may not facilitate adoption for goods where production of benefits is joint. To understand whether and when peer effects will facilitate adoption we must assess both whether or not externalities exist as well as whether communities have mechanisms for enforcing truthful information about the costs and benefits of the good. The adoption of new forms of political participation follows a different trajectory than the adoption of many agricultural practices, because political participation is subject to externalities. This insight may go a long way in explaining low rates of adoption of PCTs, but also the considerable variation in rates of adoption we observe across communities.

We further find that when villagers enforce truthful information sharing, adoption rates are significantly higher as networks support a process of 'social contagion.' Our finding that peer effects, under certain conditions, supports technology diffusion is quite robust, and likely not simply a reflection of homophily. Specifically, our estimated peer effects are robust to various matching estimators, to flexibly controlling for the size of one's network (degree), and to an innovative instrumental variable approach for dealing with endogenous treatment exposure.

Though we are able to demonstrate that not all villages solve the problem of truthful communication, our sample size at the community level is too small to explore rigorously when and how villages overcome the incentive to misrepresent the state of the world to their neighbors. In addition, our model does not consider the case of significant negative externalities. We leave these important questions for future work.

References

Abrams, Samuel, Torben Iversen and David Soskice. 2011. "Informal social networks and rational voting." *British Journal of Political Science* 41(02):229–257.

Acemoglu, Daron, Asuman Ozdaglar and Ercan Yildiz. 2011. Diffusion of innovations in social networks. In *Decision and control and European control conference (CDC-ECC), 2011 50th IEEE conference on*. IEEE pp. 2329–2334.

Alatas, Vivi, Abhijit Banerjee, Arun G Chandrasekhar, Rema Hanna and Benjamin A Olken. 2016. "Network structure and the aggregation of information: Theory and evidence from Indonesia." *The American Economic Review* 106(7):1663–1704.

An, Weihua. 2016. "On the Directionality Test of Peer Effects in Social Networks." *Sociological Methods & Research* 45(4):635–650.

Anderson, Michael L. 2008. "Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects." *Journal of the American Statistical Association* 103(484):1481–1495.

Aral, Sinan, Lev Muchnik and Arun Sundararajan. 2009. "Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks." *Proceedings of the National Academy of Sciences* 106(51):21544–21549.

Aronow, Peter M and Cyrus Samii. n.d. "Estimating Average Causal Effects under General Interference, with Application to a Social Network Experiment." *Annals of Applied Statistics* .

Bala, Venkatesh and Sanjeev Goyal. 1998. "Learning from neighbours." *The review of economic studies* 65(3):595–621.

Bandiera, Oriana and Imran Rasul. 2006. "Social networks and technology adoption in northern Mozambique." *The Economic Journal* 116(514):869–902.

Banerjee, Abhijit, Arun G Chandrasekhar, Esther Duflo and Matthew O Jackson. 2013. "The Diffusion of Microfinance." *Science* 341(6144):1236498.

Blackwell, David et al. 1951. Comparison of Experiments. In *Proceedings of the second Berkeley symposium on mathematical statistics and probability*. The Regents of the University of California.

Blair, Graeme, Rebecca Littman and Elizabeth Levy Paluck. 2017. "Motivating the adoption of new community-minded behaviors: An empirical test in Nigeria." *Unpublished manuscript* .

Buntaine, Mark T, Daniel L Nielson and Jacob T Skaggs. 2017. "Escaping the Valley of Disengagement: Two Field Experiments on Motivating Citizens to Monitor Public Goods." *Unpublished manuscript* .

Centola, Damon. 2015. "The Social Origins of Networks and Diffusion." *American Journal of Sociology* 120(5):1295–1338.

Centola, Damon and Michael Macy. 2007. "Complex contagions and the weakness of long ties." *American journal of Sociology* 113(3):702–734.

Chaudhury, Nazmul, Jeffrey Hammer, Michael Kremer, Karthik Muralidharan and F Halsey Rogers. 2006. "Missing in action: teacher and health worker absence in developing countries." *The Journal of Economic Perspectives* 20(1):91–116.

Coleman, James Samuel, Elihu Katz, Herbert Menzel et al. 1966. *Medical innovation: A diffusion study*. Bobbs-Merrill Indianapolis.

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

Cranmer, Skyler J, Philip Leifeld, Scott D McClurg and Meredith Rolfe. 2017. "Navigating the range of statistical tools for inferential network analysis." *American Journal of Political Science* 61(1):237–251.

DeGroot, Morris H. 1974. "Reaching a consensus." *Journal of the American Statistical Association* 69(345):118–121.

Dupas, Pascaline. 2014. "Short-run subsidies and long-run adoption of new health products: Evidence from a field experiment." *Econometrica* 82(1):197–228.

Eubank, Nicholas, Guy Grossman, Melina Platas and Jonathan Rodden. 2017. "Social Networks, Word of Mouth, and Turnout in Low Salience Elections." *Unpublished manuscript* .

Feigenbaum, James and Andrew B Hall. 2016. "How High-Income Areas Receive More Service from Municipal Government: Evidence from City Administrative Data." *Unpublished manuscript* .

Foster, Andrew D and Mark R Rosenzweig. 1995. "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture." *Journal of political Economy* 103(6):1176–1209.

Galeotti, Andrea, Christian Ghiglino and Francesco Squintani. 2013. "Strategic information transmission networks." *Journal of Economic Theory* 148(5):1751–1769.

Gieczewski, Germán. 2017. "Lying by Omission: Verifiable Communication on Networks." *Unpublished manuscript* .

Golub, Benjamin and Evan D Sadler. 2017. Learning in social networks. In *The Oxford Handbook of the Economics of Networks*. Oxford Handbooks Online.

Grossman, Guy and Delia Baldassarri. 2012. "The impact of elections on cooperation: Evidence from a lab-in-the-field experiment in Uganda." *American Journal of Political Science* 56(4):964–985.

Grossman, Guy, Kristin Michelitch and Marta Santamaria. 2016. "Texting Complaints to Politicians Name Personalization and Politicians' Encouragement in Citizen Mobilization." *Comparative Political Studies* .

Grossman, Guy, Macartan Humphreys and Gabriella Sacramone-Lutz. 2014. ""I wld like u WMP to extend electricity 2 our village": On Information Technology and Interest Articulation." *American Political Science Review* 108(03):688–705.

Grossman, Guy, Macartan Humphreys and Gabriella Sacramone-Lutz. 2016. "Information technology and political engagement: Mixed evidence from Uganda." *Unpublished manuscript* .

Grossman, Guy, Melina Platas and Jonathan Rodden. 2017. "Crowdsourcing Accountability: ICT for Service Delivery." *Unpublished manuscript* .

Habyarimana, James, Macartan Humphreys, Daniel N Posner and Jeremy M Weinstein. 2009. *Coethnicity: diversity and the dilemmas of collective action*. New York: Russell Sage Foundation.

Hagenbach, Jeanne and Frédéric Koessler. 2010. "Strategic Communication Networks." *The Review of Economic Studies* 77(3):1072–1099.

Jackson, Matthew O. 2008. *Social and Economic Networks*. Princeton, NJ: Princeton University Press.

Jackson, Matthew O. and Leeat Yariv. 2010. Diffusion, Strategic Interaction, and Social Structure. In *Handbook of Social Economics*, ed. Jess Benhabib, Alberto Bisin and Matthew O. Jackson. Elsevier.

Jahan, Selim, E Jespersen, S Mukherjee, M Kovacevic, A Bonini, C Calderon, C Cazabat, YC Hsu, C Lengfelder, S Lucic et al. 2015. *Human Development Report 2015: Work for Human Development*. New York, NY: UNDP.

Klofstad, Casey A, Anand Edward Sokhey and Scott D McClurg. 2013. "Disagreeing about Disagreement: How Conflict in Social Networks affects Political Behavior." *American Journal of Political Science* 57(1):120–134.

Kolaczyk, Eric D. 2009. *Statistical Analysis of Network Data*. Springer.

Kosack, Stephen and Archon Fung. 2014. "Does Transparency Improve Governance?" *Annual Review of Political Science* 17:65–87.

Kremer, Michael and Edward Miguel. 2007. "The illusion of sustainability." *The Quarterly Journal of Economics* 122(3):1007–1065.

Larson, Jennifer M and Janet I Lewis. 2017. "Ethnic networks." *American Journal of Political Science* 61(2):350–364.

Larson, Jennifer M, Janet I Lewis and Pedro Rodrıguez. 2017. "From Chatter to Action: How Social Networks Inform and Motivate in Rural Uganda." *Unpublished manuscript* .

Lewis, Jeffrey B and Drew A Linzer. 2005. "Estimating regression models in which the dependent variable is based on estimates." *Political analysis* 13(4):345–364.

Miguel, Edward and Mary Kay Gugerty. 2005. "Ethnic diversity, social sanctions, and public goods in Kenya." *Journal of public Economics* 89(11):2325–2368.

Oster, Emily and Rebecca Thornton. 2012. "Determinants Of Technology Adoption: Peer Effects In Menstrual Cup Take-Up." *Journal of the European Economic Association* 10(6):1263–1293.

Peixoto, Tiago and Micah L Sifry, eds. 2017. *Civic Tech in the Global South: Assessing Technology for the Public Good*. The World Bank.

Pietryka, Matthew T and Donald A DeBats. 2017. "It's Not Just What You Have, but Who You Know: Networks, Social Proximity to Elites, and Voting in State and Local Elections." *American Political Science Review* 111(2):360–378.

Rogers, Everett M. 1962. *Diffusion of Innovations*. New York, NY: The Free Press.

Rojo, Guadalupe, Subhash Jha and Erik Wibbels. 2014. "Political Networks, Clientelism and Public Goods: Evidence from Slums in Udaipur, India." Working paper.

