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 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 the British FixMyStreet platform (Sjoberg, Mellon and Peixoto, 2017) to text-messaging systems that rate public officials in Pakistan (Bhatti, Kusek and Verheijen, 2014), technology allows 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. However, these technologies are unlikely to affect governance if they are not widely adopted. Recent studies have demonstrated that adoption of these new technologies has been variable (Grossman, Humphreys and Sacramone-Lutz, 2016), and disappointing overall in the developing world (Peixoto and Sifry, 2017). What explains variation in the uptake of new political communication technologies? Why are adoption rates low despite their potential to transform governance?

While many factors might affect the adoption of new PCTs, this study focuses on the role of *social networks*. Past work on social diffusion explores how and why learning from peers facilitates the adoption of new technologies (Golub and Sadler, 2017). Potential adopters face uncertainty over the costs and benefits of adopting a new technology. Network ties are key because friends, family, and colleagues are often viewed as trustworthy sources of uncertainty-reducing information.

We study technology adoption in the context of Uganda, where a new mobile-based platform, U-Bridge, allows users to report service delivery problems to local government officials. Our first goal is to establish the significance of network peers in the adoption of PCTs in this context. Collecting complete social network data from more than 3000 individuals living in sixteen Ugandan villages where the new political communication technology was introduced,

we find evidence of peer effects on technology adoption decisions. A villager's decision to report a service delivery problem via U-Bridge is significantly affected by the adoption choices of her social ties (within the community's social network). Specifically, every additional neighbor (social tie) that uses U-Bridge increases the likelihood of individual's adoption by 2.7 percentage points. This result is robust, and we provide evidence suggesting it is likely causal; i.e., not simply a reflection of homophily or correlated shocks.

However, we also find variation in the extent of peer effects on U-Bridge adoption across villages. While there is strong evidence of peer effects in some villages, in others they are absent. Why do some social networks fail to support the adoption of a new PCT? In the second part of the paper, we introduce an original theory, formalized using a simple model, which demonstrates that whether or not networks support technology diffusion depends not simply on network structure, *but on the nature of the technology itself.*

The model shows that while networks foster the diffusion of technologies with minimal externalities—the focus of past work[1]—they may play no role for goods that have significant *positive externalities.* In the latter case, early adopters have incentives to exaggerate the benefits of adoption to encourage others to use the new technology. Recognizing this incentive, neighbors have reason to discount information they receive from early adopting peers. Not all social networks overcome this challenge of truthful communication, without which social diffusion does not take place. We suggest that peers help diffuse new technologies with large positive externalities only in networks where truthful communication is supported by local institutions. We test the observable implications of the theory using network, survey and behavioral experiments data, 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). Our study also contributes to a growing body of work on political

[1]For example, new technologies that increase agriculture productivity (Conley and Udry, 2010), health status (Kremer and Miguel, 2007), or access to financial services (Banerjee et al., 2013).

communication technologies. Existing work has examined the efficacy of these technologies in improving service delivery (Grossman, Platas and Rodden, 2018), political accountability (Grossman, Humphreys and Sacramone-Lutz, 2016), conflict data accuracy (Van der Windt and Humphreys, 2016), corruption reporting (Blair, Littman and Paluck, 2018), and participation in community-driven development projects (Buntaine, Daniels and Devlin, 2018). Recent work has also investigated determinants of PCT take-up, focusing on individual attributes (Grossman, Michelitch and Santamaria, 2016) and government responsiveness (Sjoberg, Mellon and Peixoto, 2017). We expand this work by focusing on the role social networks play in PCTs adoption.

Finally, we contribute to a literature exploring the effects of social networks on political behavior. Existing work focuses mostly on traditional forms of political engagement (Siegel, 2013; Rolfe, 2012; Sinclair, 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, 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 [e.g., 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 (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 join others [e.g., Larson and Lewis (2017)] in moving beyond a narrow focus on peer effects on political behavior in a small number of industrial democracies.

2 Context: U-Bridge in Uganda

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 Northwestern Uganda. Through U-Bridge, anyone can contact district officials by sending a text-message to a short-code number. Messages sent through the U-Bridge platform are both *free* and *anonymous*, lowering the cognitive, monetary and social costs for bottom-up reporting about service delivery problems. District officials in both technical and political positions were provided with tablets 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. Residents in treatment villages were invited to attend periodic community meetings in a central location within clusters of 4-5 neighboring villages. 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 cluster-level meetings was held in the last quarter of 2014 as part of the launch of the U-Bridge service. Subsequent meetings were held quarterly. The research team also conducted a door-to-door registration campaign.

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. Nevertheless, it is evident that most villagers—there are about 250 adults per village in the study area—have not used the platform. Since the effectiveness of PCT platforms hinges critically on grassroots participation, and since platform adoption reflects whose voices are heard, it is imperative to further explore the determinants of differential uptake for efficacy and equity reasons.

