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Gossip: Identifying Central Individuals in a Social Network

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GOSSIP: IDENTIFYING CENTRAL INDIVIDUALS IN A SOCIAL NETWORK

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ABSTRACT. Is it possible, simply by asking a few members of a community, to identify individuals who are best placed to diffuse information? A model of diffusion shows how members of a community can, just by tracking gossip about others, identify those who are most central in a network according to "*diffusion centrality*" – a network centrality measure that predicts the diffusion of a piece of information seeded with a network member. Using rich network data from 33 Indian villages, we find that villagers accurately nominate those who are diffusion central – not just those with many friends or in powerful positions. Via a randomized field experiment design to test this theory, in 212 villages we track the diffusion of a piece of information initially given to a small number of "seeds" in each community. Relative to random seeds, seeds nominated by villagers as good "gossips" lead to a 66% increase in the spread of information (from a low basis). The success of the nominees is partly, but not entirely, accounted for by their diffusion centrality.

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1. Introduction

"The secret of my influence has always been that it remained secret."
– Salvador Dalí

For anyone who seeks to affect a community's choices, it is essential to know who is influential, or central, in that community. Research in a wide variety of contexts has shown that the extent to which a piece of information diffuses among a population often depends on how central the initially informed are within the network.[1] Policymakers, businesses, and other organizations can thus benefit from targeting the right individuals for spreading valuable information.

Learning who is central in a social network, however, can often be difficult. Collecting detailed network data is costly, and easy "fixes" – such as targeting traditional leaders or geographically central households – can fail to identify people who are central.[2] Even for members of the community, knowledge of the network structure beyond their immediate friends is far from automatic. In fact, individuals within a network tend to have little perspective on its structure, as found in important early research by Friedkin (1983) and Krackhardt (1987), among others.[3] Can it be, then, that despite not knowing the structure of the network in which they are embedded, people can know who is central and well-placed to diffuse information through the network? And, if so, how might they come to know who is central without knowing the network? In this paper, through both theoretical and empirical approaches, we find positive answers to both of these questions.

First, we develop a model, enriching a simple model from our previous work (Banerjee, Chandrasekhar, Duflo, and Jackson, 2013), to show that individuals in a network should be able to identify central individuals within their community even *without knowing anything about the structure of the network*. We model a process that we call "gossip," in which nodes generate pieces of information that are stochastically passed from neighbor to neighbor, along with the identity of the node from which the information emanated. We assume only that individuals who hear the gossip are able to keep count of the number of times that each person in the network is mentioned as a

[1]See Katz and Lazarsfeld (1955); Rogers (1995); Kempe, Kleinberg, and Tardos (2003, 2005); Borgatti (2005); Ballester, Calvó-Armengol, and Zenou (2006); Banerjee, Chandrasekhar, Duflo, and Jackson (2013).

[2]For example, see Banerjee, Chandrasekhar, Duflo, and Jackson (2013); Beaman, BenYishay, Magruder, and Mobarak (2014).

[3]See Krackhardt (2014) for background and references.

source.[4] We show that for any listener in the network, the relative ranking under this count converges over time to the correct ranking of every node's propensity to send information to the rest of the network. The specific measure of a node's ability to send information that we use is its "diffusion centrality," which we introduced in Banerjee et al. (2013). Diffusion centrality measures how widely information from a given node diffuses in a given number of time periods and for a given random per-period transmission probability. In an appendix, we prove that this measure of centrality nests three of the most prominent measures in the literature: degree centrality at one extreme (if there is just one time period of communication), and eigenvector centrality and Katz–Bonacich centrality at the other extreme (if there are unlimited periods of communication). For intermediate numbers of periods, diffusion centrality takes on a range of other values.

In short, by listening and keeping count of how often they hear *about* someone, individuals learn the correct ranking of community members in terms of how effectively they can spread information.

Second, we use a unique dataset to assess whether this holds empirically. We asked every adult in each of 33 villages to name the person in their village best suited to initiate the spread of information. We combine their answers (which we call their "nominations") with detailed network data that include maps of a variety of interactions in each of the 33 villages. We show that individuals nominate highly diffusion central people (on average, slightly above the 75th percentile of centrality). We also show that the nominations are not simply based on the nominee's leadership status or geographic position in the village, but are significantly correlated with diffusion centrality even after controlling for these characteristics. Finally, a LASSO regularization technique[5] picks out diffusion centrality as the only relevant variable to predict the number of nominations, out of five possible measures of network positions (diffusion centrality, degree, eigenvector centrality, traditional leadership status, and geographic centrality).

Thus, our model shows that it is possible for individuals to learn who are the most central people in their network, and our empirical work suggests that they do so. The data, of course, could still be consistent with other models of how people choose individuals to nominate, and so we show that the nominees' centrality is significant

[4]We use the term "gossip" to refer to the spreading of information about particular people. Our diffusion process is focused on basic information that is not subject to the biases or manipulations that might accompany some "rumors" (e.g., see Bloch, Demange, and Kranton (2014)).

[5]See Tibshirani (1996); Belloni and Chernozhukov (2009); Belloni et al. (2014b,a).

in determining nominations well beyond other geographic and sociological attributes of the nominees. Since it is still conceivable that the correlation of nominations and centrality could be useless for diffusion, our next step is to test whether the nominees, indeed, are not just highly diffusion central but are also good diffusers.

Third, to test this prediction, we conduct an additional large randomized field experiment in 213 different villages to test whether informing nominated individuals leads to wider diffusion of information than informing either randomly selected individuals or village elders. Our experiment has three arms. In 71 villages, we seed a piece information in 3 to 5 randomly selected households (the number of seeds to be reached was randomly selected). In 71 other villages, we seed information in 3 to 5 village households who have status as "elders" in the village – leaders with a degree of authority in the community, who command respect. In the remaining 71 villages, we seed information in 3 to 5 individuals nominated by others as being well suited to spread information ("gossip nominees"). The piece of information that we spread is simple: anyone who calls a particular phone number will have a chance to win a free cell phone, and if they do not win the phone, they are guaranteed to win some cash. The chances to win cash and phones are independent of the number of people who respond, ensuring that the information is non-rivalrous and everyone was informed of that fact. The call itself is free. We then measure the extent of diffusion using the number of independent entrants.

We received on average 8.1 phone calls in villages with random seedings, 6.9 phone calls in villages with village elder seedings, and 11.7 in villages with gossip seedings. The additional 50 percent participation rate from using gossip compared to random seedings is the relevant difference for a policy maker considering whether to use a technique of asking for "gossip" nominations to seed a piece of information. We also estimate the impact of seeding with "gossip nominations": in quite a few villages with random seedings, a gossip nominee was hit by chance. We can thus measure how much better "gossip seeds" are at circulating information than other seeds. We find that in villages where no gossip (and no elders) were seeded, we received only 5.8 calls. In villages where at least one gossip was seeded, we received 9.9 calls – almost doubling the participation rate. If we instrument "hitting at least one gossip" with the gossip treatment, we find a similar result: seeding at least one gossip seed yields an extra 7.4 calls.

Thus, although call-back rates are moderate, we get about twice as many entries when we seed information with gossip nominees as compared to seeding with village elders or with random non-nominated villagers.

To test whether the increase in diffusion from gossip nominees is in fact accounted for by their diffusion centrality, we went back to most of the villages with random seeding just after the experiment, and collected full network data. Consistent with social network theory, we find that information diffuses faster when we hit at least one seed with high diffusion centrality. However, when we include both gossip nomination and diffusion centrality of the seeds in the regression, the coefficient of gossip centrality does not decline much (although it becomes less precise). This suggests that diffusion centrality does not explain all of the extra diffusion of information from gossip nominees. People may incorporate additional information, such as who is listened to in the village, or who is most charismatic or talkative, etc., which may not be picked up in the pure network data. Alternatively, it may be that our measure of the network and diffusion centrality are noisy, and villagers are even more accurate at finding central individuals than we are.

Relation to the literature. There is a voluminous literature on the role of opinion leaders and key individuals in diffusing products and information. This ranges from the early sociology literature (e.g, classic studies by Simmel (1908); Katz and Lazarsfeld (1955); Coleman, Katz, and Menzel (1966)), to the vast literature on diffusion of innovations (e.g., Rogers (1995); Centola (2010, 2011); Jackson and Yariv (2011)), to appropriate measures of centrality (e.g., Bonacich (1987); Borgatti (2005); Ballester, Calvó-Armengol, and Zenou (2006); Valente, Coronges, Lakon, and Costenbader (2008); Lim, Ozdaglar, and Teytelboym (2015); Bloch, Jackson, and Tebaldi (2016)), to a literature on identifying central and influential individuals in marketing (e.g., Krackhardt (1996); Iyengar et al. (2010); Hinz et al. (2011); Katona et al. (2011)), to the computational issues of identifying multiple individuals for seeding (e.g., (Kempe, Kleinberg, and Tardos, 2003, 2005)).

To our knowledge, this is the first paper to demonstrate that members of communities are able, easily and accurately, to nominate people in the community who are good at diffusing information, and that these nominees are highly central in a network sense. It is important to emphasize that this is very distinct from using the friendship paradox (Feld (1991)) to find high-degree individuals. That is, since high-degree individuals have more friends than low-degree people, a standard way of finding high-degree individuals is simply to ask people to name their friends (e.g., see Krackhardt (1996); Kim et al. (2015); Jackson (2016)). Here, we are trying to find people who are central in terms of measures that are more complex than degree-centrality, and the theory and techniques we develop are correspondingly different from the standard approaches in viral marketing.

Our work is also the first to describe a simple process by which people can learn things about their broader network to which they have no direct access.[6] Our results have important practical consequences, since policy makers and businesses are often looking for the best way to spread information, and asking people to identify the best person to spread the information is cheaper and easier than collecting detailed network data.

Importantly, this paper focuses on the pure transmission of information - simple knowledge that is either known or not. In some applications, people may not only need to know of an opportunity but may also be unsure of whether they wish to take advantage of that opportunity, and thus may also rely on endorsements of others. In those cases, trust in the sender will also matter in the diffusion process. We focus, for most of the paper, on the spread of simple sorts of information, and in the experiment, the piece of information we seeded was designed not to require trust in order to participate. Although issues of trust are certainly relevant in some applications, pure lack of information is often a binding and important constraint, and is therefore worthy of study. In addition, in our work on microfinance (Banerjee, Chandrasekhar, Duflo, and Jackson, 2013), for example, we could not reject the hypothesis that the role of the social network in the take up of microfinance was entirely mediated by information transmission, and endorsement played no role.

Our experiments here are limited to communities on the order of a thousand people. It is clear that peoples' abilities to name highly central individuals may not scale fully to networks that involve hundreds of thousands or millions of people. Nonetheless, our work still demonstrates that people are effective at naming central people within reasonably sized communities. There are many settings, in both the developing and developed world, in which person-to-person communication within a community, company, department, or organization of limited scale is important. Our model and empirical findings are therefore a useful first step in a broader research agenda.

The remainder of the paper is organized as follows: Section 2 develops our model of diffusion. In Section 3, we relate the notion of diffusion centrality to network gossip.

[6]There are some papers (e.g., Milgram (1967) and Dodds et al. (2003)) that have checked people's abilities to use knowledge of their friends' connections to efficiently route messages to reach distant people; those papers, however, test knowledge about peoples' own connections.

Section 4.1 describes the setting and the data used in the empirical analysis. We examine whether individuals nominate central nodes in Section 4.2. In Section 5, we describe the field experiment and results. Section 6 concludes.

2. A Model of Network Communication

We consider the following model.

2.1. **A Network of Individuals.** A society of n individuals are connected via a possibly directed and weighted network, which has an adjacency matrix $\mathbf{g} \in [0,1]^{n \times n}$.[7] Unless otherwise stated, we take the network $\mathbf{g}$ to be fixed and let $v^{(R,1)}$ be its first (right-hand) eigenvector, corresponding to the largest eigenvalue λ_1.[8] The first eigenvector is nonnegative and real-valued by the Perron–Frobenius Theorem.