Rolfe, Meredith. 2012. *Voter turnout: A social theory of political participation*. Cambridge University Press.

Shalizi, Cosma Rohilla. 2018. *The Statistical Analysis of Complex Systems Models*. Cambridge University Press.

Siegel, David A. 2011. "Social networks in comparative perspective." *PS: Political Science & Politics* 44(01):51–54.

Sinclair, Betsy. 2012. *The social citizen: Peer networks and political behavior*. University of Chicago Press.

Sjoberg, Fredrik M, Jonathan Mellon and Tiago Peixoto. 2017. "The Effect of Bureaucratic Responsiveness on Citizen Participation." *Public Administration Review* .

Van der Windt, Peter and Macartan Humphreys. 2016. "Crowdseeding in Eastern Congo: Using cell phones to collect conflict events data in real time." *Journal of Conflict Resolution* 60(4):748–781.

Data Appendix

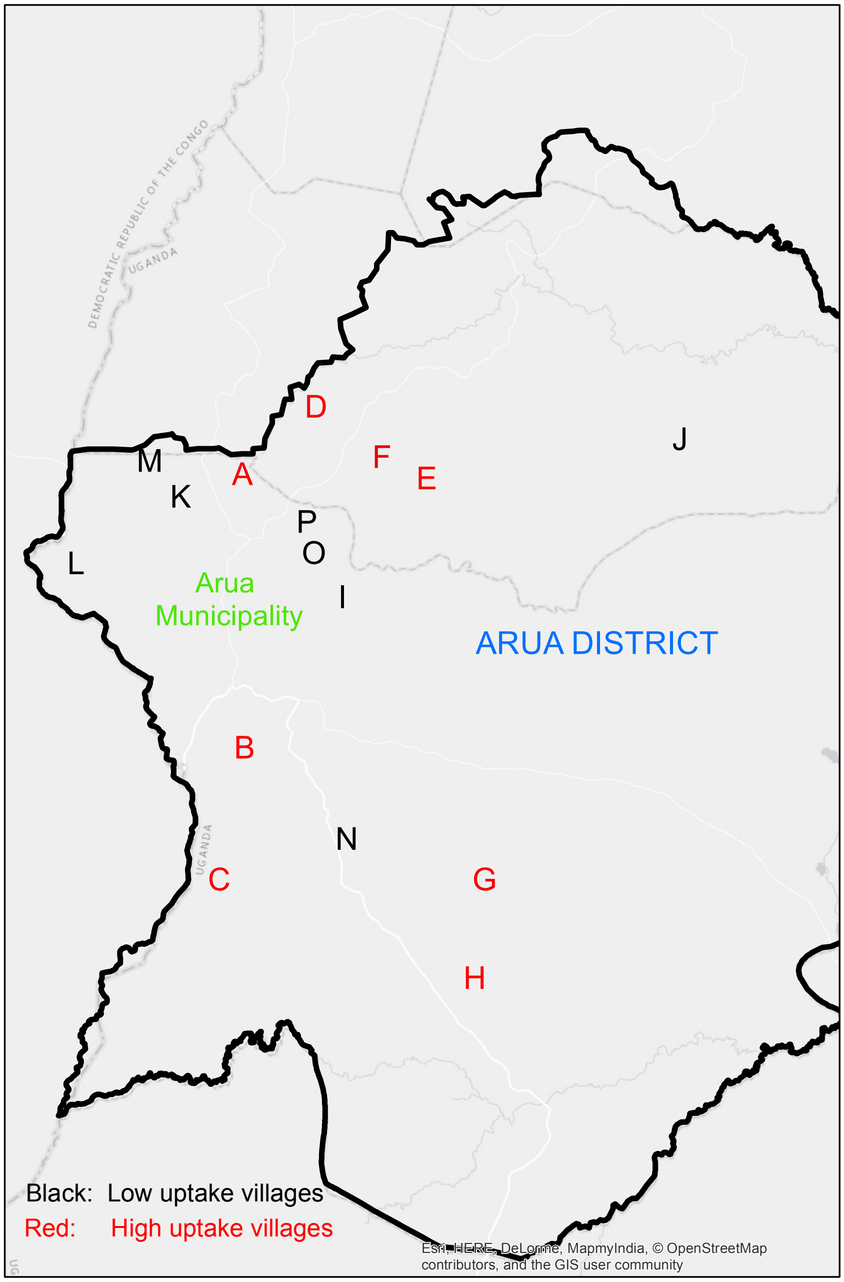

Figure A.1: High and low-uptake villages selected for complete network data collection

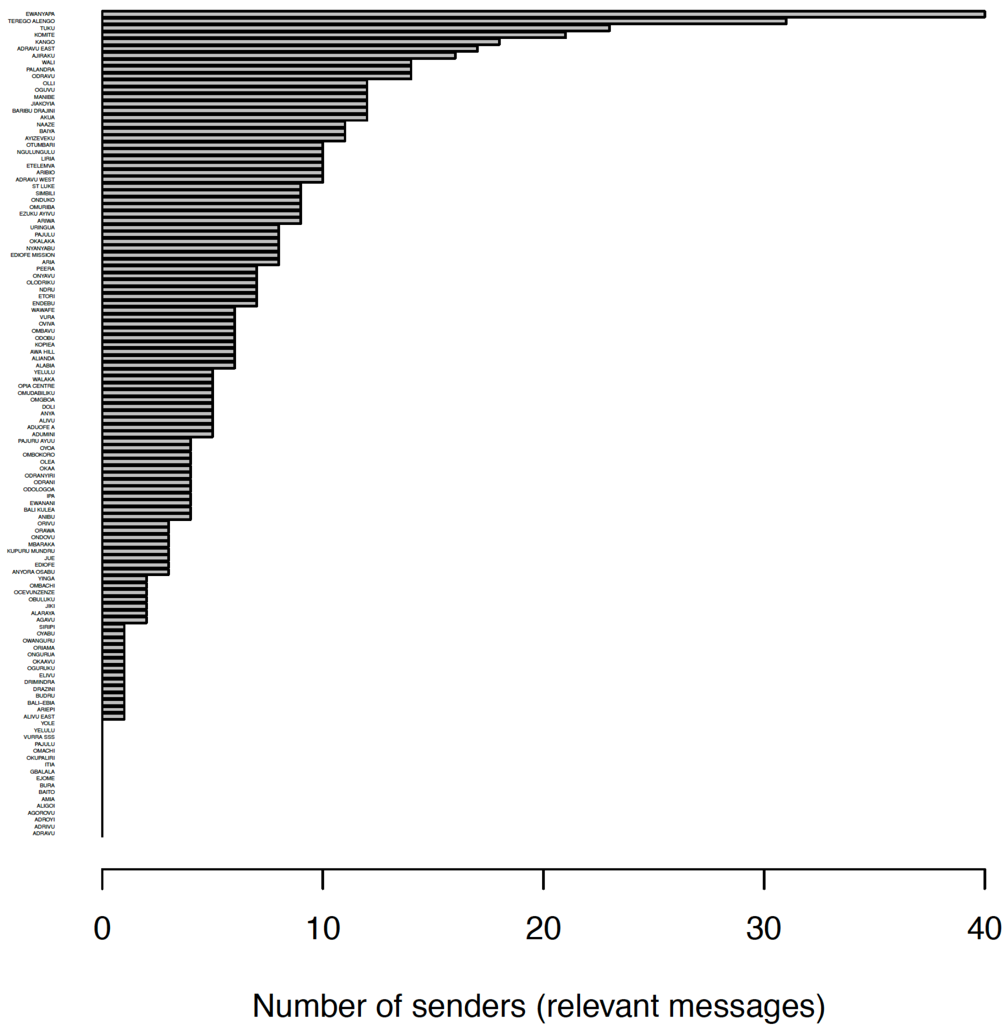

Figure A.2: Relevant message senders by village

Proofs

Proof of proposition 1. Consider a consistent strategy profile σ. I show that if σ is a perfect Bayesian equilibrium, then any agent i has a threshold strategy. Let $\hat{\pi}_i(S_{ig}) = \Pr(\theta = H|S_{ig})$ be i's posterior on the state. Using Baye's theorem,

$$\hat{\pi}_i(S_{ig}) = \frac{\Pr(S_{ig}|\theta = H)\pi_i}{\Pr(S_{ig}|\theta = H)\pi_i + \Pr(S_{ig}|\theta = L)(1-\pi_i)}$$

Sequential rationality implies that $y^*(S_{ig}) = 1 \iff \mathbb{E}_\theta[u_i(1,.,\theta)|S_{ig}] - \mathbb{E}_\theta[u_i(0,.,\theta)|S_{ig}] \geq 0$.

Consider first the case without externalities. In this case, $\mathbb{E}_\theta[u_i(1,\theta)|S_{ig}] - \mathbb{E}_\theta[u_i(0,\theta)|S_{ig}] =$

$\hat{\pi}_i(S_{ig})q_H(1) - c_i$. As such, the condition $\mathbb{E}_\theta[u_i(1,\theta)|S_{ig}] - \mathbb{E}_\theta[u_i(0,\theta)|S_{ig}] \geq 0$ is equivalent to the following condition on $\hat{\pi}_i(S_{ig})$:

$$\hat{\pi}_i(S_{ig}) \geq \frac{c_i}{q_H(1)} \tag{3}$$

Suppose that $\frac{c_i}{q_H(1)} < 1$. Then condition 3 is equivalent to $l(S_{ig}) \geq \log\left[\frac{\frac{c_i}{q_H(1)}}{1-\frac{c_i}{q_H(1)}}\frac{1-\pi_i}{\pi_i}\right] \equiv a_i$.