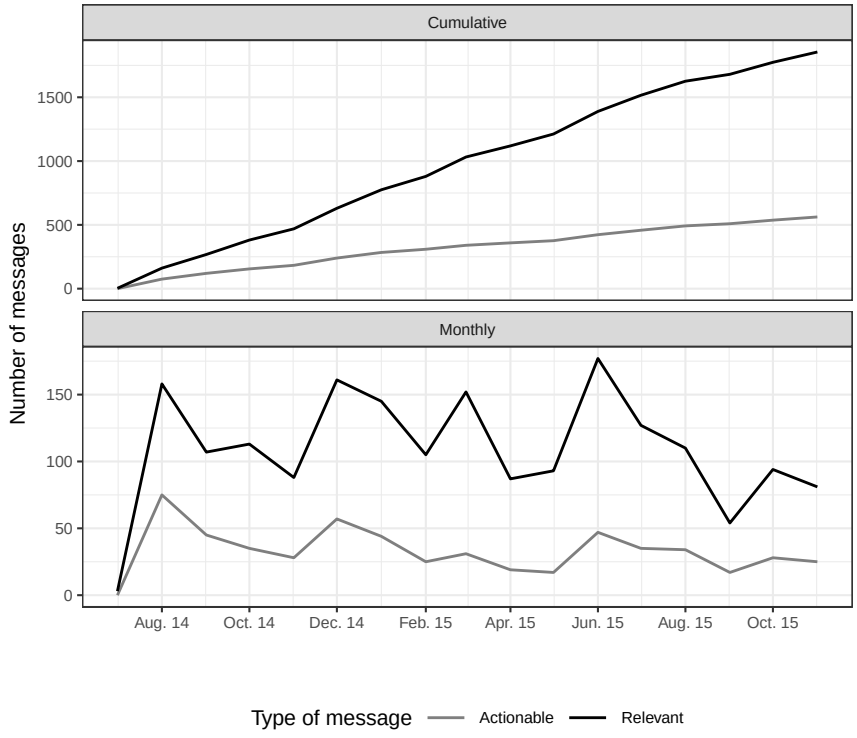

Figure 1: **Message intensity over time.** The monthly (bottom-panel) and cumulative (top-panel) number of relevant and actionable messages over time.

3 Research design

3.1 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 and half of which had low levels of adoption. These villages were selected because their adoption rates were higher or lower than would be expected given village-level factors. Specifically, we regress two measures of adoption—the number of unique message senders and the number of messages sent via U-Bridge (normalized by village adult population)—on village-level predictors, and generate predicted values for the dependent variable ($\hat{y}$). We calculate the difference between the predicted value and the actual value of the dependent variable, i.e. $\hat{\epsilon} = \hat{y} - y$, and using these residuals to select the 8 highest and 8 lowest performing (largest positive and negative $\hat{\epsilon}$; Supplementary Information (SI), Table 2).

3.2 Data Collection

Data collection took place in April and May, 2016. The survey, conducted with every available adult, 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.[2]

3.3 Network construction

We measure individuals' social networks using a standard name generator (Kolaczyk, 2009), for four kinds of relationships: (1) *family* ties, (2) *friendship* ties, (3) *lenders*: to whom they would go to borrow money, and (4) *problem solvers*: to whom they would go to solve a problem regarding public services in the village. For each relationship type, respondents named up to five co-villagers. 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 named by other respondents, but not interviewed. 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.

We first construct four different "undirected" village networks for the four different types of ties, by collapsing directed ties into undirected ones. 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 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 villages: one high uptake (village P), and one low uptake (village F).

[2]In the 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.

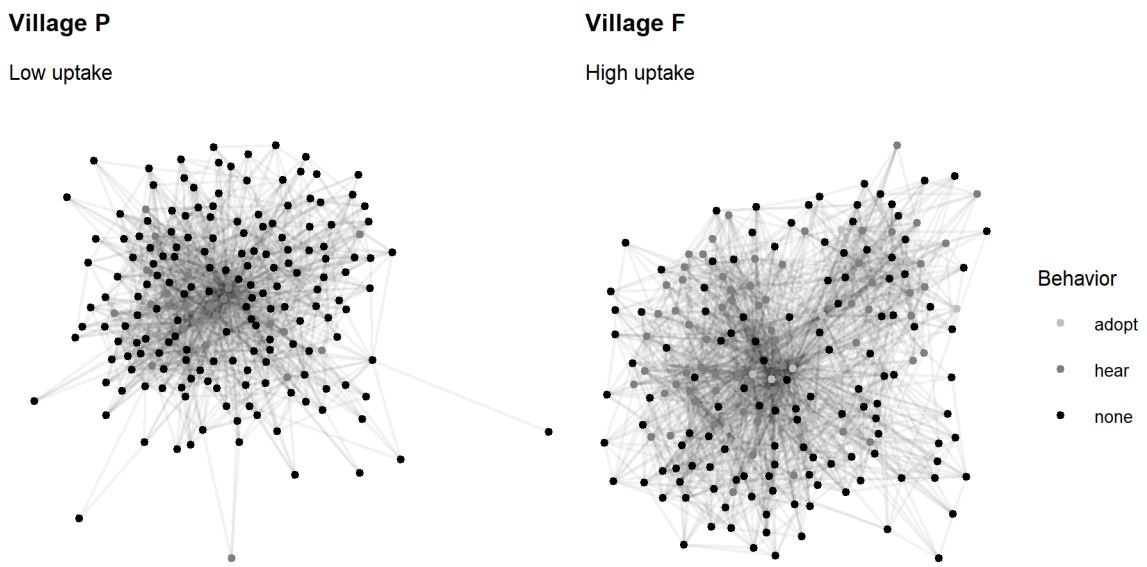

Figure 2: Graphical representation of the union network of two villages in the study area.