Throughout what follows, we assume that the network is (strongly) connected in that there exists a (directed) path from every node to every other node, so that information originating at any node could potentially make its way eventually to any other node.[9]

2.2. **Diffusion Centrality.** In Banerjee, Chandrasekhar, Duflo, and Jackson (2013), we defined a notion of centrality called *diffusion centrality*, based on random information flow through a network according to the following process, which is a variant of the standard process that underlies many models of contagion.[10]

A piece of information is initiated at node i and then broadcast outwards from that node. In each period, with probability $q \in (0,1]$, independently across neighbors and history, each informed node informs each of its neighbors of the piece of information and the identity of its original source. The process operates for T periods, where T is a positive integer.

Note that since we allow $\mathbf{g}$ to be a fully heterogeneous matrix (a weighted and directed graph), q is redundant. However, for the purposes of relating the theory to our empirical work, it is useful to think of $\mathbf{g}$ as an unweighted graph, since survey network data often just indicates whether households have a connection. For this reason, we include the q-parameter explicitly, as it will be relevant for our empirical

[7]When defining $\mathbf{g}$ in the directed case, the ij-th entry indicates that i can tell something to j. In some networks, this may not be reciprocal.
[8]$v^{(R,1)}$ is such that $\mathbf{g}v^{(R,1)} = \lambda_1 v^{(R,1)}$ where λ_1 is the largest eigenvalue of $\mathbf{g}$ in magnitude.
[9]More generally, everything that we say applies to components of the network.
[10]See Jackson and Yariv (2011) for background and references. A continuous time version of diffusion centrality was subsequently defined in Lawyer (2014).

exercise and also lead to new insights about how diffusion centrality behaves as the communication rate varies. But we remind the reader that in the Appendix, all of our results and proofs allow for an arbitrary weighted and directed graph, and thus full heterogeneity in the probability that two nodes interact, in which case q is obviously redundant.

There are many reasons to allow T to be finite. For instance, a new piece of information may only be relevant for a limited time. Also, after some time, boredom may set in or some other news may arrive and the topic of conversation may change. By allowing for a variety of T's, diffusion centrality admits important finite-horizon cases, as well as more extreme cases where agents continue to discuss a topic indefinitely.[11]

Diffusion centrality measures how extensively the information spreads as a function of the initial node. In particular, let

$$\mathbf{H}(\mathbf{g}; q, T) := \sum_{t=1}^{T} (q\mathbf{g})^t ,$$

be the "hearing matrix." The ij-th entry of $\mathbf{H}$, $H(\mathbf{g}; q, T)_{ij}$, is the expected number of times, within T periods, that j hears about a piece of information originating from i. Diffusion centrality is then defined by

$$DC(\mathbf{g}; q, T) := \mathbf{H}(\mathbf{g}; q, T) \cdot \mathbf{1} = \left(\sum_{t=1}^{T} (q\mathbf{g})^t \right) \cdot \mathbf{1}.$$

So, $DC(\mathbf{g}; q, T)_i$ is the expected total number of times that some piece of information that originates from i is heard by any of the members of the society during a T-period time interval.[12] Banerjee et al. (2013) showed that diffusion centrality of the initially informed members of a community was a statistically significant predictor of the spread of information – in that case, about a microfinance program.

Note that this measure allows people to hear the information multiple times from the same person and count those times as distinct reports, so that it is possible for

[11]Of course, this is an approximation and, moreover, different people may have different incentives to pass news, or time horizons over which they do so. The current model and definition already moves beyond the literature, but richer extensions would be easy to study.

[12]We note two useful normalizations. One is to compare this calculation to what would happen if $q = 1$ and $\mathbf{g}$ were the complete network $\mathbf{g}^c$, which produces the maximum possible entry for each ij for any given any T. Thus, each entry of $DC(\mathbf{g}; q, T)$ could be divided through by the corresponding entry of $DC(\mathbf{g}^c; 1, T)$. This produces a measure for which every entry lies between 0 and 1, where 1 corresponds to the maximum possible numbers of expected paths possible in T periods with full probability weight and full connectedness. Another normalization is to compare a given node to the total level for all nodes; that is, to divide all entries of $DC(\mathbf{g}; q, T)$ by $\sum_i DC_i(\mathbf{g}; q, T)$. This normalization tracks how relatively diffusive one node is compared to the average diffusiveness in its society.

an entry of DC to be more than $n-1$. There are several advantages to defining it in this manner. First, although it is possible via simulations to calculate a measure that tracks the expected number of informed nodes and avoids double-counting, our expression is *much* easier to calculate. Second, for many parameter values, the two measures are roughly proportional to each other. Third, this version of the measure relates nicely to other standard measures of centrality in the literature, while a measure that adjusts for multiple hearing does not. Finally, in a world in which multiple chances to hear the same thing lead to a greater probability of information retention, this count might be a better predictor of actual learning.[13]

2.3. **Properties of Diffusion Centrality.** It is useful to remind the reader of diffusion centrality's relationship to other prominent measures of centrality, though a reader impatient to see our main results is welcome to bypass this sub-section and return to it at a later stage.

As we stated in Banerjee et al. (2013), for different values of T, diffusion centrality nests three of the most prominent and widely used centrality measures: degree centrality, eigenvector centrality, and Katz–Bonacich centrality.[14] It thus provides a foundation for these measures and spans the gap between them.

In particular, it is straightforward to show that (i) diffusion centrality is proportional to (out) degree centrality at the extreme at which $T = 1$, and (ii) if $q < 1/\lambda_1$, then diffusion centrality coincides with Katz–Bonacich centrality if we set $T = \infty$. It takes more work to show that, when $q > 1/\lambda_1$, diffusion centrality approaches eigenvector centrality as T approaches ∞. Intuitively, the difference between the extremes of Katz–Bonacich centrality and eigenvector centrality depends on whether q is sufficiently small so that limited diffusion takes place even for large T, or whether q is sufficiently large so that the knowledge saturates the network and then it is only relative amounts of saturation that are picked by this measure. The exact threshold should also make sense: whether q is above or below $1/\lambda_1$ determines whether the sum in diffusion centrality converges or diverges – as we know from spectral theory that the first eigenvalue of a matrix governs its expansion properties. For completeness, a formal statement and proof of these results appears in the Appendix.

[13]One could also further enrich the measure by allowing for the forgetting of information, but with three parameters the measure would start to become unwieldy.

[14]Let $d(\mathbf{g})$ denote (out) degree centrality: $d_i(\mathbf{g}) = \sum_j g_{ij}$. Eigenvector centrality corresponds to $v^{(R,1)}(\mathbf{g})$: the first eigenvector of $\mathbf{g}$. Also, let $KB(\mathbf{g}, q)$ denote Katz–Bonacich centrality – defined for $q < 1/\lambda_1$ by $KB(\mathbf{g}, q) := \left(\sum_{t=1}^{\infty} (q\mathbf{g})^t\right) \cdot \mathbf{1}$.

Between these extremes, diffusion centrality measures how diffusion process operates for some limited number of periods. As shown in Banerjee et al. (2013), the behavior in the intermediate ranges can be more relevant for certain diffusion phenomena than either extreme.

How should one choose the "right" q and T? Clearly this is context dependent and an empirical question. In some settings, people interact or communicate frequently and so q will be high, and in other settings, their contact may be more limited corresponding to a lower q. Likewise, there may be some things that are long lasting in terms of discussion and diffusion, corresponding to a high T, while others quickly subside leading to a low T. Thus, the answer will be determined by the specifics of the the application.

Despite the fact that the "right" answer is context dependent, it is useful to identify critical levels of (q, T) that differentiate the regimes of behavior of diffusion centrality. Our earlier asymptotic results relating diffusion centrality to other standard measures of centrality do not tell us how the measure's properties vary with (q, T). Here we provide some theoretical results on diffusion centrality that show that diffusion centrality behaves fundamentally differently depending on whether q is above or below $1/\lambda_1$ (the inverse of the first eigenvalue of $\mathbf{g}$), and whether T is smaller or bigger than the diameter of the graph. We use these to suggest that the threshold case of $q = 1/\mathrm{E}[\lambda_1]$ and $T = \mathrm{E}[Diam(\mathbf{g})]$ provides a natural benchmark value for these parameters.

The intuition behind the key role of that particular threshold for q has already been discussed. The reason why T being above or below the diameter makes a difference is also intuitive. In many classes of large random graphs, the average distance between most nodes is actually almost the same as the diameter, something first discovered by Erdos and Renyi. Thus, if T is below the diameter, news from any typical node will not have a long enough time to reach most other nodes. In contrast, once T hits the diameter, then that permits news from any typical node to reach most others. If one moves beyond T, then many of the walks counted by $\mathbf{g}^T$ begin to have "echoes" in them: they visit some nodes twice. For instance, news passing from node 1 to node 2 to node 3 then back to node 2 and then to node 4, etc. Once most paths have echoes in them, the measure begins to act differently, and that eventually converges to the ergodic distribution, and essentially the first eigenvector (provided q is large enough to get saturation).

Here we report a theorem and corollary that formalize some of these intuitive statements. To do this, we consider a sequence of Erdos–Renyi networks, as those provide for clear limiting properties.[15]

Let $\mathbf{g}(n,p)$ denote an Erdos–Renyi random network drawn on n nodes, with each link having independent probability p. In the following, as is standard, p (and T) are functions of n, but we omit that notation to keep the expressions uncluttered. We also allow for self-links for ease of calculations. We consider a sequence of random graphs of size n and as is standard in the literature, consider what happens as $n \to \infty$.

Theorem **1.** *If T is not too large ($T = o(pn)$),*[16] *then the expected diffusion centrality of any node converges to $npq\frac{1-(npq)^T}{1-npq}$. That is, for any i,*

$$\frac{\mathrm{E}\left[DC\left(\mathbf{g}(n,p);q,T\right)_i\right]}{npq\frac{1-(npq)^T}{1-npq}} \to 1.$$

Theorem 1 provides a precise expression for how diffusion centrality behaves in large graphs. Provided that T grows at a rate that is not overly fast[17], then we expect diffusion centrality of a typical node to converge to $npq\frac{1-(npq)^T}{1-npq}$.

Theorem 1 thus provides us with a tool to see when a diffusion that begins at a typical node is expected to reach other nodes or not, and leads to the following corollary.

Corollary **1.** *Consider a sequence of Erdos-Renyi random networks $\mathbf{g}(n,p)$ for which $\frac{1-\varepsilon}{\sqrt{n}} \geq p \geq (1+\varepsilon)\frac{\log(n)}{n}$ for some $\varepsilon > 0$*[18] *and any corresponding $T = o(pn)$. Then for any node i:*

(1) $1/\mathrm{E}[\lambda_1]$ *is a threshold for q as to whether diffusion reaches a vanishing or expanding number of nodes :*
   (a) *If $q = o(1/\mathrm{E}[\lambda_1])$, then* $\mathrm{E}\left[DC\left(\mathbf{g}(n,p);q,T\right)_i\right] \to 0$.
   (b) *If $1/\mathrm{E}[\lambda_1] = o(q)$, then* $\mathrm{E}\left[DC\left(\mathbf{g}(n,p);q,T\right)_i\right] \to \infty$.[19]

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[15] These properties extend to more general classes of random graph models by standard arguments (e.g., see Jackson (2008a)), but an exploration of such models takes us beyond our scope here.

[16] To remind the reader, $f(n) = o(h(n))$ for functions f, h if $f(n)/h(n) \to 0$, and $f(n) = \Omega(h(n))$ if there exists $k > 0$ for which $f(n) \geq kh(n)$ for all large enough n.