Suppose that $\frac{c_i}{q_H(1)} \geq 1$. Then condition 3 is equivalent to

$$\left(1 - \frac{c_i}{q_H(1)}\right) L(S_{ig}) \geq \frac{c_i}{q_H(1)} \frac{1-\pi_i}{\pi_i},$$

with $L(S_{ig}) = \frac{\Pr(S_{ig}|\theta=H)}{\Pr(S_{ig}|\theta=L)}$ the likelihood ratio. Since $L_i > 0$, condition 3 is never met, and we define $a_i \equiv \max_{S_{ig}\in\mathcal{I}_{ig}} l(S_{ig}) + 1$.

Consider now the case with externalities. In this case, we have:

$$\mathbb{E}_\theta[u_i(1,y_{-i},\theta)|S_{ig}] - \mathbb{E}_\theta[u_i(0,y_{-i},\theta)|S_{ig}] = \hat{\pi}_i\left[\mathbb{E}_\theta\left(q_H\left(1+\sum_{j\neq i} y_j\right)\middle| S_{ig}\right) - \mathbb{E}_\theta\left(q_H\left(\sum_{j\neq i} y_j\right)\middle| S_{ig}\right)\right] - c_i$$

Because q_H is strictly increasing, we have $\mathbb{E}_\theta\left(q_H\left(1+\sum_{j\neq i} y_j\right)|S_{ig}\right) > \mathbb{E}_\theta\left(q_H\left(\sum_{j\neq i} y_j\right)|S_{ig}\right)$. As such, the condition $\mathbb{E}_\theta[u_i(1,y_{-i},\theta)|S_{ig}] - \mathbb{E}_\theta[u_i(0,y_{-i},\theta)|S_{ig}] \geq 0$ is equivalent to the following condition on $\hat{\pi}_i$:

$$\hat{\pi}_i(S_ig) \geq t = \frac{c_i}{\mathbb{E}_\theta\left(q_H\left(1+\sum_{j\neq i} y_j\right)\middle| S_{ig}\right) - \mathbb{E}_\theta\left(q_H\left(\sum_{j\neq i} y_j\right)\middle| S_{ig}\right)}$$

The rest of the proposition proves as in the case without externalities, with the exception that we consider the cases where $t < 1$ and $t \geq 1$.

■

Proof of proposition 2. This is an immediate application of Blackwell et al. (1951) theorem. For any strategy profile to satisfy sequential rationality, agent j sends the message m_{ji} that maximizes her payoff. When indifferent, she may randomize. One may *garble* the conditional distribution of m_{ij} under truthful communication to recover the conditional distribution of m_{ji} under untruthful communication. Therefore, by Blackwell's information theorem, $\tilde{V}_{ig} \leq V_{ig}$. ■

Proof of proposition 3. Define $\varphi : \mathcal{I}_{ig'} \to \mathcal{I}_{ig}$ that associates to each $S_{ig'} \in \mathcal{I}_{ig'}$ the same $S_{ig'}$ without its last message, which is an element of $\mathcal{I}_{ig}$. Define $y^0_{ig'}(S_{ig'}) = y^*_{ig}(\varphi(S_{ig'}))$. Recall that $y^*_{ig'}$ solves $\max_{y_i} \mathbb{E}_\theta[u_i(y_i,.,\theta)|S_{ig'}]$. As such, it must be that $\mathbb{E}_\theta[u_i(y^*_{ig'}(S_{ig'}),.,\theta)|S_{ig'}] \geq \mathbb{E}_\theta[u_i(y^0_{ig'}(S_{ig'}),.,\theta)|S_{ig'}]$. This implies

$$V_{ig'} = \sum_{S_{ig'} \in \mathcal{I}_{ig'}} \mathbb{E}_\theta[u_i(y^*_{ig'}(S_{ig'}),.,\theta)|S_{ig'}] \geq \sum_{S_{ig'} \in \mathcal{I}_{ig'}} \mathbb{E}_\theta[u_i(y^0_{ig'}(S_{ig'}),.,\theta)|S_{ig'}] = V_{ig}$$

■

Proof of proposition 4. Recall that $\rho(x,y) = \frac{\mathrm{Cov}(x,y)}{\sqrt{\mathbb{V}(x)\mathbb{V}(y)}}$, with $\mathrm{Cov}(x,y) = \mathbb{E}(xy) - \mathbb{E}(x)\mathbb{E}(y)$ the covariance of x and y. Suppose i receives $n_i = |\mathcal{I}_i|$ signals on g. Analogously, j receives n_j signals. Note that i and j have $n_{ij} = |\mathcal{I}_i \cap \mathcal{I}_j|$ signals in common. On g', i and j each receive one additional signal: $\mathcal{I}'_i = \mathcal{I}_i \cup \{s_j\}$ and $\mathcal{I}'_j = \mathcal{I}_j \cup \{s_i\}$.

The proof first shows that the proposition holds given $\theta = H$. Note that

$$\log l_i(g) = \sum_{k \in N_i(g)} (2s_k - 1) \log \frac{p_k}{1-p_k}$$

$$\mathbb{E}[l(S_{ig})|H] = \sum_{k \in N_i(g)} (2p_k - 1) \log \frac{p_k}{1-p_k}$$

$$\mathbb{V}[l(S_{ig})|H] = \sum_{k \in N_i(g)} p_k(1-p_k) \left(2\log \frac{p_k}{1-p_k}\right)^2$$

$$\mathrm{Cov}[l(S_{ig}), l(S_{jg})|H] = p_k(1-p_k) \sum_{k \in N_i(g) \cap N_j(g)} \left(2\log \frac{p_k}{1-p_k}\right)^2$$

Let $\lambda_i = \left(2\log \frac{p_i}{1-p_i}\right)^2 p_i(1-p_i)$. We have

$$\mathbb{V}[l(S_{ig'})|H] = \mathbb{V}[l(S_{ig})|H] + \lambda_j$$

$$\mathrm{Cov}[l(S_{ig'}), l(S_{jg'})|H] = \mathrm{Cov}[l(S_{ig}), l(S_{jg})|H] + \lambda_i + \lambda_j$$

For notational simplicity, let

$$\mathbb{V}_i = \mathbb{V}[l(S_{ig})|H]$$

$$C = \mathrm{Cov}[l(S_{ig}), l(S_{jg})|H]$$

$$C' = \mathrm{Cov}[l(S_{ig'}), l(S_{jg'})|H]$$

These identities imply:

$$\begin{aligned}
C'-C &= \frac{C+\lambda_i+\lambda_j}{\sqrt{(\mathbb{V}_i+\lambda_j)(\mathbb{V}_j+\lambda_i)}} - \frac{C}{\sqrt{\mathbb{V}_i\mathbb{V}_j}} \\
&\propto (C+\lambda_i+\lambda_j)\sqrt{\mathbb{V}_i\mathbb{V}_j} - C\sqrt{(\mathbb{V}_i+\lambda_j)(\mathbb{V}_j+\lambda_i)} \\
&\propto (C+\lambda_i+\lambda_j)^2\mathbb{V}_i\mathbb{V}_j - C^2(\mathbb{V}_i+\lambda_j)(\mathbb{V}_j+\lambda_i) \\
&= C[\mathbb{V}_i\lambda_i(2\mathbb{V}_j-C)+\mathbb{V}_j\lambda_j(2\mathbb{V}_i-C)]+2\lambda_i\lambda_j[\mathbb{V}_i\mathbb{V}_j-C^2]+\mathbb{V}_i\mathbb{V}_j[\lambda_i^2+\lambda_j^2]
\end{aligned}$$

Note that $\mathbb{V}_i = \mathbb{V}_{i\setminus j}+C$, with $\mathbb{V}_{i\setminus j} = \sum_{k\in N_i(g)\setminus N_j(g)}\left(2\log\frac{p_k}{1-p_k}\right)^2 p_k(1-p_k)$. As such, we have $2\mathbb{V}_i - C \geq 0$, $2\mathbb{V}_j - C \geq 0$, and $\mathbb{V}_i\mathbb{V}_j - C^2 = \mathbb{V}_{i\setminus j}\mathbb{V}_{j\setminus i} + C[\mathbb{V}_{i\setminus j}+\mathbb{V}_{j\setminus i}] \geq 0$. Together, this shows that $C'-C \geq 0$.

Consider the case where $\theta = L$. We have $\mathbb{E}[l(S_{ig})|L] = \sum_{k\in N_i(g)}\log\frac{p_k}{1-p_k}[2(1-p_k)-1]$, which implies $\mathbb{V}[l(S_{ig})|L] = \mathbb{V}[l(S_{ig})|H]$ and $\text{Cov}[l(S_{ig}),l(S_{jg})|L] = \text{Cov}[l(S_{ig}),l(S_{jg})|H]$. We show as when $\theta = H$ that $\rho\left[l(S_{ig'}),l(S_{jg'})\middle| L\right] - \rho\left[l(S_{ig}),l(S_{jg})|L\right] \geq 0$. ■

Proof of proposition 5. Note that $\log l_i(g,s_j=H) - \log l_i(g,s_j=L) = \log\frac{p_j}{1-p_j}$. As such,

$$\frac{\partial \log l_i(g,s_j=H)-\log l_i(g,s_j=L)}{\partial p_j} = \frac{1-p_j}{p_j} > 0$$

■

Proof of proposition 6. Consider a strategy profile σ, and compare i's expected payoff at $t=1$ when sending a vector of messages m_i^n containing $n \geq 1$ lies, $EU_i(m_i^n,s_i)$ to that of telling no lies, $EU_i(m_i^0,s_i)$, after having observed her signal s_i. We have

$$EU_i(m_i^n,s_i) - EU_i(m_i^0,s_i) = -n\kappa$$

When $\kappa = 0$, i is indifferent between lying and telling the truth, so truthful communication is an equilibrium. When $\kappa > 0$, telling the truth strictly dominates lying, so truthful communication is the unique equilibrium. ■

Proof of proposition 7. Let $\hat{\pi}_i(s_i) = \Pr(\theta = H|s_i)$ be i's posterior on the state at $t=1$. Consider a consistent strategy profile σ, and compare i's expected payoff when sending a vector of messages m_i^n containing $n > 0$ lies, $EU_i(m_i^n,s_i)$ to that of telling no lies, $EU_i(m_i^0,s_i)$ after having observed her signal s_i. We have

$$EU_i(m_i^n, s_i) - EU_i(m_i^0, s_i) = \hat{\pi}_i(s_i)\Delta\mathbb{E}_\sigma - n\kappa,$$

with $\Delta\mathbb{E}_\sigma = \mathbb{E}\left[q_H(\sum_j y_j)|s_i, m_i^n\right] - \mathbb{E}\left[q_H(\sum_j y_j)|s_i, m_i^0\right]$ the difference in the expected reward between telling those n lies and telling no lies in profile σ.