3.4 Variable description

Our core outcome measure is the adoption of U-Bridge. *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 binary variable that equals 1 if the respondent is at least somewhat satisfied with the platform.

Our key explanatory variables are network characteristics that support diffusion. 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 in the past 12 months. In some specifications, we

also consider the variable *# hearing neighbors* that counts instead the number of 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 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. The variable *geography* is a spatial lag that counts the number of adopters within the village besides node i, and assigns less weight to those who reside farther away from that node.[3]

We collect individual-level control variables that likely affect the usage of U-Bridge. These include: *age*; a *female* indicator; *secondary education*, 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. *Leader* is a binary variable that equals 1 if the respondent occupies a formal leadership position within the village. *Political participation* is a summary index aggregating across recent political actions. *Pro-sociality* is a behavioral proxy-measure of care for the community; it is measured as the amount contributed in a standard dictator game. Finally, *attend meeting* indicates whether the respondent attended the GAPP's community meetings, in which the U-Bridge platform has been introduced.

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 descriptive statistics for our 16 villages, split between high- and low-uptake.

[3]With $y_i \in \{0,1\}$ i's outcome and d_{ij} the distance between i and j, The spatial influence (*geography*) is $\text{geo}_i = \sum_{j \neq i} \frac{y_j}{\log d_{ij}}$.

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.** Table reports mean values for the full-sample, and 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.

3.5 Estimation

We estimate peer effects using a standard linear probability 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. Formally:

$$y_{ig} = \beta_{0g} + f(y_{N_i(g)})\beta_1 + x_i^T\beta_2 + \epsilon_{ig} \tag{1}$$

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. For ease of interpretation, we consider linear probability models estimated using OLS (unless otherwise noted). We use a conservative approach, accounting for village-level heterogeneity by using village fixed effects (β_{0g}). We use bootstrapped standard errors clustered at the village level with 1,000 replicates, because the number of clusters is small. In all estimation figures, we report both 95 and 90 percent confidence intervals using thin and thick bars, respectively.

4 Results: Peer effects

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.

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 – a 60 percent increase relative to the base adoption rate. 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%. Since the model fit for a absolute threshold contagion process (column 2) slightly outperforms modeling fractional threshold contagion (column 5), we use the absolute threshold model when calculating marginal effects (Figure 3).

	Dependent variable: adopt					
	Parsimonious	Baseline	Decomposition	Parsimonious	Baseline	Decomposition
	(1)	(2)	(3)	(4)	(5)	(6)
# adopting neighbors	0.035***	0.027***	0.019***			
	(0.006)	(0.005)	(0.005)			
% adopting neighbors				0.323***	0.218***	0.157***
				(0.075)	(0.063)	(0.056)
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***			
			(0.009)			
% neighbors who told me						0.871***
						(0.255)
1+ satisfied neighbors			0.012			0.024**
			(0.013)			(0.010)
Constant	0.071***	0.125***	0.124***	0.064***	0.109***	0.093***
	(0.009)	(0.034)	(0.027)	(0.017)	(0.038)	(0.032)
Controls	—	✓	✓	—	✓	✓
Observations	3,019	3,019	3,019	3,019	3,019	3,019
R^2	0.138	0.247	0.273	0.114	0.233	0.251
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 2: **Adoption of U-Bridge.** 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. See section 3.5 for details about estimation.

4.1 Robustness Checks

To ensure the robustness of our findings, we relax an assumption made in the above analysis or otherwise alter the modeling strategy. First, we fit logistic regressions instead of linear probability models (SI, Table 3). Second, we test whether our results are sensitive to dropping village A, which has a smaller number of respondents (30) as compared to other villages where the mean number of respondents is 210 (SI, Table 4). Third, we explore whether our main results are sensitive to using directed instead of undirected ties, which may capture a different notion of influence (SI, Table 5). Fourth, we explore whether our results are sensitive to the type of ties used to construct the network, and re-estimate our main specification using each of our four types of ties (SI, Table 6). In all cases, we find a strong positive relationship between the number (or share) of adopting neighbors and one's adoption choice.

Finally, one can only adopt a new technology if she has heard about it. Building on recent work by Larson, Lewis and Rodrıguez (2017), we run 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 7). 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) re-estimated using a logistic regression. These checks and their results, which strengthen our confidence in the robustness of our core peer effects finding, are described in greater detail in the SI, Section 4.