[17] Note that T can still grow at a rate that can tend to infinity and in particular can grow faster than the growth rate of the diameter of the network – T can grow up to pn, which will generally be larger than $\log(n)$, while diameter is proportional to $\log(n)/\log(pn)$.

[18] This ensures that the network is connected almost surely as n grows, but not so dense that the diameter shrinks to be trivial. See Bollobas (2001).

[19] Note that $\mathrm{E}[\lambda_1] = np$.

(2) $\mathrm{E}[Diam(\mathbf{g}(n,p))]$ *is a threshold relative for* T *as to whether diffusion reaches a vanishing or full fraction of nodes:*[20]

(a) *If* $T < (1-\varepsilon)\mathrm{E}[Diam(\mathbf{g}(n,p))]$ *for some* $\varepsilon > 0$*, then* $\frac{\mathrm{E}\left[DC(\mathbf{g}(n,p);q,T)_i\right]}{n} \to 0$.

(b) *If* $T \geq \mathrm{E}[Diam(\mathbf{g}(n,p))]$ *and* $q > 1/(\mathrm{E}[\lambda_1])^{1-\varepsilon}$ *for some* $\varepsilon > 0$*, then* $\frac{\mathrm{E}\left[DC(\mathbf{g}(n,p);q,T)_i\right]}{n} = \Omega(1)$.

Putting these results together, we know that $q = 1/\mathrm{E}[\lambda_1]$ and $T = \mathrm{E}[Diam(\mathbf{g})]$ are the critical values where the process transitions from a regime where diffusion is expected (in a large network) to reach almost nobody to one where it will saturate the network. At the critical value itself, diffusion reaches a non-trivial fraction of the network but not everybody in it.

This makes $DC\left(\mathbf{g}; 1/\mathrm{E}[\lambda_1], \mathrm{E}[Diam(\mathbf{g}(n,p))]\right)$ an interesting measure of centrality, distinct from other standard measures of centrality at these values of the parameters. This fixes q and T as a function of the graph so that the centrality measure no longer has any free parameters – enabling one to compare it to other centrality measures without worrying that it performs better simply because it has parameters that can be adjusted by the researcher. For reasons explained earlier, we will use it throughout the empirical sections. For the sake of comparison, we include other measures.

3. Relating Diffusion Centrality to Network Gossip

We now investigate whether and how individuals living in network $\mathbf{g}$ can end up with knowledge of other peoples' diffusion centralities, without knowing anything about the network structure.

3.1. A Gossip Process.

Diffusion centrality considers diffusion from the *sender's* perspective. Let us now consider the same information diffusion process but from a *receiver's* perspective. Over time, each individual hears information that originates from different sources in the network, and in turn passes that information on with some probability. The society discusses each of these pieces of information for T periods. The key point is that there are many such topics of conversation, originating from all of the different individuals in the society, with each topic being passed along for T periods.

For instance, Arun may tell Matt that he has a new car. Matt may then tell Abhijit that "Arun has a new car," and then Abhijit may tell Esther that "Arun has

[20] Again, note that $T = o(pn)$ is satisfied whenever $T = o(\log(n))$, and thus is easily satisfied given that diameter is proportional to $\log(n)/\log(pn)$.

a new car." Arun may also have told Ben that he thinks house prices will go up, and Ben could have told Esther that "Arun thinks that house prices will go up." In this model, Esther keeps track of the cumulative number of times bits of information that originated from Arun reach her and compares it with the number of times she hears bits of information that originated from other people. What is crucial, therefore, is that the news involves the name of the node of origin – in this case "Arun" – and not what the information is about. The first piece of news originating from Arun could be about something he has done ("bought a car"), but the second could just be an opinion ("Arun thinks house prices will go up"). Esther keeps track of how often she hears of things originating from Arun. Then Esther imputes peoples' centralities based on how often she hears about them. She estimates Abhijit's, Arun's, Ben's, Matt's, ..., Sara's centralities just based on the frequency that she hears things that originated at each one of them.

Recall that

$$\mathbf{H}(\mathbf{g}; q, T) = \sum_{t=1}^{T} (q\mathbf{g})^t ,$$

is such that the ij-th entry, $H(\mathbf{g}; q, T)_{ij}$, is the expected number of times j hears a piece of information originating from i.

We define the *network gossip heard* by node j to be the j-th column of $\mathbf{H}$,

$$NG(\mathbf{g}; q, T)_j := H(\mathbf{g}; q, T)_{\cdot j}.$$

Thus, NG_j lists the expected number of times a node j will hear a given piece of news as a function of the node of origin of the information. So, if $NG(\mathbf{g}; q, T)_{ij}$ is twice as high as $NG(\mathbf{g}; q, T)_{kj}$ then j is expected to hear news twice as often that originated at node i compared to node k, presuming equal rates of news originating at i and k.

Note the different perspectives of DC and NG: diffusion centrality tracks how well information spreads from a given node, while network gossip tracks relatively how often a given node hears information from (or about) each of the other nodes.

To end this sub-section, two remarks are in order. First, again we emphasize that all of our results hold for fully directed and weighted graphs, where passing probabilities to differ by information type and pairs of nodes. Indeed, in Banerjee et al. (2013), we allowed different nodes to pass information with different probabilities, and in Banerjee et al. (2014), we allow the probability of communication to depend on the listener's network position.

Second, we could allow nodes to differ in how frequently they generate new information, which is then transmitted to its neighbors. Provided this generation rate is positively related to nodes' centralities, the results that we present below still hold (and, in fact, the speed of convergence would be increased), though of course if the rate of generation of information about nodes is negatively correlated with their position, then our results below would be attenuated. Regardless, the result is still of interest.

3.2. **Identifying Central Individuals.** With the measure of network gossip in hand, we show how individuals in a society can estimate who is central simply by counting how often they hear gossip that originated with others. We first show that, on average, individuals' rankings of others based on NG_j, the amount of gossip that j has heard about others, is positively correlated with diffusion centrality for any q, T.

Theorem **2.** *For any* $(\mathbf{g}; q, T)$*,*

$$\sum_j \mathrm{cov}(DC(\mathbf{g}; q, T), NG(\mathbf{g}; q, T)_j) = \mathrm{var}(DC(\mathbf{g}; q, T)).$$

Thus, in any network with differences in diffusion centrality among individuals, the average covariance between diffusion centrality and network gossip is positive.

It is important to emphasize that although both measures, network gossip and diffusion centrality, are based on the same sort of information process, they are really two quite different objects. Diffusion centrality is a gauge of a node's ability to send information, while the network gossip measure tracks the reception of information by different nodes. Indeed, the reason that Theorem 2 is only stated for the sum, rather than any particular individual j's network gossip measure, is that for small T it is possible that some nodes have not even heard about other relatively distant nodes, and moreover, they might be biased towards their local neighborhoods.[21]

Next, we show that if individuals exchange gossip over extended periods of time, every individual in the network is eventually able to *perfectly* rank others' centralities – not just ordinally, but cardinally.

[21] One might conjecture that more central nodes would be better "listeners": for instance, having more accurate rankings than less central listeners after a small number of periods. Although this might happen in some networks, and for many comparisons, it is not guaranteed. None of the centrality measures considered here ensure that a given node, even the most central node, is positioned in a way to "listen" uniformly better than all other less central nodes. Typically, even a most central node might be farther than some less central node from some other important nodes. This can lead a less central node to hear some things before even the most central node, and thus to have a clearer ranking of at least some of the network before the most central node. Thus, for small T, the $\sum$ is important in Theorem 2.

THEOREM **3.** *If $q \geq 1/\lambda_1$ and $\mathbf{g}$ is aperiodic, then as $T \to \infty$ every individual j's ranking of others under $NG(\mathbf{g}; q, T)_j$ converges to be proportional to diffusion centrality, $DC(\mathbf{g}; q, T)$, and hence according to eigenvector centrality, $v^{(R,1)}$.*

The intuition is that individuals hear (exponentially) more often about those who are more diffusion/eigenvector central, as the number of rounds of communication tends to infinity. Hence, in the limit, they assess the rankings according to diffusion/eigenvector centrality correctly. The result implies that even with very little computational ability beyond remembering counts and adding to them, agents can come to learn arbitrarily accurately complex measures of the centrality of everyone in the network, including those with whom they do not associate.

More sophisticated strategies where individuals try to infer network topology, could accelerate learning. Nonetheless, learning is possible even in an environment where individuals do not know the structure of the network and do not tag anything but the source of the information.

The restriction to $q \geq 1/\lambda_1$ is important. When q tends to 0, individuals hear about others in the network with vanishing frequency, and as a result, the network distance between people can influence who they think is the most important.

The model presented here is restrictive in a number of ways. We rule out hearing about people in other ways than through communication with friends: information only travels through edges in the network. This is realistic in the contexts we study. Note, however, that things like media outlets are easily treated as nodes in the network, especially given that our analysis allows for weighted and directed networks. Also, agents do not doubt on the quality of the information, either in the gossip process or in the information transmission process: there is no notion of trust, or endorsement. It could be, for example, that gossips are people who love to talk but are not necessarily reliable. In that case, their friends may resist passing on information originating with them even though they themselves may be much talked about. This could be of interest in some settings and is an interesting issue for further research.

Again, we emphasize that although in the above we do not allow the probability of transmitting information to depend on the person, this is only for presentation purposes. As noted above, in the Appendix we work with a fully weighted and directed graph $\mathbf{g}$ which allows the probability of transmission to vary arbitrarily by pair. Our results still hold exactly, substituting a condition on the first eigenvalue of $\mathbf{g}$ being bigger than 1 in place of the comparison between q and $1/\lambda_1$ in the case presented here. Thus, people who are effective (or whose friends are effective) at communicating information would be heard about a lot, and information communicated to them would also circulate effectively - being fully accounted for both in diffusion centrality and the network gossip measure.

4. Evidence: who are the gossips?

4.1. **Data Collection.** As a first empirical study of the our gossip results above, we use a rich network data set that we gathered from villages in rural Karnataka (India). We collected network data in 2006 in order to study the spread of their microfinance product (Banerjee et al., 2013). We again collected network data in 2012, which is the data we use here.

We use the the network data combined with "gossip" information from 33 villages. To collect the network data (described in detail in Banerjee, Chandrasekhar, Duflo, and Jackson (2013), and publicly available at http://economics.mit.edu/faculty/eduflo/social), we asked adults to name those with whom they interact in the course of daily activities.[22] We have data concerning 12 types of interactions for a given survey respondent: (1) whose houses he or she visits, (2) who visits his or her house, (3) his or her relatives in the village, (4) non-relatives who socialize with him or her, (5) who gives him or her medical help, (6) from whom he or she borrows money, (7) to whom he or she lends money, (8) from whom he or she borrows material goods (e.g., kerosene, rice), (9) to whom he or she lends material goods, (10) from whom he or she gets important advice, (11) to whom he or she gives advice, and (12) with whom he or she goes to pray (e.g., at a temple, church or mosque). Using these data, we construct one network for each village, at the household level, where a link exists between households if any member of either household is linked to any other member of the other household in at least one of the 12 ways. Individuals can communicate if they interact in any of the 12 ways, so this is the network of potential communications, and using this network avoids the selection bias associated with data-mining to find the most predictive subnetworks. The resulting objects are undirected, unweighted networks at the household level.

After the network data were collected, to collect gossip data, we asked the adults the following two additional questions:

[22]We have network data from 89.14% of the 16,476 households based on interviews with 65% of all adult individuals aged 18 to 55. This is a new wave of data relative to our original microfinance study.

(Event) *If we want to spread information to everyone in the village about tickets to a music event, drama, or fair that we would like to organize in your village, to whom should we speak?*

(Loan) *If we want to spread information about a new loan product to everyone in your village, to whom do you suggest we speak?*

Table 1 provides summary statistics. The networks are sparse: the average number of households in a village is 196 with a standard deviation of 61.7, while the average degree is 17.7 with a standard deviation of 9.8.