Note that truthful communication is an equilibrium if and only if $EU_i(m_i^n) - EU_i(m_i^0) \leq 0$ for all i, which requires $\Delta\mathbb{E}_{\text{truthful}} \geq 0$. Under truthful communication, we have $\Delta\mathbb{E}_{\text{truthful}} \geq 0 \iff s_i = L$. Suppose this is true. Then for truthful communication to be an equilibrium, it must be that $\kappa \geq \frac{\hat{\pi}_i(s_i)\Delta\mathbb{E}_{\text{truthful}}}{n}$ for any i and any n lies. Let $M_{ig} = \{0,1\}^{|}N_i(g)|$ be the set of vectors of messages that i can send. Truthful communication is an equilibrium for any $\kappa \geq \bar{\kappa}_1 \equiv \max_{i \in N, m_i^n \in M_i, s_i \in \{H,L\}} \frac{\hat{\pi}_i(s_i)\Delta\mathbb{E}_{\text{truthful}}}{n}$.

Consider a strategy profile σ where there is some lying, with Σ the set of such profiles. This profile is not a PBE if $EU_i(m_i^n) - EU_i(m_i^0) < 0$ for all i and all $m_i^n \in M_i$. Define $\bar{\kappa}_\sigma \equiv \max_{i \in N, m_i^n \in M_i, s_i \in \{H,L\}} \frac{\hat{\pi}_i(s_i)\Delta\mathbb{E}}{n}$, and note that $\bar{\kappa}_\sigma \leq 1$. If the maximum exists, define $\bar{\kappa}_2 \equiv \max_{\sigma \in \Sigma} \bar{\kappa}_\sigma$. Otherwise, define $\kappa_2 \equiv 1$. ■

Table A.1: **Determinants of Uptake at the Village-level**

	Senders/adult pop			Messages/adult pop		
	(1)	(2)	(3)	(4)	(5)	(6)
GAPP activities						
Registration drive	2.357***	2.327***		10.296***	9.768***	
	(0.223)	(0.362)		(1.909)	(2.398)	
Community meeting venue	0.572	0.436	0.521	3.851	3.307	3.638
	(0.496)	(0.369)	(0.409)	(3.216)	(2.838)	(3.426)
Service points (binary)						
Primary school	0.306	0.465	0.410	1.269	1.661	1.622
	(0.336)	(0.295)	(0.433)	(2.321)	(2.119)	(3.309)
Health center	-0.622	-1.091**	-1.046*	-3.478	-6.095*	-6.243
	(0.365)	(0.428)	(0.556)	(2.417)	(3.058)	(3.975)
Distance to district capital		0.511***	0.538**		2.845***	3.126**
		(0.162)	(0.221)		(0.909)	(1.294)
Distance to Health Center		-0.384**	-0.093		-2.013	-0.869
		(0.176)	(0.197)		(1.272)	(1.213)
Census data						
ELF		0.751	0.583		2.027	0.954
		(0.644)	(0.502)		(3.378)	(3.208)
% Secondary education		0.726*	1.336***		3.861*	6.714***
		(0.408)	(0.275)		(1.949)	(1.920)
Village pop (log)		-0.778**	-1.122***		-2.892	-4.176**
		(0.354)	(0.289)		(1.883)	(1.765)
Constant	0.036	0.386	2.600***	-0.086	1.651	10.852***
	(0.213)	(0.294)	(0.246)	(1.123)	(1.404)	(2.282)
N	120	120	91	120	120	91
R^2	0.217	0.520	0.580	0.147	0.332	0.342
Sample	All villages	All villages	Registration villages	All villages	All villages	Registration villages

- Robust standard errors in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

Peer effects and externalities in technology adoption: Evidence from community reporting in Uganda

Supplementary Information

January 23, 2018

Contents

1 Glossary of network concepts **3**

2 Descriptive statistics **4**

3 Full regression models **6**

4 Robustness checks **10**
4.1 Exclude village A . . . 10
4.2 Two-stage selection model . . . 12
4.3 Instrumental variable . . . 14
4.4 Degree and other network characteristics . . . 18
4.5 Matching . . . 21

5 Heterogeneous effects by village **23**

6 Lab-in-the-field games **24**

List of Tables

1 Network sampling . . . 5
2 Main specifications, controls included . . . 7
3 Network types, controls included . . . 8
4 Leader vs. peer effects, controls included . . . 9
5 Main specifications, village A excluded . . . 11
6 Two-stage selection model . . . 13
7 Instrumental variable approach . . . 16
8 Instrumental variable approach, first stage . . . 17
9 Placebo tests for IV . . . 17
10 Flexible controls for degree . . . 19
11 Network covariates . . . 20
12 Matching estimates . . . 22

List of Figures

1 Degree distribution by network type . . . 4
2 Matching, balance diagnostics . . . 23
3 Determinants of village-level peer effect . . . 24

1 Glossary of network concepts

A network, often called a graph, is a collection of nodes and of ties between these nodes. We write the graph $g = (G,N)$, where N is the set of nodes, and G is the set of ties, and a tie is a pair $(i,j), i,j \in N$. Networks can also be represented by an $(N \times N)$ adjacency matrix m, where $m_{ij} = 1$ if there is a tie from i to j, and $m_{ij} = 0$ otherwise. The size of g is its amount of nodes.

A graph can be directed or undirected. In the former case, there is a distinction between a tie from i to j and a tie from j to i. That is, we do not require that m is symmetric. In the latter case, there is no distinction, and we require that m is symmetric. In what follows, we define the network concepts used in the paper in the case of an undirected network.

- Neighbor: j is a neighbor of i if they are connected; that is, if $(i,j) \in G$. The neighborhood of i is the set of i's neighbors.
- Degree: the degree d_i of i is the number of neighbors i has. That is, $d_i = \sum_{j \neq i} m_{ij}$.
- Isolate: i is an isolate if it has a degree of 0.
- Density: captures the amount of ties in g, relative to its size. A network of size n has $T_g = n(n-1)/2$ ties. Let $t_g = \sum_{i<j} m_{ij}$ be the amount of ties in g. The density of g is $D_g = t_g/T_g$.
- Clustering coefficient: the extent to which the friends of i are friends with each other. Formally, it is the amount of triangles in i's neighborhood normalized by the amount of triangles in i's neighborhood. It writes $c_i = \sum_j \sum_k m_{ij} m_{ik} m_{jk} / \sum_j \sum_k m_{ij} m_{ik}$, with $i \neq j, i \neq k, j < k$.
- Path: a path between i and j is a route from i to j on the graph g. Formally, it is a sequence of ties $(i_1,i_2),(i_2,i_3),...,(i_{K-1},i_K)$ such that $(i_k,i_{k+1}) \in G$ for each $k \in \{1,...,K-1\}$, with $i_1 = i, i_K = j$, and each node in the sequence $i_1,...,i_K$ is distinct.
- Connected graph: a graph is connected if there is a path between any $i,j \in N$
- Path length: the number of steps it takes to get from i to j on some path. Formally, the length of path $p = (i_1,i_2),(i_2,i_3),...,(i_{K-1},i_K)$ is $K-1$.
- Distance: the distance l_{ij} between i and j is the length of the shortest path between i and j.
- Closeness centrality: how close is node i from the rest of the graph? The closeness centrality of i is the mean distance between i and all other nodes of the graphs. It writes $L_i = \sum_{j \neq i} l_{ij}/(N-1)$. The concept is not well-defined when the graph g is not connected.
- Betweenness centrality: how much do people have to go through node i? Betweenness centrality is, for any $j,k \neq i$, the amount of shortest paths that go through i. The concept is not well-defined when the graph g is not connected.

2 Descriptive statistics

In this section, we discuss the construction of network ties (e.g., survey question verbatim; how we deal with missingness), and provide additional information on the distribution of ties across network types.

First, we provide verbatim excerpt from our in-person survey used to construct adjacency matrices capturing within-village network ties.

"In each of the following questions, we will ask you to think about people in your community and their relationships to you."

- **Family**: "Think about up to five family members in this village not living in your household with whom you most frequently spend time. For instance, you might visit one another, eat meals together, or attend events together."
- **Friends**: "Think about up to five of your best friends in this village. By friends I mean someone who will help you when you have a problem or who spends much of his or her free time with you. If there are less than five, that is okay too."
- **Lender**: "Think about up to five people in this village that you would ask to borrow a significant amount of money if you had a personal emergency."
- **Problem solver**: "Imagine there is a problem with public services in this village. For example, you might imagine that a teacher has not come to school for several days or that a borehole in your village needs to be repaired. Think about up to five people in this village whom you would be most likely to approach to help solve these kinds of problems."