4.2 Causally identifying peer effects

As with all social diffusion studies, we face an empirical challenge of casually identifying peer effects. First, the initial encouragements to adopt the technology might be endogenous. Even in the absence of social learning, two connected individuals may exhibit similar behavior as a result of homophily (Jackson, 2008), or because they are subject to related (unobserved) shocks (Conley and Udry, 2010). Second, exposure to peer influence is endogenous to one's

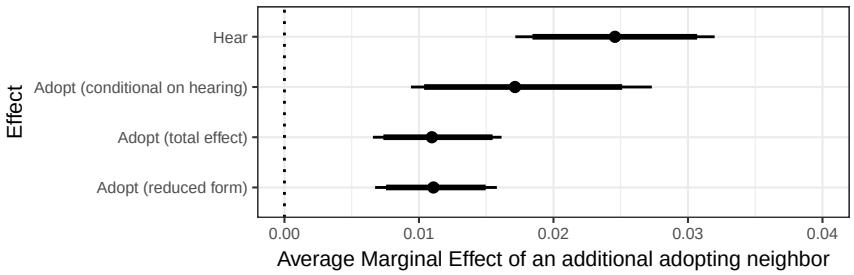

Figure 3: **Selection model with hearing.** Average marginal effect of an adopting neighbor on hearing (first stage) and of adopting conditional on hearing (second stage). The selection model's total effect matches the estimate from a reduced form logistic regression described in section 3.5.

network position. 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 social 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. Meetings covered 4-5 neighboring villages, and exact location choice depended on our partner NGO's ease of securing a venue large enough to hold a relatively big crowd on a specific day. Given this venue selection process, individual characteristics are poor predictors of distance to meeting location. We thus view residing closer to the meeting as 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, arguably because it increases 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 correlation (-.04)

between physical distance and having a social tie.[4] The results of our IV models, reported in SI, Table 9, 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. 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 11).

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 12). 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 recode the continuous centrality measures into three equally sized bins (low, medium and high), and run separate model for each centrality measure. While confirming our main result, this analysis also yields an insight that echoes previous findings: individuals in highly clustered neighborhoods are less likely to adopt (Centola and Macy, 2007).

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

[4]We also conduct placebo tests for potential violations of the exclusion restriction (SI, Table 10). While 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.

bias common in observational peer effects studies, we match villagers sharing similar individual and network 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 observables. We discuss our choice of matching covariates and matching procedure in the SI, Section 5.3, where we show that our main result on peer effects is robust to various matching estimates (SI, Table 13).

5 Village-level variation in peer effects

Thus far, we have focused on individuals' adoption choices, pooling data from sixteen villages. However, past work suggests that social influence depends not only on individuals' ties, but on the properties of the network. Indeed, Table 2 above and Figure A.1 (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 re-estimate our main specification (Table 2, column 2) to allow for heterogeneous peer effects among villages by using a Bayesian multilevel model with random intercepts and slopes (see SI, section 6 for additional details about estimation). With $n_{ig} = \sum_{j \in N_i(g)} y_j$ the number of adopting neighbors that i has in village g, the SAR model in equation 1 becomes:

$$y_{ig} = \beta_{0g} + \beta_{1g} n_{ig} + x_i^T \beta_2 + \epsilon_{ig}, \tag{2}$$

where β_{0g} and β_{1g} are, respectively, random intercepts and slopes.[5] Figure 4 shows the estimated random slopes in each village. In 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.

[5]This model and its extensions are estimated using a Bayesian multilevel model, as implemented in the `rstanarm` package.

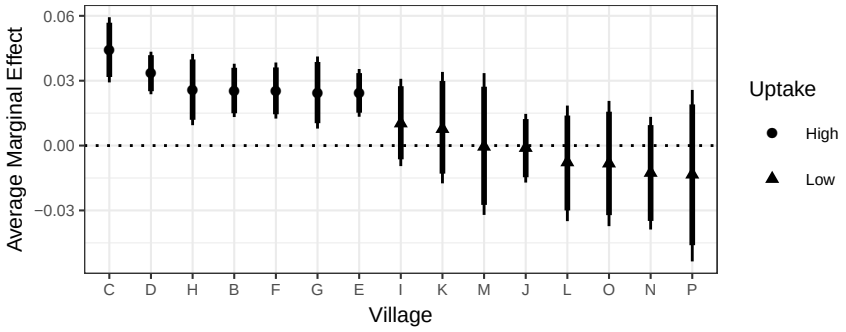

Figure 4: **Average marginal effect of one adopting neighbor on adoption by village.** Estimates from our main specification estimated using a multilevel model. High uptake villages have large, significant peer effects. Low uptake villages have small, statistically insignificant peer effects. Village A is omitted because its sample size is too small.