Only half of the households were willing to respond to our "gossip" questions. This is in itself intriguing. Perhaps people are unwilling to offer an opinion when they are unsure of the answer.[23] They might instead have been worried about singling someone out.

Conditional on naming someone, however, there is substantial concordance of opinion. Only 4% of households were nominated in response to the Event question (and 5% for the Loan question) with a cross-village standard deviation of 2%. Conditional on being nominated, the median household was nominated nine times.[24] This is perhaps a first indication that the answers may be meaningful, since if people are good at identifying central individuals, we would expect their nominations to coincide.

In this data set, we label as "leaders" households that contain shopkeepers, teachers, and leaders of self-help groups – almost 12 percent of households fall into this category. This was how the bank in our microfinance study defined leaders, who were identified as people to be seeded with information about their product (because it was believed they would be good at transmitting the information). The bank's theory was that such leaders were likely to be well-connected in the villages and thereby would contribute to more diffusion of microfinance.[25]

There is some overlap between leaders and gossip nominees. We refer to the nominees as "gossips." Overall, 86% of the population were neither gossips nor leaders, just 1% were both, 3% were nominated but not leaders, and 11% were leaders but not nominated. This means that 8% of leaders were nominated as a gossip under the

[23] See Alatas et al. (2014) for a model that builds on this idea.

[24] We work at the household level, in keeping with Banerjee et al. (2013) who used households as network nodes; a household receives a nomination if any of its members are nominated.

[25] In our earlier work, Banerjee et al. (2013), we show that there is considerable variation in the centrality of these "leaders" in a network sense, and that this variation predicts the eventual take up of microfinance.

event question whereas 92% where not nominated. Similarly, 25% of nominated gossips under the event question were leaders, whereas 75% were not. The loan question demonstrates very similar results, and Figure 1 presents this information.

4.2. **Do individuals nominate central nodes?** Our theoretical results suggest that people can learn others' diffusion centralities simply by tracking news that they hear through the network, and therefore should be able to name central individuals when asked whom to use as a "seed" for diffusion. In this section, we examine whether this is the case.

4.2.1. *Data description.* As motivating evidence, Figure 1 shows the distribution of diffusion centrality (normalized by its standard deviation across the sample for interpretability) across households that were nominated for the event question, those who were nominated as leaders, and those who were named for both or neither. Very clearly, the distribution of centrality of those who are both nominated and are also leaders first order stochastically dominates the other distributions. Moreover, the distribution of centralities of those who are nominated but not leaders dominates the distribution of those who are leaders but were not nominated. Finally, those who are neither nominated nor a leader exhibit a distribution that is dominated by the rest. Taken together, this shows that individuals who are both nominated and leaders tend to be more central than those who are nominated but not leaders, who are in turn more central than those who are not nominated but are leaders.

Figure 2 presents the distribution of nominations as a function of the network distance from a given household. If information did not travel well through the social network, we might imagine that individuals would only nominate households with whom they are directly connected. Panel A of Figure 2 shows that fewer than 13% of individuals nominate someone within their direct neighborhood, compared to about 9% of nodes within this category. At the same time, over 28% of nominations come from a network distance of at least three or more (41% of nodes are in this category). Therefore, although respondents tend to nominate people who are closer to them than the average person in the village, they are also quite likely to nominate someone who is far away. Moreover, it is important to note that highly central individuals are generally closer to people than the typical household (since they have many friends – the famous "friendship paradox"), so it does make sense that people tend to nominate individuals who are closer to them. Taken together, this suggests that information about centrality does indeed travel through the network.

Panel B of Figure 2 shows that the average diffusion centrality in percentile terms of those named at distance 1 is higher than of those named at distance 2, which is higher than of those named at distance 3 or more. This suggests that individuals have more accurate information about central individuals that are closer to them, and when they don't, they are careful not to nominate (recall that fewer than half of the households nominate anyone).

4.2.2. *Regression Analysis.* Motivated by this evidence, we present a more systematic analysis of the correlates of nominations, using a discrete choice framework for the decision to nominate someone.

Our theory suggests that if people choose whom to nominate based on who they hear about most frequently, then diffusion centrality should be a leading predictor of nominations. While the aforementioned results are consistent with this prediction, there are several plausible alternative interpretations that do not rely on the information mechanism from our model. For example, individuals may nominate the person who has the most friends, and people with many friends tend to be more diffusion central than those with fewer friends (i.e., diffusion centrality and degree centrality are correlated). Alternatively, it may be that people simply nominate the "leaders" within their village, or people who are central geographically, and these also correlate with diffusion/eigenvector centrality. There are reasons to think that leadership status and geography may be good predictors of network centrality, since, as noted in Banerjee et al. (2013), the microfinance organization selected "leaders" precisely because they believed these people would be central. Previous research has also shown that geographic proximity increases the probability of link formation (Fafchamps and Gubert, 2007; Ambrus et al., 2014; Chandrasekhar and Lewis, 2014) and therefore, one might expect geographic data to be a useful predictor of centrality. For that reason, since in addition to leadership data we have detailed GPS coordinates for every household in each village, we include these in our analysis below as controls.[26]

We recognize that the correlations below do not constitute proof that the causal mechanism is indeed gossip, but they do rule out these obvious confounding factors.

[26]To operationalize geographic centrality, we use two measures. The first uses the center of mass. We compute the center of mass and then compute the geographic distance for each agent i from the center of mass. Centrality is the inverse of this distance, which we normalize by the standard deviation of this measure by village. The second uses the geographic data to construct an adjacency matrix. We denote the ij entry of this matrix to be $\frac{1}{d(i,j)}$ where $d(\cdot,\cdot)$ is the geographic distance. Given this weighted graph, we compute the eigenvector centrality measure associated with this network. Results are robust to either definition.

To operationalize our analysis we use $DC\,(1/\mathrm{E}[\lambda_1], \mathrm{E}[Diam(\mathbf{g}(n,p))])$ as our measure of diffusion centrality, as discussed in Section 2.3.

We estimate a discrete choice model of the decision to nominate an individual. Note that we have large choice sets, as there are $n-1$ possible nominees and n nominators per village network. We model agent i as receiving utility $u_i(j)$ for nominating individual j:

$$u_i(j) = \alpha + \beta' x_j + \gamma' z_j + \mu_v + \epsilon_{ijv},$$

where x_j is a vector of network centralities for j (eigenvector centrality, diffusion centrality, and degree centrality), z_j is a vector of demographic characteristics (e.g., leadership status, geographic position, and caste controls), μ_v is a village fixed effect, and ϵ_{ijv} is a Type-I extreme value distributed disturbance. For convenience given the large choice sets, we estimate the conditional logit model by an equivalent Poisson regression, where the outcome is the expected number of times an alternative is selected (Palmgren, 1981; Baker, 1994; Lang, 1996; Guimaraes et al., 2003). This is presented in Table 3. A parallel OLS specification leads to the same conclusion, and is presented in Appendix B.

We begin with a number of bivariate regressions in Table 4. First, we show that diffusion centrality is a significant driver of an individual nominating another (column 1). A one standard deviation increase in diffusion centrality is associated with a 0.607 log-point increase in the number of others nominating a household (statistically significant at the 1% level). Columns 2 to 5 repeat the exercise with two other network statistics (degree and eigenvector centrality), with the "leader" dummy, and with an indicator for geographic centrality. All of these variables, except for geographic centrality, predict nomination, and the coefficients are similar in magnitude.

The different network centrality measures are all correlated. To investigate whether diffusion centrality remains a predictor of gossip nomination after controlling for the other measures, we start by introducing them one by one as controls in column 1 to 4 in Table 4. Degree is insignificant, and does not affect the coefficient of diffusion centrality. Eigenvector centrality is quite correlated with diffusion centrality (as it should be, since they converge to each other with enough time periods), and hard to distinguish from it. Introducing it cuts the effect of diffusion centrality by about 50%, though it remains significant. The leader dummy is close to being significant, but the coefficient of diffusion centrality remains strong and significant. The geographic centrality variable now has a negative coefficient, and does not affect coefficient of the diffusion centrality variable.

These results provide suggestive evidence that a key driver of the nomination decision involves diffusion centrality with $T > 1$, although it may be more difficult to separate eigenvector centrality and diffusion centrality from each other, which is not surprising since they are closely related concepts.

To confirm this pattern, in the last column, we introduce all the variables together and perform a LASSO analysis, which "picks" out the variable that is most strongly associated with the outcome variable, the number of nominations. Specifically, we use the post-LASSO procedure of Belloni and Chernozhukov (2009). It is a two-step procedure. In the first step, standard LASSO is used to select the support: which variables matter in predicting our outcome variable (the number of nominations). In the second step, a standard Poisson regression is run on the support selected in the first stage.[27,28]

As we did before, we consider the variables diffusion centrality, degree centrality, eigenvector centrality, leadership status, and geographic centrality in the standard LASSO to select the support. For the event nomination, LASSO picks out only one predictor: diffusion centrality. The post-LASSO coefficient and standard error thus exactly replicate the Poisson regression of using just DC(0.2,3). This confirms that diffusion centrality is the key predictor of gossip nomination. For the loan nomination, the LASSO picks out both degree and diffusion as relevant, though degree is insignificant. We repeat the analysis with OLS instead of Poisson regression in Appendix B, with identical qualitative results.

5. Experiment: Do gossip nominees spread information widely?

We have shown that individuals nominate diffusion central people. Prior research demonstrated that providing information to more central individuals leads to greater diffusion (Banerjee et al., 2013; Beaman et al., 2014). Therefore, a natural question is whether using our gossip nomination protocol picks out individuals who lead to faster diffusion of information compared to other ways of choosing the seeds. This is a key policy implication of our theory.

[27] The problem with the returned coefficients from LASSO in the first step is that it shrinks the coefficients towards zero. Belloni and Chernozhukov (2009), Belloni et al. (2014b) and Belloni et al. (2014a) show that running the usual OLS (in our case, Poisson) on the variables selected in the first stage in a second step will recover consistent estimates for the parameters of interest.

[28] To our knowledge, the post-LASSO procedure has not been developed for nonlinear models, so we only conduct the selection using OLS.

5.1. **Information Diffusion and Gossip Seeding.** We compare seeding of information to gossips (nominees) to two benchmarks: (1) a set of village elders and (2) randomly selected households. Seeding information among random households provides the most relevant benchmark, because it allows us to study how information circulates starting from random households. Seeding information with village elders provides an interesting benchmark, because they are traditionally respected as social and political leaders and one might presume that they are the right place to start. They have the advantage of being easy to identify, and it could be, for instance, that information spreads widely only if it has the backing of someone who can influence opinion, not just convey information.

We conducted an experiment in 213 villages in Karnataka that were not involved in the microfinance diffiusion project and that were not villages in which we had previously worked. In every village, we attempted to contact k households and inform them about a promotion run by our partner, a cellphone sales firm. The promotion gave villagers a non-rivalrous chance to win a new mobile phone or a cash prize.

The promotion worked as follows. Anyone who wanted to participate could give us a "missed call" (a call that we registered, but did not answer, and which was thus free). In public, a few weeks later, the registered phone numbers were randomly awarded cash prizes ranging from 50 to 275 rupees, or a free cell phone. Which prize any given entrant was awarded was determined by the roll of two dice, ensuring that the awarding of prizes was non-rivalrous and there was no strategic incentive to withhold information about the promotion.

In each treatment, the seeded individuals were encouraged to inform others in their community about the promotion. Our primary outcome data is thus the number of calls from unique households that we received.[29] In half of the villages, we set $k = 3$, and in half of the villages we set $k = 5$. This was done because we were not sure of the right number of seeds that were needed to avoid either the process dying out or complete and rapid diffusion. In practice, we find that there is no significant difference between 3 and 5 seeds on the outcome variable (number of calls received).