Second, we report in Figure 1 the degree distribution across the four types of networks, as well as in the union network:

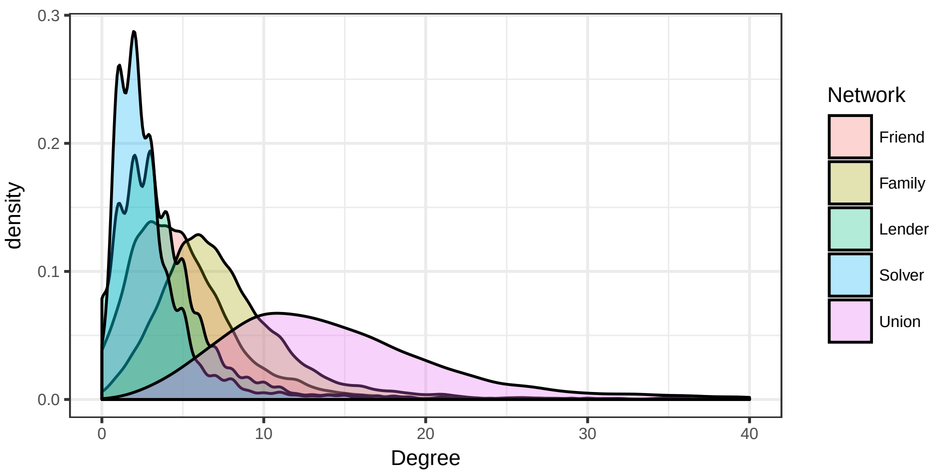

Figure 1: Degree distribution by network type.

Understandably, we were unable to interview every individual in the village. This means there are villagers for whom we only observe a fraction of their network: they were mentioned as ties by other respondents, but were not interviewed in-person. About 25% of named individuals fall in this category. Following standard practice, we exclude those nodes from the analysis. Table 1 reports the number of individuals we surveyed in each village, the number of individuals mentioned by at least one person ("alters"), and the number of adults living in each village, according to 2014 census data. This information allows calculating the number of missing nodes.

Village	N respondents	N alters	Adult population	Pct. non-interviewed alters	Pct. non-interviewed population
A	30	42	32	0.29	0.06
B	237	335	320	0.29	0.26
C	160	218	180	0.27	0.11
D	283	374	355	0.24	0.20
E	263	382	429	0.31	0.39
F	205	298	292	0.31	0.30
G	163	212	230	0.23	0.29
H	254	322	358	0.21	0.29
I	168	309	251	0.46	0.33
J	185	267	313	0.31	0.41
K	204	283	296	0.28	0.31
L	229	308	269	0.26	0.15
M	197	281	303	0.30	0.35
N	225	291	226	0.23	0.00
O	189	265	198	0.29	0.05
P	192	276	258	0.30	0.26
Total	3184	4463	4310	0.29	0.26

Table 1: **Network sampling.** N alters reports the number of individuals mentioned as alters in the network survey. Adult population from 2014 census data.

3 Full regression models

This section reproduces the regression models in the main text, including control variables.

	Dependent variable: adopt					
	Parsimonious	Baseline	Decomposition	Parsimonious	Baseline	Decomposition
	(1)	(2)	(3)	(4)	(5)	(6)
# adopting neighbors	0.035***	0.027***	0.019***			
	(0.005)	(0.005)	(0.006)			
% adopting neighbors				0.325***	0.218***	0.157***
				(0.052)	(0.048)	(0.057)
degree	0.002***	0.001*	0.0002	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# neighbors who told me			0.062***			
			(0.012)			
% neighbors who told me						0.871***
						(0.198)
1+ satisfied neighbors			0.012			0.024**
			(0.012)			(0.011)
age		−0.001***	−0.001***		−0.001***	−0.001***
		(0.0002)	(0.0002)		(0.0002)	(0.0002)
female		0.006	0.007		0.002	0.005
		(0.007)	(0.007)		(0.007)	(0.007)
income		−0.002	−0.002		−0.002	−0.002
		(0.003)	(0.003)		(0.003)	(0.003)
secondary education		0.072***	0.068***		0.078***	0.071***
		(0.012)	(0.012)		(0.012)	(0.012)
use phone		0.004	0.002		0.004	0.002
		(0.005)	(0.005)		(0.005)	(0.005)
leader		−0.008	−0.006		−0.007	−0.007
		(0.013)	(0.012)		(0.013)	(0.012)
political participation		0.025***	0.025***		0.027***	0.027***
		(0.008)	(0.008)		(0.008)	(0.008)
meeting attendance		0.178***	0.163***		0.187***	0.175***
		(0.026)	(0.026)		(0.027)	(0.026)
pro-sociality		−0.056***	−0.056***		−0.059***	−0.062***
		(0.018)	(0.017)		(0.018)	(0.017)
geography		−0.118***	−0.123***		−0.103***	−0.114***
		(0.023)	(0.022)		(0.023)	(0.023)
Constant	0.061	0.125*	0.124*	0.052	0.109	0.093
	(0.073)	(0.076)	(0.075)	(0.073)	(0.075)	(0.075)
Observations	3,184	3,019	3,019	3,184	3,019	3,019
R^2	0.139	0.247	0.273	0.116	0.233	0.251
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 2: **Main specifications, controls included.** This table reproduces Table **??** in the main text, and reports control variables.

	Dependent variable: adopt	
	Simple vs. complex ties	Types of relationships
	(1)	(2)
# adopting simple ties, β_s	0.024^{***}	
	(0.005)	
# adopting simple family		0.015^{*}
		(0.008)
# adopting simple friends		0.032^{***}
		(0.011)
# adopting simple lender		0.018
		(0.011)
# adopting simple solver		0.010
		(0.010)
# adopting complex ties, β_c	0.039^{***}	0.038^{***}
	(0.010)	(0.010)
degree	0.001^{*}	0.001^{*}
	(0.001)	(0.001)
age	-0.001^{***}	-0.001^{***}
	(0.0002)	(0.0002)
female	0.006	0.010
	(0.007)	(0.007)
income	−0.002	−0.002
	(0.003)	(0.003)
secondary education	0.072^{***}	0.071^{***}
	(0.012)	(0.012)
use phone	0.004	0.002
	(0.005)	(0.005)
leader	−0.009	−0.008
	(0.013)	(0.013)
political participation	0.025^{***}	0.026^{***}
	(0.008)	(0.008)
meeting attendance	0.177^{***}	0.173^{***}
	(0.026)	(0.026)
pro-sociality	-0.056^{***}	-0.054^{***}
	(0.018)	(0.018)
geography	-0.118^{***}	-0.116^{***}
	(0.023)	(0.023)
Constant	0.119	0.114
	(0.077)	(0.079)
$\beta_c - \beta_s \neq 0$, F statistic	2.21	—
Observations	3,019	3,019
R^2	0.248	0.254
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 3: **Network types, controls included.** This table reproduces Table **??** in the main text, and reports control variables.

	Dependent variable: adopt		
	Leader: all	Leader: high	Leader: low
	(1)	(2)	(3)
# adopting peers, β_p	0.021***	0.020**	0.008
	(0.007)	(0.009)	(0.008)
# adopting leaders, β_l	0.032***	0.029***	0.012
	(0.008)	(0.010)	(0.008)
degree (peers)	0.003**	0.004**	0.003*
	(0.001)	(0.002)	(0.002)
degree (leaders)	0.002	0.003	0.002
	(0.003)	(0.004)	(0.004)
age	−0.0005**	−0.001**	−0.0002
	(0.0002)	(0.0004)	(0.0003)
female	0.012*	0.007	0.014**
	(0.007)	(0.014)	(0.007)
income	−0.002	−0.002	−0.001
	(0.003)	(0.005)	(0.003)
secondary education	0.067***	0.089***	0.046***
	(0.012)	(0.020)	(0.014)
use phone	0.003	0.010	−0.001
	(0.005)	(0.009)	(0.005)
political participation	0.024***	0.029**	0.017**
	(0.008)	(0.015)	(0.007)
meeting attendance	0.184***	0.196***	0.153***
	(0.030)	(0.040)	(0.048)
pro-sociality	−0.060***	−0.106***	−0.024
	(0.018)	(0.035)	(0.018)
geography	−0.097***	−0.086***	−0.157***
	(0.023)	(0.026)	(0.041)
Constant	0.094	0.076	0.152***
	(0.081)	(0.085)	(0.047)
$\beta_p - \beta_l \neq 0$, F statistic	0.97	0.42	0.1
Observations	2,585	1,202	1,383
R^2	0.233	0.251	0.180
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4: **Leader vs. peer effects, controls included.** This table reproduces Table **??** in the main text, and reports control variables.

4 Robustness checks

4.1 Exclude village A

We first test whether our main results are sensitive to dropping village A, which has a significantly smaller number of respondents (30) compared to the other villages (mean number of respondents is 210). Table 5 shows that results are virtually unchanged. We find a strong positive relationship between the number (or share) of adopting neighbors and one's adoption choice, with magnitudes almost identical to the main specification.