To reject more formally the null hypothesis that random slopes in high-uptake villages have the same mean as in low-uptake villages, we estimate the following multilevel model:

$$y_{ig} = \beta_{0g} + (\beta_{1g} + \gamma \text{high}_g) n_{ig} + x_i^T \beta_2 + \delta \text{high}_g + \epsilon_{ig}, \tag{3}$$

whereby $\text{high}_j = 1$ if village g is high-uptake and the null is $\gamma = 0$. On average, the marginal effect of an adopting neighbor on adoption decisions is 3.1 percentage points higher in high-uptake villages (SI Table 14, column 4; 95 percent CI: $[2.2, 4.0]$). What then explains variation in the magnitude of peer effects across villages? Moreover, why are peers not universally supporting a social diffusion process in the adoption of a new PCT?

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 diffusion processes are highly dependent of network properties—clustering, path length and bridge width. However, comparing core network-level properties (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.

	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
	% immigrants	0.63	0.60	0.68	-0.08	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	177	85	92		

Table 3: **Descriptive statistics meeting of attendees in the 16 villages sampled.** *p<0.1; **p<0.05; ***p<0.01.

In addition, we rule out two possible political economy explanations. First, villagers are more likely to contact their local government if they expect greater level of responsiveness (Sjoberg, Mellon and Peixoto, 2017). This could be the case, for example, if clientelistic exchange took place at the community-level (Rueda, 2015), and high-uptake villages voted for the incumbent district chairperson at greater rate. We show, instead, that vote share for the incumbent district chairperson was *lower* in high-uptake villages (SI, Table 21). Second, we rule out the possibility that greater uptake of the PCT platform at the village-level simply reflects greater demand to better public services. We show, in the SI Section 8 that there is no difference between high and low-uptake villages with respect to the stock of public goods (SI, Table 19), nor the quality of education services (SI, Table 20); a high-priority sector among message senders (SI, Figure 6).

To better account for the finding that neighbors influence technology adoption in some but not all communities, we develop a new theory. This theory is grounded in intuitions and assumptions gleaned from focus group discussions (FGDs) and interviews in the study area.

We use a simple model to formalize our argument and derive a set of observable implications which we then test using survey and network data.

6 Model: networks and (political) technology adoption

Our model of social networks and technology adoption builds upon a simple intuition: that the importance of peers in supporting social learning and facilitating technology adoption depends crucially on whether a new technology is subject to externalities.

6.1 Assumptions: Uncertainty over costs and benefits of adoption

As in all models of social diffusion, our starting point is that potential adopters of a new technology face uncertainty over costs and benefits. In our case, the major cost villagers reported was the possibility their identify as message-senders would be revealed. The potential benefit was improved service provision.

While villagers lauded U-Bridge's guarantee of anonymity, many were unsure if messages were truly anonymous. Some FGD participants cited a general distrust of claims made by both NGOs and the government; others simply stated that they had no way knowing whether they could be identified by sending messages through U-Bridge. Specifically, villagers expressed fear of retribution from the district government if their identities were known. One went so far as to say that if district officials were unhappy with the messages and the user's identity was known, that individual would "probably" be tortured. FGD participants further suggested social conflict would result if messages sent via U-Bridge could be traced back to them, frequently invoking the term "fear." One villager explained:

> *"If [our identities] are known, it would cause enmity between us since we are reporting mostly negative issues that might concern other people who have failed to do their jobs. [A lack of anonymity] would make us not send these messages."*

Potential users also faced uncertainty over U-Bridge's benefits, due to uncertainty regarding the ability and political will of government officials to address public service deficiencies reported via the platform. In surveys and focus groups two years after the project's launch, villagers varied in their assessments of government ability and effort. Some users said improvements in local public service provision increased their own sense of efficacy and inclination to use the platform. However, even high-frequency users admitted that it was not always possible to attribute positive changes to any specific complaint message.

Faced with uncertainty over costs and benefits, potential adopters turn to the experience of peers (Rogers, 1962). Agents with a 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.

Unlike private good technologies, political communication technologies produce substantial positive externalities– the benefits from adoption increase with the number of adopters. Many users we interviewed felt strongly that *collectively* sending messages was central to the program's success. Their rationale was that the more people that sent a message on a specific issue, the greater the likelihood that the issue would be addressed. One user explained:

> *"I expected the government would respond because they said responses would be given after collecting many messages. So, if many people send the same message, then the district leaders will take action."*

As briefly discussed in SI, Section 7, in the 2,000 substantive messages sent through U-Bridge, some users asked questions or offered opinions, and sometimes the information was vague or not actionable, but the vast majority of these messages concerned substantive service provision problems in identifiable issue areas. Very few were private requests (SI, Figure 6). In many cases, different users reported similar service failures at the same school or health center, often on the same day, suggesting that at least some users hoped their reports would have a cumulative effect.

If people believe that reporting involves positive externalities, peers may no longer facilitate a process of social diffusion. With positive externalities, early adopters who have come to believe in the usefulness of the program have greater incentive to convince others to adopt, and therefore are more likely to exaggerate its benefits. Indeed, many early adopters reported that they were active in trying to convince others in the community to use the platform, and we can see evidence of their efforts in the message data. Recognizing the incentive of these "true believers" to exaggerate benefits, neighbors may discount information they receive from early adopters.