We randomly divided the sample of 213 into three arms of 71 villages, where the k seeds were selected as follows. A few days before the experiment, we interviewed up to 15 households in every village (selected randomly via circular random sampling via

[29]The calls from the seeds are included in the main specification, and so we include seed number fixed effects.

the right-hand rule method) to identify "elders" and "gossips," as described below.[30, 31]

T1. Elder: k households were chosen from the list of village elders obtained one week prior. The notion of "village elder" is well recognized in these villages: there are people who are recognized authorities, and believed to be influential.

T2. Random: k households were chosen uniformly at random, also using the right-hand rule method and going to every n/k households.

T3. Gossip: k households were chosen from the list of gossip nominees obtained one week prior.

Note that this seeding does not address the challenging problem of choosing the optimal set of nodes for diffusion given their centralities. The solution is not simply to pick the highest ranked nodes, since the positions of the seeds relative to each other also matters. This results in a computationally challenging problem (in fact, an NP-complete one, see Kempe, Kleinberg, and Tardos (2003, 2005)). Here, we randomly selected seeds from the set of nominees, which if anything biases the test against the gossip treatment. We could have instead used the most highly nominated nodes in combination with caste or other demographic information to pick combinations of highly central nodes that are likely to be well-spaced in the network.

The main outcome variable that we are interested in is the number of calls received. This represents the number of people who heard about the promotion and wanted to participate. The mean number of calls in the sample is 9.35 (with standard deviation 15.64). The median number of villagers who participated is 3 across all villages. In 80.28% of villages, we received at least one call, and the 95th percentile is 39. This is not a very large number, which is not surprising, since many villagers already own cell phones and may not have been particularly interested in a chance of winning another one. Nonetheless, there is enough variation from village to village to allow us to identify the effect of information diffusion. Note that, given these small numbers, we exclude one village in our analysis in which the number of calls was 106. In this village one of the seeds (who happened to be a gossip nominee in a random village) prepared posters to broadcast the information broadly. The diffusion in this villages

[30] Circular sampling is a standard survey methodology where the enumerator starts at the end of a village, and, using a right-hand rule, spirals throughout the entire village, when enumerating households. This allows us to cover the entire geographic span of the village which is desirable in this application, particularly as castes are often segregated, which may lead to geographic segregation of the network: we want to make sure the nominations reflect the entire village.

[31] We asked the same questions in all villages so to be sure that the surveying had no impact on the treatment, and to allow us to rack which sorts of seeds were reached in each treatment.

does not have much to do with the network process we have in mind. We thus use data from 212 villages in all the regressions that follow. The results including this village are presented in Appendix D. They are qualitatively similar, but the OLS is larger and more precise, while the IV estimate is similar but noisier.

Figure 3 presents the results graphically. The distribution of calls in the gossip villages clearly stochastically dominates that of the elder and random graphs. Moreover, the incidence of a diffusive event, where a large number of calls is received, is rare when we seed information randomly or with village elders – but we do see such events when we seed information with gossip nominees.

We begin with the analysis of our experiment as designed, which is the policy-maker's experiment: what is the impact on diffusion of purposefully seeding gossips or elders, as compared to random villagers?

$$y_j = \theta_0 + \theta_1 GossipTreatment_j + \theta_2 ElderTreatment_j + \theta_3 NumberSeeds_j + \theta_4 NumberGossip_j + \theta_5 NumberElder_j + u_j, \tag{5.1}$$

where y_j is the number of calls received from village j (or the number of calls per seed), $GossipTreatment_j$ is a dummy equal to 1 if seeds were assigned to be from the gossip list, $ElderTreatment_j$ is a dummy equal to 1 if seeds were assigned to be from the elder list, $NumberSeeds_j$ is the total number of seeds, 3 or 5, in the village, $NumberGossip_j$ is the total number of gossips nominated in the village, and $NumberElder_j$ is the total number of elders nominated in the village.

Table 5 presents the regression analysis. The results including the broadcast village are presented in Appendix D.[32] Column 1 shows the reduced form (5.1). In control villages, we received 8.077 calls, or an average of 1.967 per seeds. In gossip treatment villages, we received 3.65 more calls ($p = 0.19$) in total or 1.05 per seed ($p = 0.13$).

While this exercise is of independent interest, it is not the most direct test of our theory. Our theory predicts that information seeded with a gossip will flow faster than information seeded to someone who is not a gossip. Thus, the most direct test of our model is to compare diffusion in villages in which a gossip was hit to diffusion in villages where no gossip was hit. The seeding does not exclude gossips in the random and elder treatment villages. In some random and elder treatment villages, gossip nominees were included in our seeding set by chance. On an average, 0.59 seeds were gossips in random villages.

[32] The OLS specification is larger, while the IV has a similar point estimate but is noisier.

Our next specification is thus to compare villages where "at least 1 gossip was hit," or "at least 1 elder was hit" (both could be true simultaneously) to those where no elder or no gossip was hit (the control group). Although the selection of households under treatments is random, the event that at least one gossip (elder) being hit is random only conditional on the number of potential gossip (elder) seeds present in the village. We thus include as controls in the OLS regression of number of calls on "at least 1 gossip (elder) seed hit". This specification should give us the causal effect of gossip (elder) seeding, but to assess the robustness, we also make directly use of the variation induced by the village level experiment, and we instrument "at least 1 gossip (elder) seed hit" is instrumented by the gossip (elder) treatment status of the village.

Therefore, we are interested in

$$y_j = \beta_0 + \beta_1 GossipReached_j + \beta_2 ElderReached_j + \beta_3 NumberSeeds_j + \beta_4 NumberGossip_j + \beta_5 NumberElder_j + \epsilon_j. \tag{5.2}$$

This equation is estimated either by OLS, or by instrumental variables, instrumenting $GossipReached_j$ with $GossipTreatment_j$ and $ElderReached_j$ with $ElderTreatment_j$. There the first stage equations are

$$GossipReached_j = \pi_0 + \pi_1 GossipTreatment_j + \pi_2 ElderTreatment_j + \pi_3 NumberSeeds_j + \pi_4 NumberGossip_j + \pi_5 NumberElder_j + v_j, \tag{5.3}$$

and

$$ElderReached_j = \rho_0 + \rho_1 GossipTreatment_j + \rho_2 ElderTreatment_j + \rho_3 NumberSeeds_j + \rho_4 NumberGossip_j + \rho_5 NumberElder_j + \nu_j. \tag{5.4}$$

Column 2 of Table 5 shows the OLS. The effect of hitting at least one gossip seed is 3.79 for the total number of calls (p-value = 0.04), or 0.95 (p-value = 0.06) calls per seed (which represents a 65% increase, relative to villages where no gossip seed was hit). Column 5 presents the IV estimates (Columns 3 and 4 present the first stage results for the IV). They are larger than the OLS estimates, and statistically indistinguishable, albeit less precise.

Given the distribution of calls, the results are potentially sensitive to outliers. We therefore present quantile regressions of the comparison between gossip/no gossip and Gossip treatment/Random villages in Figure 4. The specification that compares villages with or without gossip hit (Panel B) is much more precise. The treatment effects are significantly greater than zero starting at the 35th percentile. Specifically, hitting a gossip significantly increases the median number of calls by 122% and calls at the 80th percentile by 71.27%.

This is our key experimental result: gossip nominees are much better seeds for diffusing a piece of information, at least in these experiments.

5.2. **Mechanism: does gossip seed diffusion capture diffusion centrality?** We have seen, in the first part of our empirical investigation, that villagers nominate individuals who are diffusion central. In our previous work (Banerjee, Chandrasekhar, Duflo, and Jackson, 2013), we showed that diffusion central seeds are associated with greater diffusion. To what extent is the greater diffusion of information in the experiment mediated by the diffusion centrality of the gossip seeds, and to what extent does it reflect the villagers' ability to capture other dimensions of individuals that would make them good at diffusing information?

To get at this issue, a few weeks after the experiment, we collected network data in 69 villages in which seeds were randomly selected (2 of the 71 villages were not accessible at the time). In these villages, by chance, some seeds happened to be gossips and/or elders. We create a measure of centrality that parallels the gossip dummy and elder dummy by forming a dummy for "high diffusion centrality." We defined a household has "high diffusion centrality" if its diffusion centrality is at least one standard deviation above the mean. With these measures, in our 69 villages, 13% of households are defined to have "high diffusion centrality", while 1.7% were nominated as seeds, and 9.6% are "leaders." Twenty-four villages have exactly one high diffusion centrality seed and 14 have more than one. Twenty-three villages have exactly one gossip seed, and 8 have more than one.[33]

[33]We continue to exclude the one village in which a gossip seed broadcasted information. The results including that village are in Appendix D.2: they reinforce the conclusion that diffusion centrality does not capture everything about why gossips are good seeds, since this particular gossip seed had low diffusion centrality. With this village in, the coefficient of hitting at least one gossip does not

Column 1 of Table 6 runs the same specification as in Table 5 but in the 68 random villages. In these villages, hitting a gossip by chance increases the number of calls by 6.65 (compared to 3.78 in the whole sample). In column 3, we regress the number of calls on a dummy for hitting = a high DC seed: high DC seeds do increase the number of calls (by 5.18 calls). Finally, we regress number of calls received only on dummy of hitting a high DC seed, and we see that the number of calls increase by 5.18. In column 2, we augment the specification in column 1 to add the dummy for "at least one DC central seed". Since DC and Gossip are correlated, the regression is not particularly precise. The point estimate of gossip, however, only declines slightly.

Taking the point estimates seriously, we see that the results suggest that diffusion centrality captures part of the impact of a gossip nomination, but likely not all of it. Gossip seeds tend to be highly central, and information does spread more from highly central seeds. This accounts for some part of the reason why information diffuses more extensively from gossip nominated seeds. At the same time, it is also appears that the model does not capture the entire reason why gossip seeds are best for diffusing information: even controlling for their diffusion centrality, gossip seeds still lead to greater diffusion. It is likely that our measures of the network are imperfect, and so part of the extra diffusion from the gossip nominations could reflect that villagers have better estimates of diffusion centrality from their network gossip than we do from our surveys. It also could be that the gossip nomination is a richer proxy for information diffusion than the model-based centrality measure. For instance, there are clearly other factors that predict whether a seed will be good at diffusing information beyond their centrality (altruism, interest in the information, etc.) and villagers may be good at capturing those factors. However, the standard errors do not allow us to pinpoint how much of the extra diffusion coming from being nominated as a gossip is explained by network centrality.

6. Conclusion

Our model illustrates that it should be easy for even very myopic and non-Bayesian (as well as fully rational) agents, simply by counting, to have an idea of who is central in their community – according to fairly complex measures of centrality. Motivated by this, we asked villagers to identify good diffusers in their village. They do not simply name locally central individuals (the most central among those they know), but actually name ones that are globally central within the village. Moreover, in a

decline when we control for diffusion centrality, and in fact diffusion centrality, even on its won, is not significantly associated with more diffusion.

specially designed experiment, we find that nominated individuals are indeed much more effective at diffusing a simple piece of information than other individuals, even village elders. This suggests that people can use simple observations to learn valuable things about the complex social systems within which they are embedded.

Although our model focuses on the network-based mechanics of communication, in practice, considerations beyond simple network position may determine who the "best" person is to spread information, as other characteristics may affect the quality and impact of communication. It seems that villagers take such characteristics into account and thus nominate individuals who are not only highly central but who are even more successful at diffusing information than the average highly central individual.

Our findings have important policy implications, since such nominations are easy to collect and therefore can be used in a variety of contexts, either on their own or combined with other easily collected data, to identify effective seeds for information diffusion. Thus, using this sort of protocol may be a cost-effective way to improve diffusion and outreach.