	Dependent variable: adopt					
	Parsimonious	Baseline	Decomposition	Parsimonious	Baseline	Decomposition
	(1)	(2)	(3)	(4)	(5)	(6)
# adopting neighbors	0.036^{***}	0.028^{***}	0.021^{***}			
	(0.005)	(0.005)	(0.006)			
% adopting neighbors				0.342^{***}	0.235^{***}	0.173^{***}
				(0.052)	(0.048)	(0.057)
degree	0.002^{***}	0.001^{*}	0.0002	0.004^{***}	0.003^{***}	0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# neighbors who told me			0.062^{***}			
			(0.012)			
% neighbors who told me						0.870^{***}
						(0.199)
1+ satisfied neighbors			0.011			0.024^{**}
			(0.012)			(0.011)
age		-0.001^{***}	-0.001^{***}		-0.001^{***}	-0.001^{***}
		(0.0002)	(0.0002)		(0.0002)	(0.0002)
female		0.007	0.008		0.002	0.006
		(0.007)	(0.007)		(0.007)	(0.007)
income		−0.002	−0.002		−0.002	−0.002
		(0.003)	(0.003)		(0.003)	(0.003)
secondary education		0.072^{***}	0.068^{***}		0.078^{***}	0.071^{***}
		(0.012)	(0.012)		(0.012)	(0.012)
use phone		0.004	0.002		0.004	0.002
		(0.005)	(0.005)		(0.005)	(0.005)
leader		−0.008	−0.006		−0.007	−0.008
		(0.012)	(0.012)		(0.013)	(0.012)
political participation		0.025^{***}	0.025^{***}		0.027^{***}	0.027^{***}
		(0.008)	(0.008)		(0.008)	(0.008)
meeting attendance		0.174^{***}	0.159^{***}		0.183^{***}	0.171^{***}
		(0.026)	(0.026)		(0.027)	(0.026)
pro-sociality		-0.061^{***}	-0.061^{***}		-0.063^{***}	-0.067^{***}
		(0.018)	(0.017)		(0.018)	(0.017)
geography		-0.118^{***}	-0.123^{***}		-0.103^{***}	-0.114^{***}
		(0.023)	(0.022)		(0.023)	(0.022)
Constant	0.008	0.439^{***}	0.467^{***}	−0.008	0.379^{***}	0.414^{***}
	(0.018)	(0.087)	(0.083)	(0.017)	(0.087)	(0.084)
Observations	3,154	2,991	2,991	3,154	2,991	2,991
R^2	0.141	0.248	0.274	0.117	0.232	0.250
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 5: **Main specifications, village A excluded.** This table reproduces Table **??** in the main text but excludes village A from the sample.

4.2 Two-stage selection model

We probe into the mechanism underlying neighbors' influence. Do neighbors foster adoption by spreading news about the existence of the technology, or by pushing individuals who already know of the innovation to adopt it? We answer this question by estimating a type-2 Tobit model for binary outcomes (Cameron and Trivedi, 2005). This selection model separates the fact of having heard about the platform from the decision to adopt it. Our outcomes are:

$$y_{1i} = \begin{cases} 1, & \text{if } i \text{ hears about the platform} \\ 0, & \text{otherwise} \end{cases}$$

$$y_{2i} = \begin{cases} 1, & \text{if } i \text{ adopts the platform and } y_{1i} = 1 \\ 0, & \text{if } i \text{ does not adopt the platform and } y_{1i} = 1 \\ \_, & \text{if } y_{1i} = 0 \end{cases}$$

That is, deciding whether to adopt the platform (y_{2i}) is defined if and only if one heard about it ($y_{1i} = 1$). Let x_{1i} and x_{2i} be column vectors of individual-level predictors for hearing about the platform and adopting it, respectively. We consider the following binary type-2 Tobit model:

$$\underbrace{p(y_{2i}|x_{1i}, x_{2i})}_{\text{adopting}} = \underbrace{p(y_{2i}|x_{2i}, y_{1i})}_{\text{adopting conditional on hearing}} \underbrace{p(y_{1i}|x_{1i})}_{\text{hearing}} \tag{1}$$

We estimate the model using logistic regression, and account for village-level effects by adding village indicators. This model can easily be estimated using two logistic regressions: the first regresses y_1 on X_1 for the whole sample, and the second regresses y_2 on X_2 for those observations where $y_{1i} = 1$. In the first stage, we regress hearing about the technology on the number of hearing neighbors. In the second stage, we regress adopting the technology on the number of adopting neighbors. We use the same set of controls as in the main text, with the exception that we exclude meeting attendance from the first stage, because it perfectly predicts hearing about the platform. We also estimate a reduced-form specification identical to our baseline specification using logistic regression (Table **??**, model 2) to compare effect sizes in the second stage to a corresponding reduced-form specification.

Table 6 reports the results. Neighbors influence both hearing about the technology and adopting it. Controls reveal an additional interesting pattern: if females are less likely to adopt, it is only because they are less likely to hear about the technology, not because they are less likely to adopt it, conditional on having heard about it.

	Dependent variable:		
	heard	adopt	
	First stage	Second stage	Reduced form
	(1)	(2)	(3)
# adopting neighbors		0.339***	0.364***
		(0.096)	(0.091)
# hearing neighbors	0.150***		
	(0.021)		
degree	−0.001	0.005	0.008
	(0.008)	(0.008)	(0.008)
age	−0.014***	−0.027**	−0.030***
	(0.003)	(0.012)	(0.011)
female	−0.323***	−0.041	−0.211
	(0.098)	(0.303)	(0.289)
income	0.027	−0.084	−0.064
	(0.039)	(0.113)	(0.106)
secondary education	0.611***	1.386***	1.616***
	(0.112)	(0.281)	(0.282)
use phone	0.548***	1.296**	1.617***
	(0.111)	(0.530)	(0.536)
leader	0.190	−0.186	−0.110
	(0.138)	(0.348)	(0.361)
political participation	0.527***	0.733***	0.841***
	(0.092)	(0.217)	(0.205)
meeting attendance		1.112***	1.966***
		(0.263)	(0.266)
pro-sociality	−0.240	−1.060	−1.271*
	(0.237)	(0.691)	(0.663)
geography	0.097	−2.580***	−2.084***
	(0.208)	(0.636)	(0.544)
Constant	−1.518***	−1.829	−3.834***
	(0.547)	(1.373)	(1.292)
Observations	3,019	938	3,019
Akaike Inf. Crit.	3,000.939	570.499	664.305
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6: **Two-stage selection model.** Logistic regression estimates with village-level fixed effects. Coefficients are log-odds ratios. Heteroskedastic robust standard errors in parentheses. Model (1) reports the first stage (hearing about the platform), model (2) reports the second stage (adopting the platform conditional on hearing), and model (3) reports the corresponding reduced-form model.

4.3 Instrumental variable

As discussed in the main text, initial encouragements to adopt the technology might be endogenous. Patterns of social influence may be confounded by other effects: two peers may adopt the technology due to similar unobservable characteristics, or because they have been exposed to related unobservable shocks. We address this issue using a generalization of An (2016) instrumental variable (IV) approach. Consider the following linear model of adoption:

$$y = X\beta + \lambda My + \epsilon \tag{2}$$

with y a vector of outcomes of length N, with $y_i = 1$ if i adopts the platform, and 0 otherwise, X an $N \times K$ matrix of individual covariates, M an $N \times N$ adjacency matrix, with diagonal entries set to 0, and ϵ an error term. Formally, the problem is that the autoregressive term My is quite possibly correlated with the error term ϵ.

To address the issue of endogeneity, An (2016) recommends using an instrument z that is correlated with y, but not with ϵ. Using the two stages least squares (2SLS) procedure, we estimate the following models with OLS:

$$\begin{aligned} y &= X\beta_0 + \lambda_0 z + \epsilon_0 \\ y &= X\beta + \lambda z + \gamma M\hat{y} + \epsilon, \end{aligned}$$

with $\hat{y} = X\hat{\beta}_0 + \hat{\lambda}_0 z$.[1]

Our instrument is the distance from one's household to the location of the venue that GAPP used to hold its U-Bridge inception meeting. The idea is that the shorter the distance to the meeting venue, the more likely a villager is to adopt U-Bridge, simply by increasing the likelihood that she attends the meeting and learns about the new political communication technology. For the instrument to be valid, the exclusion restriction must be satisfied; i.e., we must assume that j's distance to the location of GAPP's inception meeting does not affect i's adoption via alternative channels than j's influence on i. This would be the case if contacts tended to cluster around locations that were more or less exposed to the meeting. Encouragingly, we find little (.15) correlation between physical distance and having a social tie. We also conduct several placebo tests to further explore potential violations of the exclusion restriction by conducting several placebo tests. If the exclusion restriction holds, mean peer distance from

[1] Let $\hat{\theta}_{2SLS} = (\hat{\beta}, \hat{\lambda}, \hat{\gamma})$, $H = (X, z, Wy)$, and $\hat{H} = (X, z, W\hat{y})$. The variance covariance matrix writes $\mathbb{V}(\hat{\theta}_{2SLS}) = \hat{\sigma}^2(\hat{H}^{\intercal}H)^{-1}$ with $\hat{\sigma}^2 = e^{\intercal}e/N$ and $e = y - H\hat{\theta}_{2SLS}$.

the meeting should affect one's adoption decision, but should not affect other theoretically meaningful predictors of adoption, such as political participation, leadership status, or phone ownership. Table 9 shows that this is indeed the case.

Note, furthermore, that our IV specification matches imperfectly our main specification (main text, Table **??**). In particular, we omit our geographic control and meeting attendance. Indeed, because the instrument is the random choice of a meeting location, these controls are post-treatment covariates in this approach, and should therefore be excluded from the model.

The results of our IV models, reported in Table 7, confirms our basic adoption model. Again, results suggest a better model for for absolute threshold model (column 1) as compared to the fractional model (column 2). F-tests suggest, however, that our instrument is rather weak, with F statistics below 10. Note, furthermore, that our IV estimates are larger than comparable OLS estimates. We believe that using distance to the meeting as an instrument magnifies the effect of meeting attendance, because it compounds the effect of all neighbors attending the meeting, which is a very important predictor of adoption. Furthermore, given that our instrument is weak, results should be interpreted with care.