Communities can address the problem of truthful communication by using a variety of 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 honest assessments of the program, and others are more likely to take those claims at face value. With truthful communication, goods with positive externalities display the same benefits as goods with no externalities. However, communities vary in their ability to enforce truthful communication. Some communities, perhaps due to pre-existing but largely unobservable informal institutions and norms, are able to enforce truthful communication while others are not. Thus, compared to goods without externalities, goods with externalities will exhibit greater variation in the extent to which networks facilitate adoption of new innovations. Moreover, the role of peer effects in adoption will be assuaged in communities where truthful communication is not enforced.

6.2 Formalization

Our model clarifies 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 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.

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. For a good with positive externalities, this may capture whether the government is responsive to or ignores incoming messages. 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. 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; $u_i = u_i(y_i, \theta)$. Specifically:

$$u_i(y_i, \theta) = q_\theta(y_i) - y_i c_i \tag{4}$$

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 positive 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:

$$u_i(y_i, y_{-i}, \theta) = q_\theta \left(y_i + \sum_{j \neq i} y_j \right) - y_i c_i \tag{5}$$

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.

6.3 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.

In equilibrium, agents have threshold strategies: they adopt the technology if they are sufficiently certain to be in the high state. Agent i chooses the action that maximizes her expected payoff, using 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. 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, 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 one's threshold a_i. Agents that have a higher cost of adoption or were originally too pessimistic about the state have higher thresholds. 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 communicate information that matches 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 (e.g. misrepresent benefits) about their signal with some probability. Intuitively, i's information is most valuable under truthful communication, because sharing inaccurate information introduces additional noise that make 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 key 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 (θ). In other words, the value of i's information increases with the size of her neighborhood:

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*

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

Second, because neighbors share their experiences, they learn from the same sources of information and make more similar inferences. Such peer effects 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*

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

Third, experts are more likely to observe correct signals.[6] 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 when making inferences about state θ. In the limit, the messages they receive are uninformative, and agents only use their own signal to derive posterior: $\mathcal{I}_i = \{s_i\}$. In such a case, propositions 3, 4 and 5 no longer hold: agents with larger neighborhoods do not learn faster, the posteriors of neighbors are not more correlated than those that are not connected, and expert neighbors do not wield more influence.

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

6.4 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 misrepresenting information. This may represent a moral cost of lying (Bénabou and Tirole, 2011), or 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. With $1\{.\}$ being an indicator function, payoff functions become:

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

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

Without externalities, agents have no incentive to misrepresent: doing so brings no benefits, and creates costs. In such cases, 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, increasing j's posterior, to encourage j to adopt. A high enough cost of misrepresenting information 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 model clarifies when social networks facilitate diffusion. For goods with no (or minimal) externalities, agents with larger neighborhoods learn faster, and outcomes of neighbors are more highly correlated because such technological innovations are compatible with truthful communication. However, for goods with positive externalities, truthful communication can break down, in which case social ties do not provide additional advantage. This, however, is not a forgone outcome. 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, which we test in turn:

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 exert a stronger peer effect than novices when a network supports diffusion, as their signal carries greater weight.

First, while we have shown variation in our core result on peer effects (Figure 4), a key implication of the model is that villages differ in the extent to which peer effects foster adoption above and beyond what can be explained by diffusion of information about the platform's existence. Specifically, the model emphasizes that differential effects owe to agents processing differently the information they obtain from their peers about the technology. We thus compare the magnitude of peer effects in hearing (to peer effects in adopting) across high- and low-uptake villages using the same multilevel model as for peer effects in adoption (equation 3). The effect of a peer on adopting is 3.1 percentage points higher in high-uptake villages than in low-uptake ones (95 percent CI: $[2.2, 4.1]$). By contrast, the effect of a peer

hearing is only 1.3 percentage point higher in high-uptake villages than in low-uptake ones (CI: $[.1, 2.7]$). See Figure 5 and SI, Table 14.