Beyond these applications, the work presented here opens a rich agenda for further research, as one can explore which other aspects of agents' social environments can be learned in simple ways. For example, can individuals also identify individuals who are trusted by others? A piece of information about a cell-phone giveaway is probably innocuous enough to be transmitted by a "gossip," but what about advice on immunization, for example?

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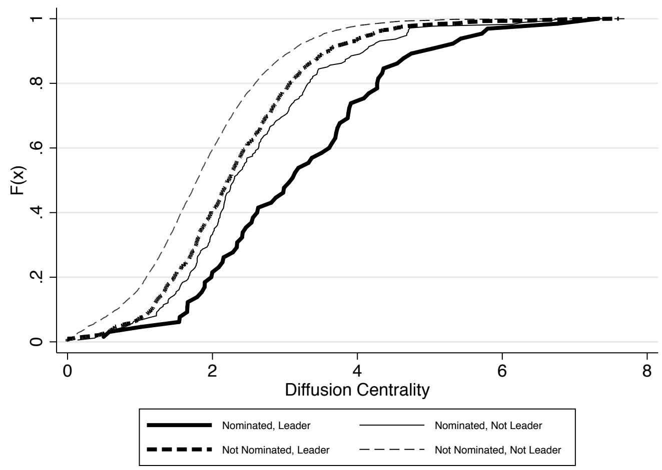
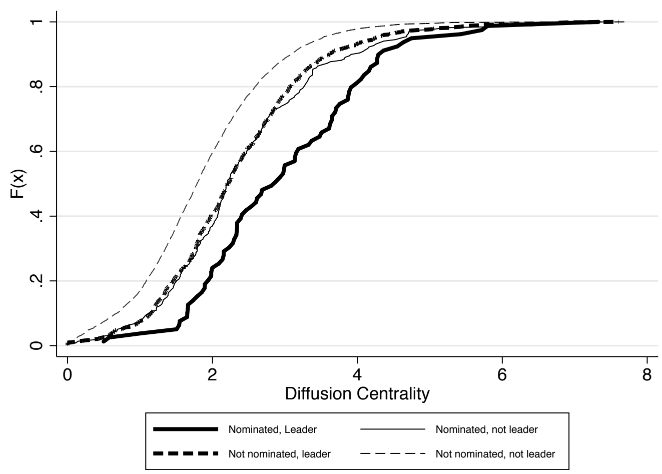
Figures



(A) Event question

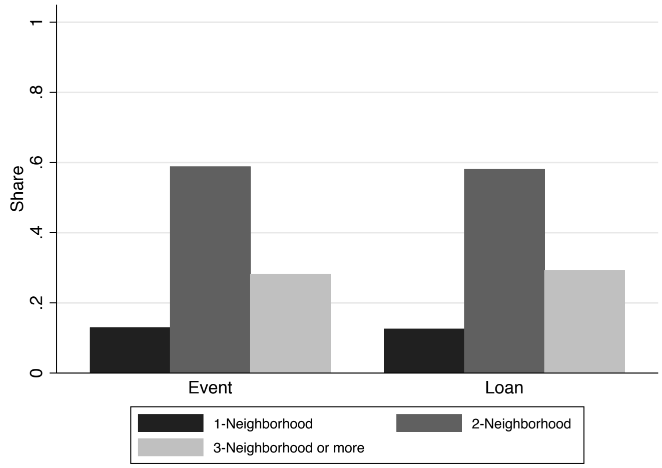
	population share
nominated, leader (event)	0.01
not nominated, leader (event)	0.11
nominated, not leader (event)	0.03
not nominated, not leader (event)	0.86



(B) Loan question

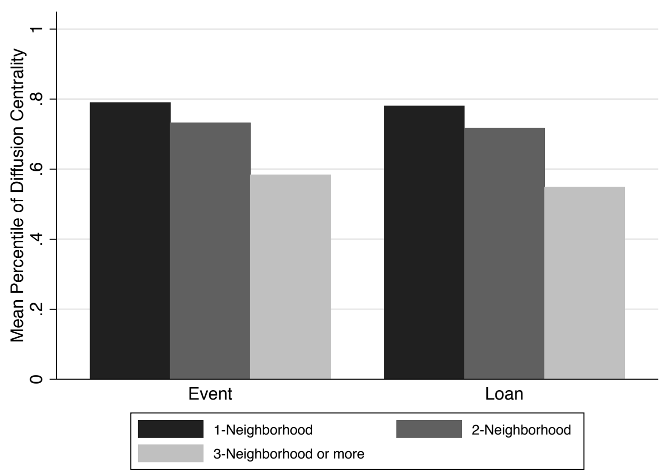
	population share
nominated, leader (loan)	0.01
not nominated, leader (loan)	0.10
nominated, not leader (loan)	0.03
not nominated, not leader (loan)	0.85

Figure 1. This figure uses the Phase 1 dataset. It presents CDFs of the (normalized) diffusion centrality, diffusion centrality divided by the standard deviation, conditional on classification (whether or not it is nominated under the event question in Panel A and the loan question in Panel B and whether or not it has a village leader).



(A) Share of nominees in specified neighborhood

	share
Nodes in 1-Neighborhood	0.09
Nodes in 2-Neighborhood	0.50
Nodes in 3-Neighborhood or more	0.41



(B) Average diffusion centrality percentile of nominees in specified neighborhood

FIGURE 2. Distribution of nominees and their diffusion centrality by network distance in the Phase 1 dataset.

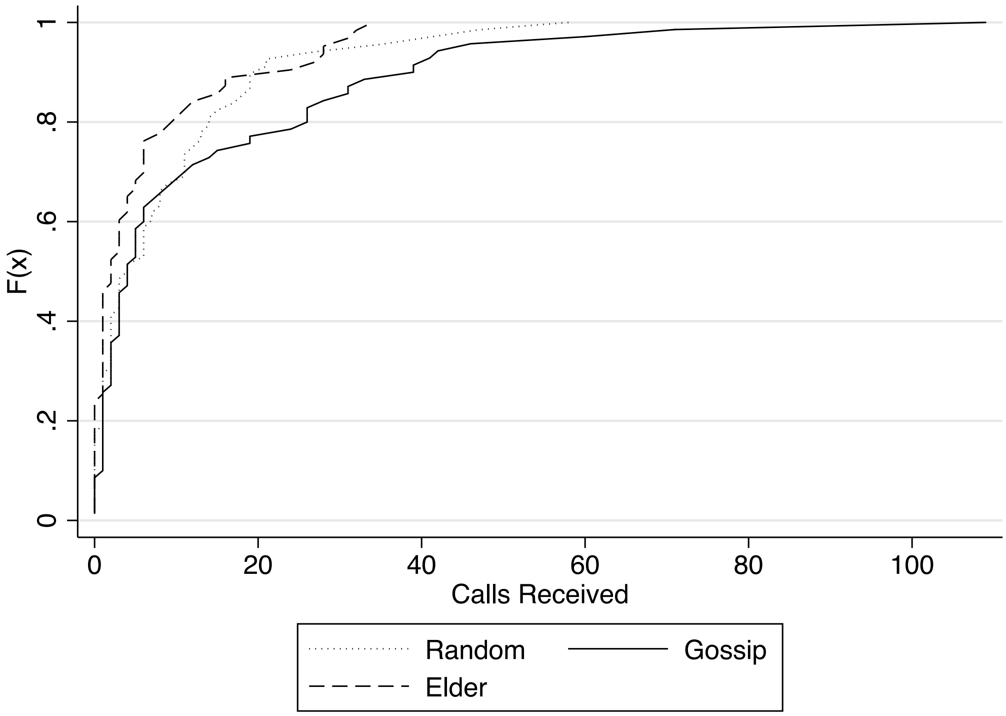
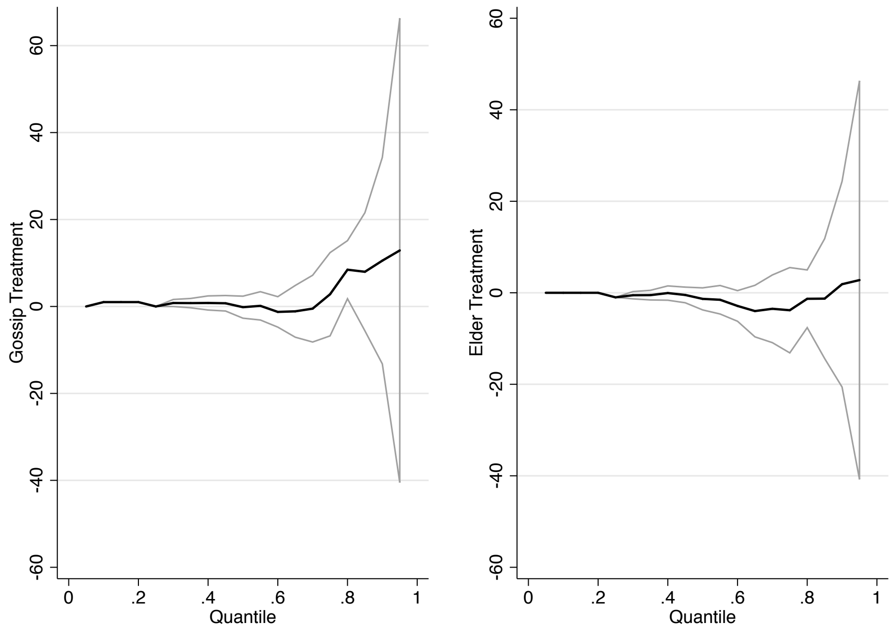
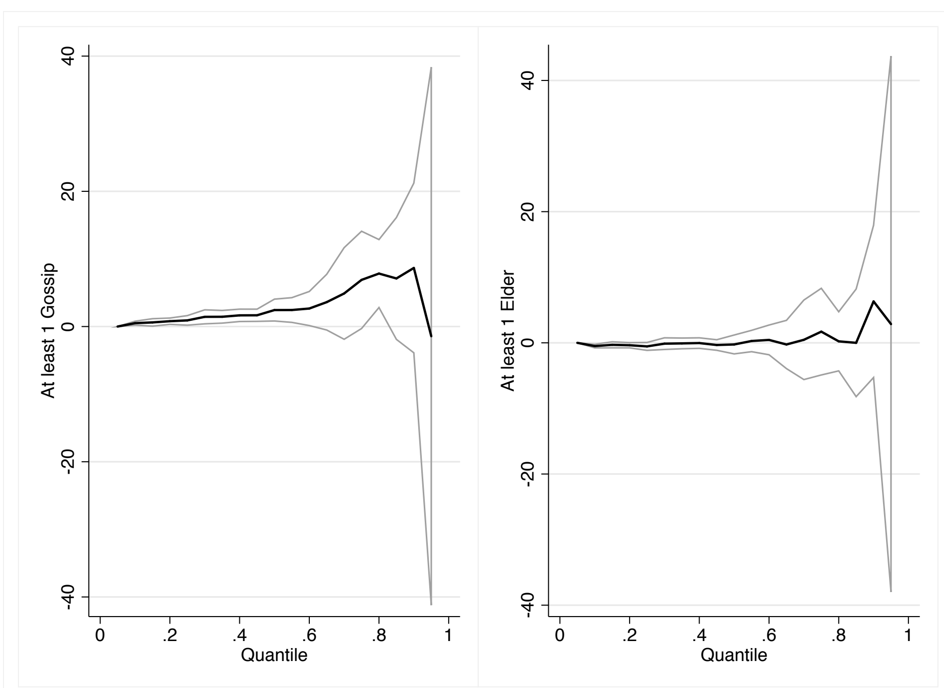


Figure 3. Distribution of calls received by treatment in the Phase 2 experiment.