	Dependent variable: adopt					
	Parsimonious IV	IV	OLS	Parsimonious IV	IV	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
# adopting neighbors	0.043***	0.045***	0.029***			
	(0.014)	(0.013)	(0.006)			
% adopting neighbors				0.107	0.106	0.149***
				(0.072)	(0.070)	(0.047)
degree	0.002**	0.001	0.002***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
distance to meeting (km)	−0.004	−0.008**	−0.007*	−0.005	−0.010**	−0.009**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
age		−0.001***	−0.001**		−0.001***	−0.001***
		(0.0002)	(0.0002)		(0.0002)	(0.0002)
female		−0.003	−0.007		−0.012	−0.012
		(0.008)	(0.008)		(0.008)	(0.008)
income		−0.001	−0.001		−0.001	−0.0005
		(0.003)	(0.003)		(0.003)	(0.003)
secondary education		0.094***	0.092***		0.103***	0.100***
		(0.014)	(0.014)		(0.014)	(0.014)
use phone		0.004	0.005		0.007	0.006
		(0.005)	(0.005)		(0.005)	(0.005)
leader		−0.001	−0.003		−0.002	−0.002
		(0.013)	(0.013)		(0.013)	(0.013)
political participation		0.030***	0.029***		0.033***	0.032***
		(0.009)	(0.009)		(0.009)	(0.009)
pro-sociality		−0.050**	−0.047**		−0.050**	−0.050**
		(0.020)	(0.020)		(0.020)	(0.020)
Constant	0.104	0.066	0.083	0.145*	0.106	0.092
	(0.084)	(0.084)	(0.085)	(0.085)	(0.085)	(0.086)
F statistic	1.28	5.92**	_	1.28	5.92**	_
Observations	2,832	2,832	2,832	2,832	2,832	2,832
R^2	0.103	0.174	0.182	0.092	0.160	0.164
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 7: **Instrumental variable estimates.** 2SLS estimates with village-level fixed effects (models 1, 2, 4, 5), and corresponding OLS estimates (models 3, 6). We report F-statistics for instrument strength. Although the instrument is weak, there is evidence of peer effects.

	Dependent variable: adopt	
	Parsimonious IV	IV
	(1)	(2)
distance to meeting (km)	−0.005	−0.011**
	(0.004)	(0.004)
degree	0.004***	0.003***
	(0.001)	(0.001)
age		−0.001***
		(0.0002)
female		−0.013*
		(0.008)
income		−0.001
		(0.003)
secondary education		0.105***
		(0.014)
use phone		0.007
		(0.005)
leader		−0.002
		(0.013)
political participation		0.034***
		(0.009)
pro-sociality		−0.050**
		(0.020)
Constant	0.169**	0.131
	(0.083)	(0.082)
Observations	2,832	2,832
R^2	0.092	0.160
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 8: **Instrumental variable approach, first stage.** OLS estimates of first stage of 2SLS models in table 7 with village-level fixed effects. The instrument is weak.

	Dependent variable:			
	adopt	pol. participation	leader	phone
	(1)	(2)	(3)	(4)
mean peer distance to meeting (km)	−0.021***	−0.015	−0.007	0.009
	(0.008)	(0.026)	(0.013)	(0.021)
age	0.0001	0.004***	0.006***	−0.004***
	(0.0002)	(0.001)	(0.0005)	(0.001)
female	−0.041***	−0.231***	−0.094***	−0.132***
	(0.008)	(0.022)	(0.013)	(0.018)
income	0.003	0.046***	0.016***	0.045***
	(0.003)	(0.009)	(0.005)	(0.007)
secondary education	0.122***	0.174***	0.002	0.270***
	(0.015)	(0.028)	(0.017)	(0.018)
pro-sociality	−0.058***	0.042	−0.016	0.032
	(0.021)	(0.058)	(0.032)	(0.043)
Constant	0.154*	−0.014	−0.089	0.784***
	(0.082)	(0.134)	(0.067)	(0.068)
Observations	2,832	2,832	2,832	2,832
R^2	0.105	0.123	0.099	0.167
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 9: **Placebo tests for IV.** OLS estimates with village-level fixed effects. Heteroskedastic standard errors in parentheses. Mean peer distance to meeting location affects adoption (model 1), but does not affect political participation (model 2), being a leader (model 3), or using a phone (model 4).

4.4 Degree and other network characteristics

As Aronow and Samii (n.d.) argue, exposure to peer influence is endogenous to one's network position. If the technology diffuses through patterns of social influence, then individuals with more central network positions are more likely to be exposed to such influence. In the limit, agents with no neighbors cannot be exposed to any influence, while agents with many neighbors are subjected to much influence.

To address this issue, we compare between individuals with similar network positions. Yet, network positions can only be described partially, using centrality scores that each capture different aspects of one's network position.

We reestimate our baseline specification but control very flexibly for one major centrality score: degree centrality. Table 10 reports the results from two specifications. One uses degree strata that split the population into degree deciles. The second controls from degree non-parametrically using generalized additive modelling, with thin-plate splines. Peer influence is robust to such controls.

Second, we reestimate our baseline by controlling for a host of standard centrality scores: degree, betweenness, closeness, eigenvector, Bonacich centralities, and clustering. Eigenvector and Bonacich centralities are recursive metrics where a node is more central to the extent that it is connected to more central node. Other concepts are defined in section 1 of this SI. We estimate one model per centrality score, and divide the population in three strata based on which tercile they belong to. Again, peer influence is robust to such controls.

	Dependent variable: adopt	
	OLS	*GAM (continuous)*
	degree strata	GAM
	(1)	(2)
# adopting neighbors	0.029***	0.027***
	(0.005)	(0.003)
degre $\in [8, 9]$	−0.001	
	(0.010)	
degree $= 10$	−0.006	
	(0.011)	
degre $\in [11, 12]$	−0.017*	
	(0.009)	
degree $= 13$	−0.021**	
	(0.010)	
degre $\in [14, 15]$	−0.013	
	(0.011)	
degre $\in [16, 17]$	−0.022**	
	(0.011)	
degre $\in [18, 20]$	−0.001	
	(0.014)	
degre $\in [21, 25]$	−0.006	
	(0.015)	
degree > 25	0.049**	
	(0.022)	
age	−0.001***	−0.001***
	(0.0002)	(0.0002)
female	0.008	0.008
	(0.007)	(0.007)
income	−0.002	−0.002
	(0.003)	(0.003)
secondary education	0.072***	0.073***
	(0.012)	(0.009)
use phone	0.003	0.002
	(0.005)	(0.007)
leader	−0.007	−0.008
	(0.013)	(0.010)
political participation	0.028***	0.027***
	(0.008)	(0.006)
meeting attendance	0.178***	0.177***
	(0.026)	(0.013)
pro-sociality	−0.057***	−0.058***
	(0.018)	(0.017)
geography	−0.120***	−0.113***
	(0.023)	(0.015)
Constant	0.140*	0.138***
	(0.076)	(0.041)
Observations	3,019	3,019
R^2	0.250	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 10: **Flexible controls for degree.** OLS estimates with village-level fixed effects. Heteroskedastic standard errors in parentheses. Model 1 controls for degree using degree strata based on sample deciles. Degree < 8 is the reference category. Model 2 uses a generalized additive model, and controls for degree using thin-plate regression splines. Peer influence is robust to such controls.

	Dependent variable: adopt					
	Degree	Betweenness	Closeness	Eigenvector	Bonacich	Clustering
	(1)	(2)	(3)	(4)	(5)	(6)
# adopting neighbors	0.032^{***}	0.033^{***}	0.034^{***}	0.032^{***}	0.032^{***}	0.032^{***}
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
medium degree	-0.013^{*}					
	(0.007)					
high degree	0.005					
	(0.009)					
medium betweenness		-0.017^{**}				
		(0.007)				
high betweenness		-0.003				
		(0.009)				
medium closeness			-0.003			
			(0.007)			
high closeness			-0.015			
			(0.010)			
medium eigenvector				-0.002		
				(0.007)		
high eigenvector				0.011		
				(0.009)		
medium bonacich					0.006	
					(0.008)	
high bonacich					0.001	
					(0.008)	
medium clustering						-0.021^{**}
						(0.009)
high clustering						-0.014^{*}
						(0.008)
Constant	0.127^{*}	0.126^{*}	0.131^{*}	0.117	0.121	0.141^{*}
	(0.076)	(0.076)	(0.076)	(0.076)	(0.077)	(0.077)
Observations	3,019	3,019	3,019	3,019	3,019	3,019
R^2	0.244	0.244	0.244	0.244	0.243	0.245
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 11: **Network covariates.** OLS estimates with village-level fixed effects. Heteroskedastic standard errors in parentheses. Network controls use tercile strata, with the lowest tercile as the reference category. Peer effects are robust to these network controls. Consistently with simple contagion, low clustering individuals adopt more. Controls not shown.

4.5 Matching

Following Aral, Muchnik and Sundararajan (2009), we use matching to address simultaneously the problems of endogenous initial encouragements to adopt the technology, and endogenous exposure to peer influence due to network position. Our matched sample matches both on individual and network characteristics. We selected individual characteristics that are substantially and theoretically meaningful predictors of uptake: phone ownership, secondary education, political participation, and meeting attendance. Our network characteristics are degree and eigenvector centrality. Matching alleviates bias by constructing a treatment and a control group that more are comparable on such observable characteristics. It has the additional benefit of constructing groups that are also presumably more comparable on other network characteristics, since centrality scores tend to be highly correlated.

Matching requires using a binary treatment. As in Aral, Muchnik and Sundararajan (2009), we make our treatment binary by defining cutoffs in the number of adopting neighbors above which we consider that an observation is treated. Specifically, we use cutoffs of one, two, and three neighbors. Having defined these cutoffs, we compared, for each cutoff, three different matching procedures: neighbor, coarsened exact, and full matching. We chose full matching because it is the procedure that achieved the highest distance reduction for all three cutoffs.

Figure 2 shows the results of our matching procedure for a cutoff of one neighbor. Our matched sample is balanced on degree, eigenvector centrality, and political participation. It is not balanced on the other characteristics.