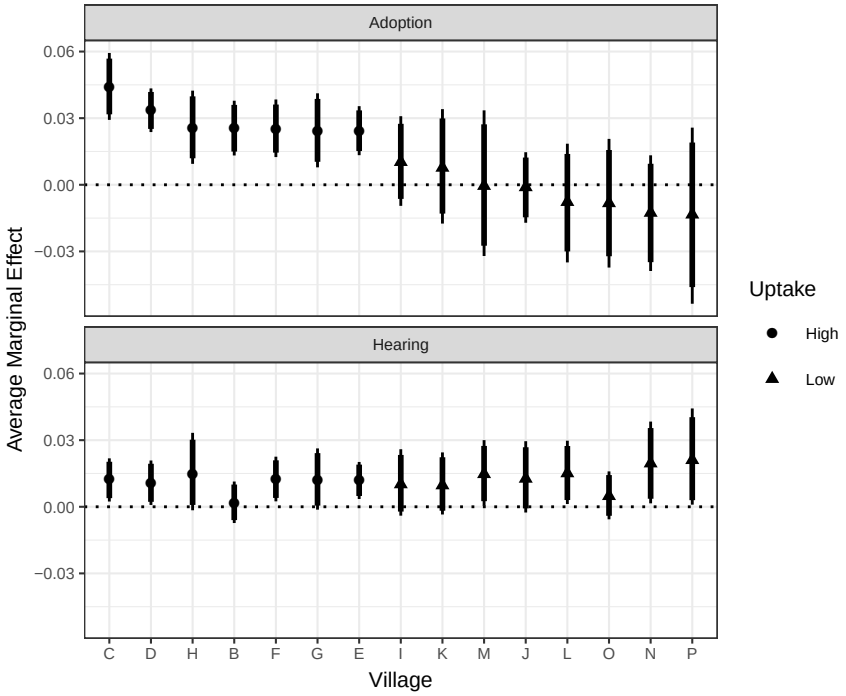

Figure 5: Comparing peer effects on adopting (top-panel) to peer effects on hearing (bottom) using a multilevel model (equation 3). See also SI, Table 14.

Second, we find evidence of *discounting* signals about the technology from peers. Our model suggests that for technologies with positive externalities, agents would not trust neighbors' messages, but only in villages that do not support diffusion. We test this by decomposing peer effects into three components: (1) whether i's neighbors (j) adopted the technology, (2) whether those neighbors js report discussing 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 6 confirms this 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.

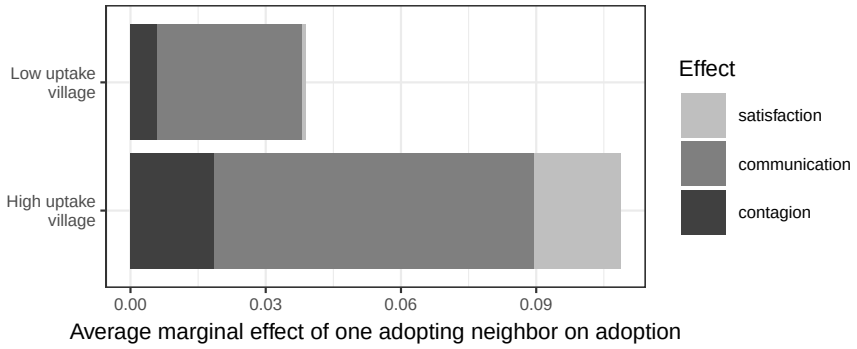

Figure 6: **Components of social influence in high and low uptake villages.** Marginal effect of one adopting neighbor (contagion) on the probability of adoption, with the additional effects of interpersonal communication with the neighbor (communication), and of that neighbor being satisfied (satisfaction). Communication fosters adoption, but high-uptake villages have much larger effect sizes. Satisfaction has almost no effect in low-uptake villages.

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 misrepresenting 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 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 (SI, Table 15, column 1). 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. To test this proposition, we modify our main specification by disaggregating our core explanatory variable—the number of adopting neighbors—

into two variables measuring the number of adopting *peers* and of adopting *leaders*, and estimate this model on the set of peers. Results, reported in SI, Table 16 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.

7.1 Informal institutions and peer effects

Our model suggests that for new technologies with positive externalities, peer effects support social diffusion when formal or informal institutions make it more likely that communication is truthful. While we cannot say with certainty which specific institutions these are, we test several alternatives derived from the extant literature. One possible institution is concentrated leadership, which improves communities' ability to coordinate around shared goals and to sanction (potential) defectors (Grossman and Baldassarri, 2012). These may, in turn, help communities enforce truthful communication in the face of positive externalities. Other theoretically-driven (potential) mediators we test include ethnic and religious homogeneity, and (mean) pro-sociality.

To explore the mediating role of concentrated leadership, we conducted a modified public goods game in all sixteen villages. Following conventional practice, villagers were given an opportunity to contribute to the village any share of their survey participation renumeration, and the research team matched those contributions. In our version of the public goods game, villagers were asked to name which individual they would like to handle funds on behalf of the village, regardless of whether that individual holds formal leadership position. We measure leadership concentration as a Herfindahl index based on these responses.

We rerun our multilevel specification allowing the coefficient on the number of adopting neighbor to be a function of not only the village-level random component b_{1g}, but also z_g

which is the village-level leadership concentration.

$$y_{ig} = \beta_{0g} + (\beta_{1g} + z_g^T \gamma) n_{ig} + x_i^T \beta_2 + \epsilon_{ig} \tag{6}$$

We find that leadership concentration is likely a mediator of the relationship between peer effects and adoption. The coefficient on the interaction is 0.083 [95% CI: 0.029 - 0.135], suggesting that the more concentrated leadership is, the stronger peer effects are (SI, Table 17).[7] This finding is consistent with the idea that leadership concentration supports truthful communication in the face of externalities.