(A) Quantile treatment effect by treatment - Reduced Form



(B) Quantile treatment effect by hitting at least one gossip or elder

FIGURE 4. Quantile treatment effects where for $j \in \{Gossip,\ Elder\}$, $\widehat{\beta}_j(u)$ is computed for $u = \{0.05, ..., 0.95\}$. The intercept $\alpha(u)$ (not pictured) in each case is the omitted category corresponding to the random treatment.

Tables

Table 1. Summary Statistics

	mean	sd
households per village	196	61.70
household degree	17.72	9.81
clustering in a household's neighborhood	0.29	0.16
avg distnace between nodes in a village	2.37	0.33
fraction in the giant component	0.98	0.01
is a leader	0.12	0.32
nominated someone for event	0.38	0.16
nominated someone for loan	0.48	0.16
was nominated for event	0.04	0.2
was nominated for loan	0.05	0.3
number of nominations received for event	0.34	3.28
number of nominations received for loan	0.45	3.91

Notes: This table presents summary statistics from the Phase 1 dataset: 33 villages of the Banerjee et al. (2013) networks dataset where nomination data was originally collected in 2011/2012. For the variables "nominated someone for loan (event)" and "was nominated for loan (event)" we present the cross-village standard deviation.

Table 2. Leader Gossip Overlap

	share
leaders who are nominated (loan)	0.11
nominated who are leaders (loan)	0.27
leaders who are not nominated (loan)	0.89
nominated who are not leaders (loan)	0.73
leaders who are nominated (event)	0.09
nominated who are leaders (event)	0.27
leaders who are not nominated (event)	0.91
nominated who are not leaders (event)	0.73

Notes: This table presents the overlap between "leaders" in the sample and those nominated as gossips (for loan and event).

Table 3. Factors predicting nominations

	(1) Event	(2) Event	(3) Event	(4) Event	(5) Event
Diffusion Centrality	0.607				
	(0.085)				
Degree Centrality		0.460			
		(0.078)			
Eigenvector Centrality			0.605		
			(0.094)		
Leader				0.915	
				(0.279)	
Geographic Centrality					-0.082
					(0.136)
Observations	6,466	6,466	6,466	6,466	6,466
	(1) Loan	(2) Loan	(3) Loan	(4) Loan	(5) Loan
Diffusion Centrality	0.625				
	(0.075)				
Degree Centrality		0.490			
		(0.067)			
Eigenvector Centrality			0.614		
			(0.084)		
Leader				1.013	
				(0.263)	
Geographic Centrality					-0.113
					(0.082)
Observations	6,466	6,466	6,466	6,466	6,466

Notes: This table uses data from the Phase 1 dataset. It reports estimates of Poisson regressions where the outcome variable is the expected number of nominations. Panel A presents results for the event question, and Panel B presents results for the loan question. Degree centrality, eigenvector centrality, and diffusion centrality, $DC\left(\mathbf{g}; 1/\mathrm{E}[\lambda_1], \mathrm{E}[Diam(\mathbf{g}(n,p))]\right)$, are normalized by their standard deviations. Standard errors (clustered at the village level) are reported in parentheses.

Table 4. Factors predicting nominations

	(1) Event	(2) Event	(3) Event	(4) Event	(5) Event	(6) Event
Diffusion Centrality	0.642	0.354	0.567	0.606	0.374	0.607
	(0.127)	(0.176)	(0.091)	(0.085)	(0.206)	(0.085)
Degree Centrality	-0.039				-0.020	
	(0.101)				(0.101)	
Eigenvector Centrality		0.283			0.281	
		(0.186)			(0.186)	
Leader			0.535			
			(0.301)			
Geographic Centrality				-0.082		
				(0.142)		
Observations	6,466	6,466	6,466	6,466	6,466	6,466
Post-LASSO						✓

	(1) Loan	(2) Loan	(3) Loan	(4) Loan	(5) Loan	(6) Loan
Diffusion Centrality	0.560	0.431	0.578	0.624	0.339	0.560
	(0.122)	(0.130)	(0.081)	(0.075)	(0.170)	(0.122)
Degree Centrality	0.070				0.088	0.070
	(0.086)				(0.084)	(0.086)
Eigenvector Centrality		0.219			0.231	
		(0.138)			(0.138)	
Leader			0.623			
			(0.288)			
Geographic Centrality				-0.115		
				(0.089)		
Observations	6,466	6,466	6,466	6,466	6,466	6,466
Post-LASSO						✓

Notes: This table uses data from the Phase 1 dataset. It reports estimates of Poisson regressions where the outcome variable is the expected number of nominations under the event question. Panel A presents results for the event question, and Panel B presents results for the loan question. Degree centrality, eigenvector centrality, and diffusion centrality, $DC\left(\mathbf{g}; 1/\mathrm{E}[\lambda_1], \mathrm{E}[Diam(\mathbf{g}(n,p))]\right)$, are normalized by their standard deviations. Column (6) uses a post-LASSO procedure where in the first stage LASSO is implemented to select regressors and in the second stage the regression in question is run on those regressors. Omitted terms indicate they were not selected in the first stage. Standard errors (clustered at the village level) are reported in parentheses.

Table 5. Calls received by treatment

	(1) RF Calls Received	(2) OLS Calls Received	(3) IV 1: First Stage At least 1 Gossip	(4) IV 2: First Stage At least 1 Elder	(5) IV: Second Stage Calls Received
Gossip Treatment	3.651		0.644	0.328	
	(2.786)		(0.0660)	(0.0824)	
Elder Treatment	-1.219		0.230	0.842	
	(2.053)		(0.0807)	(0.0509)	
At least 1 Gossip		3.786			7.436
		(1.858)			(4.266)
At least 1 Elder		0.792			-3.475
		(2.056)			(2.259)
Observations	212	212	212	212	212
Control Group Mean	8.077	5.846	0.391	0.184	5.805

	(1) RF $\frac{\text{Calls Received}}{\text{Seeds}}$	(2) OLS $\frac{\text{Calls Received}}{\text{Seeds}}$	(3) IV 1: First Stage At least 1 Gossip	(4) IV 2: First Stage At least 1 Elder	(5) IV: Second Stage $\frac{\text{Calls Received}}{\text{Seeds}}$
Gossip Treatment	1.053		0.644	0.328	
	(0.698)		(0.0660)	(0.0824)	
Elder Treatment	-0.116		0.230	0.842	
	(0.518)		(0.0807)	(0.0509)	
At least 1 Gossip		0.952			1.979
		(0.501)			(1.071)
At least 1 Elder		0.309			-0.677
		(0.511)			(0.588)
Observations	212	212	212	212	212
Control Group Mean	1.967	1.451	0.391	0.184	1.317

Notes: This table uses data from the Phase 2 experimental dataset. Panel A uses the number of calls received as the outcome variable. Panel B normalizes the number of calls received by the number of seeds, 3 or 5, which is randomly assigned. For both panels, Column (1) shows the reduced form results of regressing number of calls received on dummies for gossip treatment and elder treatment. Column (2) regresses number of calls received on the dummies for if at least 1 gossip was hit and for if at least 1 elder was hit in the village. Columns (3) and (4) show the first stages of the instrumental variable regressions, where the dummies for "at least 1 gossip" and "at least 1 elder" are regressed on the exogenous variables: gossip treatment dummy and elder treatment dummy. Column (5) shows the second stage of the IV; it regresses the number of calls received on the dummies for if at least 1 gossip was hit and if at least 1 elder was hit, both instrumented by treatment status of the village (gossip treatment or not, elder treatment or not). All columns control for number of gossips, number of elders, and number of seeds. For columns (1), (3), and (4) the control group mean is calculated as the mean expectation of the outcome variable when the treatment is "random". For columns (2) and (5) the control group mean is calculated as the mean expectation of the outcome variable when no gossips or elders are reached. The control group mean for the second stage IV is calculated using IV estimates. Robust standard errors are reported in parentheses.

TABLE 6. Calls received by seed type

	(1) Calls Received	(2) Calls Received	(3) Calls Received	(4) Calls Received / Seeds	(5) Calls Received / Seeds	(6) Calls Received / Seeds
At least 1 Gossip	6.645	5.574		1.637	1.370	
	(3.867)	(4.119)		(0.949)	(0.992)	
At least 1 Elder	0.346	0.0566		0.245	0.173	
	(3.602)	(3.576)		(0.926)	(0.912)	
At least 1 High *DC* Seed		3.663	5.183		0.916	1.312
		(2.494)	(2.383)		(0.623)	(0.649)
Observations	68	68	68	68	68	68
Control Group Mean	5.586	5.586	5.719	1.353	1.353	1.402

Notes: This table uses data from the Phase 2 experimental and network dataset. It presents OLS regressions of number of calls received (and number of calls received normalized by the number of seeds, 3 or 5, which is randomly assigned) on characteristics of the set of seeds. High *DC* refers to a seed being above the mean by one standard deviation of the centrality distribution. All columns control for total number of gossips, number of elders, and number of seeds. For columns (1), (2), (4), and (5), the control group mean is calculated as the mean expectation of the outcome variable when no gossips or elders are reached. For columns (3) and (6), the control group mean is calculated as the mean expectation of the outcome variable when no high *DC* seeds are reached. Robust standard errors are reported in parentheses.

Appendix A. Proofs

A.1. **Relation of Diffusion Centrality to Other Measures.**

We prove all of the statements for the case of weighted ($g_{ij} \in [0,1]$) and directed networks (g_{ij} can differ from g_{ji}). Thus, we can take $\mathbf{g} \in [0,1]^{n\times n}$ and to allow for full heterogeneity in communication. For instance, g_{ij} and g_{ik} could both be positive, and yet differ from each other. In what follows, we still include q as an explicit multiplier, noting that this is redundant given the generality of the $\mathbf{g}$ matrix. The reader who finds this distracting can set $q = 1$.

Let $v^{(L,k)}$ indicate k-th left-hand side eigenvector of $\mathbf{g}$ and similarly let $v^{(R,k)}$ indicate $\mathbf{g}$'s k-th right-hand side eigenvector. In the case of undirected networks, $v^{(L,k)} = v^{(R,k)}$.

Let $d(\mathbf{g})$ denote (out) degree centrality (so $d_i(\mathbf{g}) = \sum_j g_{ij}$). Eigenvector centrality corresponds to $v^{(R,1)}(\mathbf{g})$: the first eigenvector of $\mathbf{g}$. Also, let $KB(\mathbf{g}, q)$ denote Katz–Bonacich centrality – defined for $q < 1/\lambda_1$ by:[34]

$$KB(\mathbf{g}, q) := \left(\sum_{t=1}^{\infty} (q\mathbf{g})^t\right) \cdot \mathbf{1}.$$

It is direct to see that (i) diffusion centrality is proportional to degree centrality at the extreme at which $T = 1$, and (ii) if $q < 1/\lambda_1$, then diffusion centrality coincides with Katz–Bonacich centrality if we set $T = \infty$. We now show that when $q > 1/\lambda_1$ diffusion centrality approaches eigenvector centrality as T approaches ∞, which then completes the picture of the relationship between diffusion centrality and extreme centrality measures.

The difference between the extremes of Katz–Bonacich centrality and eigenvector centrality depends on whether q is sufficiently small so that limited diffusion takes place even in the limit of large T, or whether q is sufficiently large so that the knowledge saturates the network and then it is only relative amounts of saturation that are being measured.[35]

Theorem **A.1.**

[34]See (2.7) in Jackson (2008b) for additional discussion and background. This was a measure first discussed by Katz, and corresponds to Bonacich's definition when both of Bonacich's parameters are set to q.

[35]Saturation occurs when the entries of $\left(\sum_{t=1}^{\infty} (q\mathbf{g})^t\right) \cdot \mathbf{1}$ diverge (note that in a [strongly] connected network, if one entry diverges, then all entries diverge). Nonetheless, the limit vector is still proportional to a well defined limit vector: the first eigenvector.