We then reestimate our baseline specification on each matched sample. Table 12 shows that our results are largely robust to using a matched sample. The magnitude of the treatment effect increases with the strength of the treatment. While having at least one adopting neighbor does not significantly foster adoption, having at least two, and at least three adopting neighbors significantly fosters adoption.

	Dependent variable: adopt		
	Matched sample, $t = 1$	Matched sample, $t = 2$	Matched sample, $t = 3$
	(1)	(2)	(3)
# adopting neighbors $\geq t$	0.027^{*}	0.054^{***}	0.091^{***}
	(0.017)	(0.017)	(0.026)
degree	0.003^{***}	0.004^{**}	0.002
	(0.001)	(0.002)	(0.002)
age	-0.001^{***}	-0.001^{**}	-0.002^{*}
	(0.0003)	(0.001)	(0.001)
female	−0.004	0.003	0.002
	(0.008)	(0.013)	(0.018)
income	−0.005	−0.008	−0.015
	(0.003)	(0.008)	(0.010)
secondary education	0.081^{***}	0.091^{***}	0.093^{***}
	(0.014)	(0.026)	(0.031)
use phone	0.005	0.009	0.019
	(0.006)	(0.011)	(0.016)
leader	−0.010	−0.022	−0.030
	(0.018)	(0.041)	(0.041)
political participation	0.026^{**}	0.032	0.047^{**}
	(0.010)	(0.024)	(0.021)
meeting attendance	0.179^{***}	0.208^{***}	0.163^{***}
	(0.029)	(0.054)	(0.045)
pro-sociality	-0.084^{***}	-0.090^{**}	-0.121^{**}
	(0.024)	(0.043)	(0.061)
geography	-0.114^{***}	-0.156^{***}	-0.241^{***}
	(0.028)	(0.045)	(0.065)
Constant	0.277	0.187	0.498^{***}
	(0.170)	(0.123)	(0.190)
Observations	3,019	3,019	3,019
R^2	0.231	0.306	0.221
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 12: **Matching estimates.** OLS estimates with village-level fixed effects on a matched sample using full matching (see figure 2 for details on matching procedure). Heteroskedastic standard errors in parentheses. Additional robustness checks. Standard errors in parentheses. Treatment is an indicator variable that equals 1 if i has at least t adopting adopting neighbors. Peer influence is robust to using a matched sample.

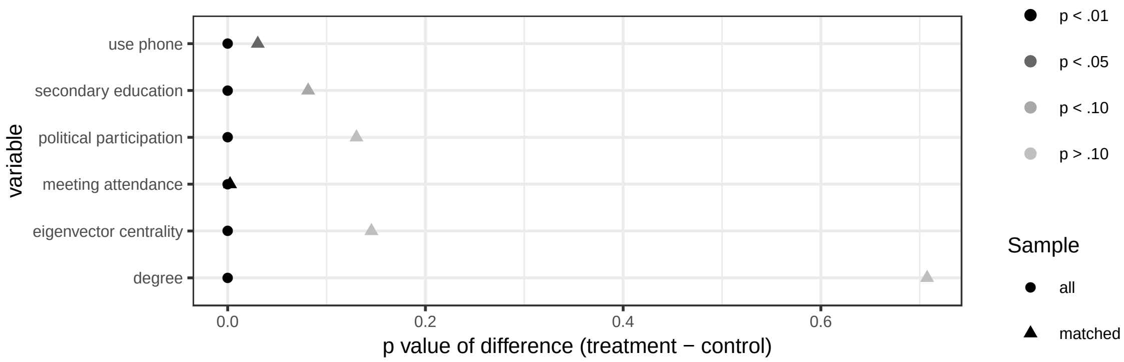

Figure 2: **Covariate balance on dimensions used for matching, $t = 1$.** We report the p-value of the difference in means in the treatment and control group in the full and matched sample, using full matching. Matching achieves balance in degree, eigenvector centrality, and political participation. It does not achieve balance in the remaining dimensions.

5 Heterogeneous effects by village

Figure 3 shows scatter plots of the data used to construct figure **??** in the main text.

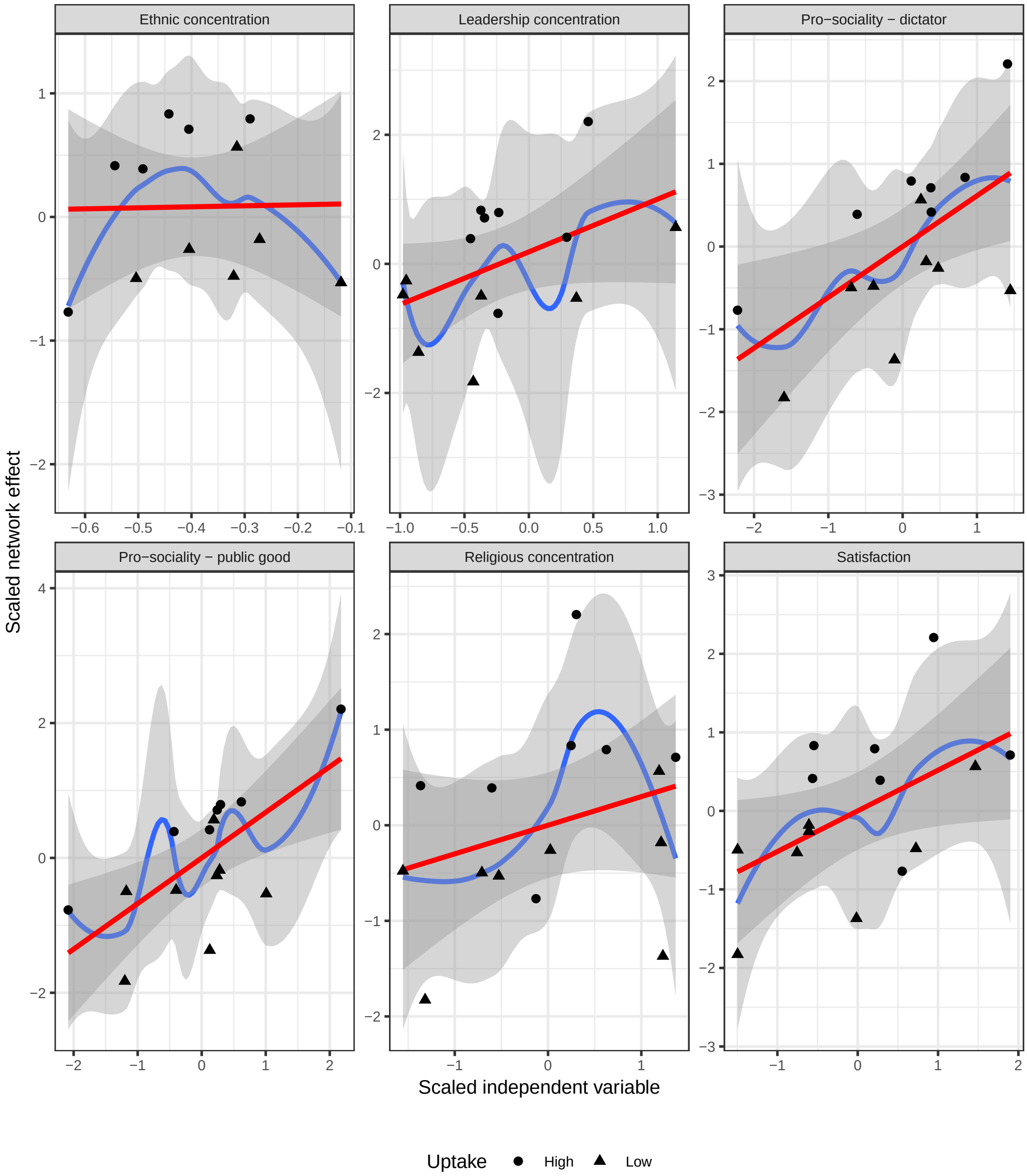

Figure 3: **Determinants of village-level peer effect.** Scatter plots of selected scaled village-level characteristics and village level peer effect. We report the linear trend line (red) and a loess fit (blue).

6 Lab-in-the-field games

Upon conclusion of the survey, each respondent was given 2,000 Ugandan Shillings (about 60 cents in US dollars), half of which was used for a dictator game, and half of which was used in a public goods game. While 60 cents may seem like a trivial amount of money, it is a meaningful about to respondents in this context, where GDP per capita is just over US$600, and where the district in question is among the poorest regions in the country, according to recent poverty estimates.

In the dictator game the respondent decides how to divide the money between herself and another player. In practice, this second player was an anonymous individual who resided in the same district, but not in the same village. The respondent keeps whatever she has decided to allocate to herself, and the remainder stays with the enumerator who then gives it to the second player. Both players are anonymous; the respondent does not know the name of the recipient and the recipient does not know the name of the respondent.

In the public goods game, respondents were asked to divide Ushs1000 between private and public accounts. The share of respondents' initial endowment that they placed in the private account remained theirs and what they donated to the public account was doubled by the research team and delivered to local leaders to invest in a community project. By construction, the most profitable outcome for the community occurs when all members contribute their entire endowment to the village project. However, the most profitable strategy for each individual is to keep the entire endowment and benefit from what everyone else contributes to the public account.

Herein, we average across experimental conditions, analyzing the effect of treatment assignment on contribution levels in a companion paper.

References

An, Weihua. 2016. “On the Directionality Test of Peer Effects in Social Networks.” Sociological Methods & Research 45(4):635–650.

Aral, Sinan, Lev Muchnik and Arun Sundararajan. 2009. “Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks.” Proceedings of the National Academy of Sciences 106(51):21544–21549.

Aronow, Peter M and Cyrus Samii. n.d. “Estimating Average Causal Effects under General Interference, with Application to a Social Network Experiment.” Annals of Applied Statistics .

Cameron, Adrian Colin and Pravin K. Trivedi. 2005. Microeconometrics - Methods and Applications. Cambridge University Press.