We do not find support for the the other alternative mediators (SI, Table 18). First, we examine ethnic and religious homogeneity, measured by Herfindahl indexes calculated from the 2014 Census. Ethnic homogeneity does not mediate the effect of peers, but do find that peer effects are somewhat larger in villages that are more religiously homogeneous. Next, we examine pro-sociality, measured as village-level mean contributions to dictator and public goods games. Here again, the interaction effect is significant. As one might expect, peer effects are significantly larger in villages with higher levels of pro-sociality. However, unlike leadership concentration, high-uptake villages do not have higher values of religious homogeneity nor pro-sociality as compared to low-uptake villages (SI, Figure 4). As such, these mediators do not help explain the pronounced cross-village variation in the strength of peer effects. Since we have only sixteen villages, these results, while interesting and consistent with our theoretical framework, should be viewed primarily as an invitation for further research.

[7] Our findings are robust to different definitions of leadership concentration; i.e., whether a villager is deemed a leader if named by at least one, two, three or four respondents.

8 Conclusion

What explains variation in the uptake of new political communication technologies? 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.

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. Peer effects were only observed in a subset of villages, suggesting that diffusion processes of PCT may differ from those of more commonly studied innovations, such as agricultural and financial products. We develop a model motivated by the intuition that the information sharing process within a network may differ for goods that have substantial positive externalities compared to those with minimal externalities. The model highlights differences in the diffusion process across these two types of technologies.

Our study qualifies the long-standing argument that peer effects are ubiquitous in the process of technology adoption. 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.

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Appendix

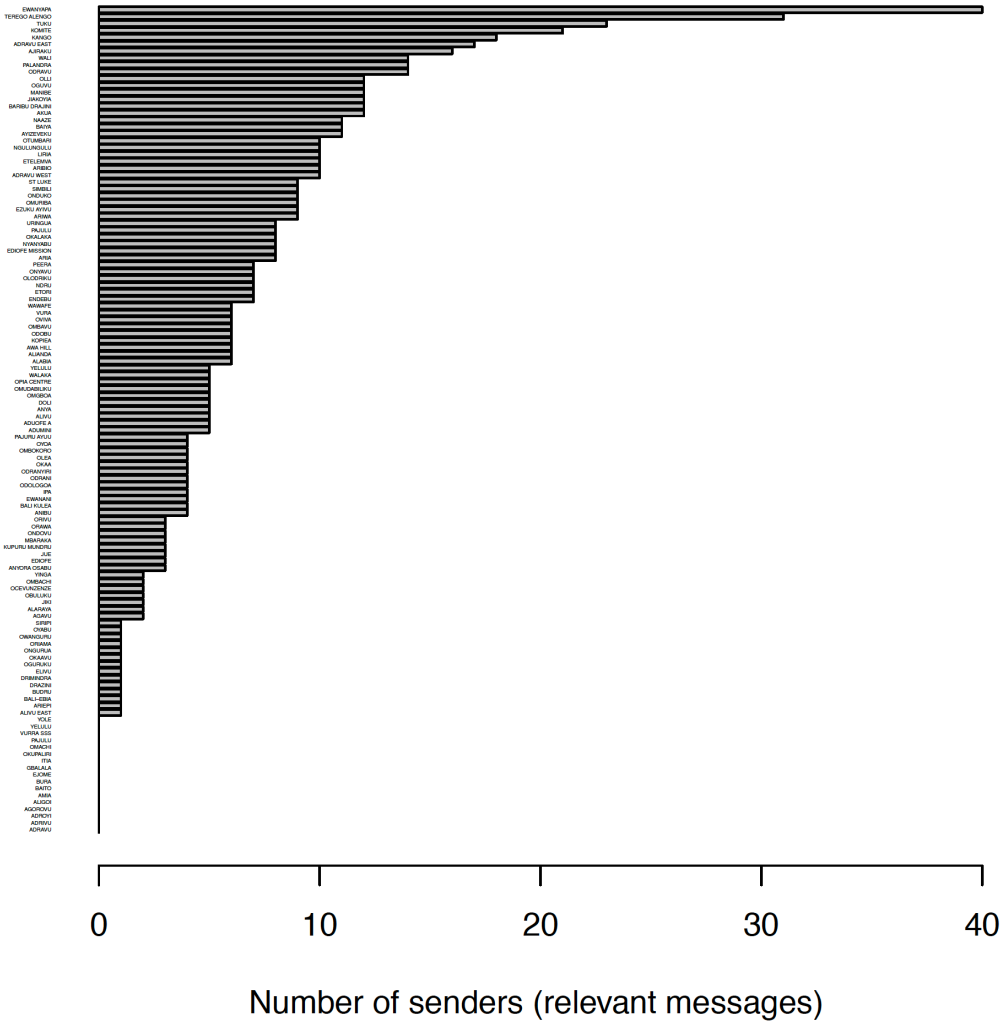

Figure A.1: Relevant message senders by village