(1) *Diffusion centrality is proportional to (out) degree when* $T = 1$*:*

$$DC(\mathbf{g}; q, 1) = qd(\mathbf{g}).$$

(2) *If* $q \geq 1/\lambda_1$ *and* $\mathbf{g}$ *is aperiodic, then as* $T \to \infty$ *diffusion centrality approximates eigenvector centrality:*

$$\lim_{T \to \infty} \frac{DC(\mathbf{g}; q, T)}{\sum_{t=1}^{T} (q\lambda_1)^t} = v^{(R,1)}.$$

(3) *For* $T = \infty$ *and* $q < 1/\lambda_1$*, diffusion centrality is Katz–Bonacich centrality:*

$$DC(\mathbf{g}; q, \infty) = KB(\mathbf{g}, q); \quad q < 1/\lambda_1.$$

This is a result we mention in Banerjee, Chandrasekhar, Duflo, and Jackson (2013). An independent formalization appears in Benzi and Klymko (2014).

We also remark on the comparison to another measure: the influence vector that appears in the DeGroot learning model (see, e.g., Golub and Jackson (2010)). That metric captures how influential a node is in a process of social learning. It corresponds to the (left-hand) unit eigenvector of a stochasticized matrix of interactions rather than a raw adjacency matrix. While it might be tempting to use that metric here as well, we note that it is the right conceptual object to use in a process of *repeated averaging* through which individuals update opinions based on averages of their neighbors' opinions. It is thus conceptually different from the diffusion process that we study. Nonetheless, one can also define a variant of diffusion centrality that works for finite iterations of DeGroot updating.

Proof of Theorem A.1. We show the second statement as the others follow directly.

First, consider any irreducible and aperiodic nonnegative (and hence primitive) $\mathbf{g}$. If the statement holds for any arbitrarily close positive and diagonalizable $\mathbf{g}'$ (which are dense in a nonnegative neighborhood of $\mathbf{g}$), then since $\frac{DC(\mathbf{g};q,T)}{\sum_{t=1}^{T}(q\lambda_1)^t}$ is a continuous function (in a neighborhood of a primitive $\mathbf{g}$, which has a simple first eigenvalue) as is the first eigenvector, then the statement also holds at $\mathbf{g}$.[36] Thus, it is enough to prove the result for a positive and diagonalizable $\mathbf{g}$.

We show the following for a positive and diagonalizable $\mathbf{g}$:

[36]As is shown below, $\frac{DC(\mathbf{g};q,T)}{\sum_{t=1}^{T}(q\lambda_1)^t}$ has a well-defined limit, and so this holds also for the limit.

- If $q > \lambda_1^{-1}$, then

$$\lim_{T\to\infty} \frac{DC\left(\mathbf{g}; q, T\right)}{\sum_{t=1}^{T}\left(q\lambda_1\right)^t} = \lim_{T\to\infty} \frac{DC\left(g; q, T\right)}{\frac{q\lambda_1-(q\lambda_1)^{T+1}}{1-(q\lambda_1)}} = v^{(R,1)}.$$

- If $q = \lambda_1^{-1}$, then

$$\lim_{T\to\infty} \frac{1}{T} DC\left(\mathbf{g}; \lambda_1^{-1}, T\right) = v^{(R,1)}.$$

Let $\widetilde{\mathbf{g}} = \mathbf{g}/\lambda_1$, and normalize the eigenvectors to lie in ℓ_1, so that the entries in each column of $\mathbf{V}^{-1}$ and each row of $\mathbf{V}$ sum to 1.

Let us show the statement for the case where $q = 1/\lambda_1$. It is sufficient to show

$$\lim_{T\to\infty} \left\| \frac{DC\left(\mathbf{g}; \lambda_1^{-1}, T\right)}{T} - v^{(R,1)} \right\| = 0.$$

First, note that given the diagonalizable matrix, straightforward calculations show that

$$DC_i\left(\mathbf{g}; \lambda_1^{-1}, T\right) = \sum_j \sum_{t=1}^{T} \sum_k v_i^{(R,k)} v_j^{(L,k)} \widetilde{\lambda}_k^t.$$

Thus,

$$\begin{aligned}
\left| \frac{DC_i\left(\mathbf{g}; \lambda_1^{-1}, T\right)}{T} - v_i^{(R,1)} \right| &= \left| \frac{\sum_j \sum_{t=1}^{T} \sum_{k=1}^{n} v_i^{(R,k)} v_j^{(L,k)} \widetilde{\lambda}_k^t}{T} - v_i^{(R,1)} \right| = \\
&= \left| \frac{1}{T} \sum_j \sum_{t=1}^{T} \sum_{k=2}^{n} v_i^{(R,k)} v_j^{(L,k)} \widetilde{\lambda}_k^t \right| \leq \frac{1}{T} \sum_{t=1}^{T} \sum_{k=2}^{n} 1 \cdot \underbrace{\left| \sum_{j=1}^{n} v_j^{(L,k)} \right|}_{\leq 1} \cdot \left| \widetilde{\lambda}_k^t \right| \\
&\leq \frac{n}{T} \sum_{t=1}^{T} \left| \widetilde{\lambda}_2^t \right| = \frac{n}{T} \frac{\left|\widetilde{\lambda}_2\right|}{1 - \left|\widetilde{\lambda}_2\right|} \left(1 - \left|\widetilde{\lambda}_2\right|^T\right) \to 0.
\end{aligned}$$

Since the length of the vector (which is n) is unchanging in T, pointwise convergence implies convergence in norm, proving the result.

The final piece repeats the argument for $q > 1/\lambda_1$. It follows that the eigenvalues of $q\mathbf{g}$ are $\widetilde{\Lambda} = \text{diag}\left\{\widetilde{\lambda}_1, ..., \widetilde{\lambda}_n\right\}$ with $q\lambda_k = \widetilde{\lambda}_k$. We show

$$\lim_{T\to\infty} \left\| \frac{DC\left(\mathbf{g}; q, T\right)}{\sum_{t=1}^{T}\left(q\lambda_1\right)^t} - v^{(R,1)} \right\| = 0.$$

By similar derivations as above,

$$\begin{aligned}\left|\frac{DC_i\left(\mathbf{g};\lambda_1^{-1},T\right)}{\sum_{t=1}^T \widetilde{\lambda}_1^t}-v_i^{(R,1)}\right| &= \left|\frac{\sum_j\sum_{t=1}^T\sum_{k=1}^n v_i^{(R,k)}v_j^{(L,k)}\widetilde{\lambda}_k^t}{\sum_{t=1}^T\widetilde{\lambda}_1^t}-v_i^{(R,1)}\right| \\ &= \left|\frac{\sum_j\sum_{t=1}^T\sum_{k=2}^n v_i^{(R,k)}v_j^{(L,k)}\widetilde{\lambda}_k^t}{\sum_{t=1}^T\widetilde{\lambda}_1^t}+\frac{\sum_j\sum_{t=1}^T v_i^{(R,1)}v_j^{(L,1)}\widetilde{\lambda}_1^t}{\sum_{t=1}^T\widetilde{\lambda}_1^t}-v_i^{(R,1)}\right| \\ &= \left|\frac{\sum_j\sum_{t=1}^T\sum_{k=2}^n v_i^{(R,k)}v_j^{(L,k)}\widetilde{\lambda}_k^t}{\sum_{t=1}^T\widetilde{\lambda}_1^t}+\frac{\sum_{t=1}^T v_i^{(R,1)}\widetilde{\lambda}_1^t}{\sum_{t=1}^T\widetilde{\lambda}_1^t}-v_i^{(R,1)}\right| \\ &= \left|\frac{1}{\sum_{t=1}^T\widetilde{\lambda}_1^t}\sum_j\sum_{t=1}^T\sum_{k=2}^n v_i^{(R,k)}v_j^{(L,k)}\widetilde{\lambda}_k^t\right| \\ &\le \frac{1}{\sum_{t=1}^T\widetilde{\lambda}_1^t}\sum_{t=1}^T\sum_{k=2}^n 1\cdot\left|\sum_{j=1}^n v_j^{(L,k)}\right|\cdot\left|\widetilde{\lambda}_k^t\right| \\ &\le \frac{n}{\sum_{t=1}^T\widetilde{\lambda}_1^t}\sum_{t=1}^T\left|\widetilde{\lambda}_2^t\right|.\end{aligned}$$

Note that this last expression converges to 0 since $\widetilde{\lambda}_1 > 1$, and $\widetilde{\lambda}_1 > \widetilde{\lambda}_2$.[37] which completes the argument. ■

A.2. **Other Proofs.**

Proof of Theorem 1 .

$$\begin{aligned}\mathrm{E}\left[DC\left(\mathbf{g}(n,p);q,T\right)\right]_i &= \left[\sum_1^T \mathrm{E}\left[q^t\mathbf{g}(n,p)^t\right]\cdot\mathbf{1}\right]_i \\ &= \sum_1^T q^t n\mathrm{E}\left[\mathbf{g}(n,p)^t\right]_{ij},\end{aligned}$$

where the last equality comes from the fact that $\mathrm{E}\left[\mathbf{g}(n,p)^t\right]_{ij} = \mathrm{E}\left[\mathbf{g}(n,p)^t\right]_{ik}$ for all i,j,k in an Erdos–Renyi random graph.

Next, note that

$$\mathrm{E}\left[\mathbf{g}(n,p)^t\right]_{ij} = \mathrm{E}\left[\sum_{k_1,k_2,\ldots,k_{t-1}\in\{1,\ldots,n\}^{t-1}} g_{ik_1}g_{k_1k_2}\cdots g_{k_{t-1}j}\right]$$

[37]Note that it is important that $q \ge 1/\lambda_1$ for this claim, since if $q < 1/\lambda_1$, then $q\lambda_1 < 1$. In that case, observe that

$$\frac{\sum_{t=1}^T\left|\tilde{\lambda}_2\right|^t}{\sum_{t=1}^T\widetilde{\lambda}_1^t} = \frac{\widetilde{\lambda}_2}{\widetilde{\lambda}_1}\cdot\frac{1-\tilde{\lambda}_1}{1-\tilde{\lambda}_2}$$

by the properties of a geometric sum, which is of constant order. Thus, higher order terms ($\widetilde{\lambda}_2$, etc.) persistently matter and are not dominated relative to $\sum_t^T\widetilde{\lambda}_1^t$.

If all the indexed $g_{..}$'s were distinct, the right hand side of this equation would simply be $n^{t-1}p^t$. However, in the summand sometimes terms repeat. For example, if there were exactly x repetitions, the probability of getting the walk would be p^{t-x} instead of p^t. Thus, it follows directly that

$$\mathrm{E}\left[\mathbf{g}(n,p)^t\right]_{ij} \geq n^{t-1}p^t$$

and so

$$\begin{aligned}\mathrm{E}\left[DC\left(\mathbf{g}(n,p);q,T\right)\right]_i &= \sum_1^T q^t n \mathrm{E}\left[\mathbf{g}(n,p)^t\right]_{ij} \\ &\geq \sum_1^T q^t n^t p^t = npq\frac{1-(npq)^T}{1-npq}\end{aligned}$$

Note also, that

$$\mathrm{E}\left[\sum_{k_1,k_2,\ldots,k_t\in\{1,\ldots,n\}^t} g_{ik_1}g_{k_1k_2}\cdots g_{k_{t-1}j}\right] \leq n^{t-1}p^t + tn^{t-2}p^{t-1} + t^2n^{t-3}p^{t-2} + \ldots + t^t.$$

This last inequality is a very loose upper bound generated by setting a loose upper bound on how many $g_{..}$'s could conceivably repeat, and then putting in the expression that would ensue if they did repeat. Despite how loose the bound is, it suffices for our purposes.

Given that $t \leq T < pn$, it follows that

$$\begin{aligned}\mathrm{E}\left[\sum_{k_1,k_2,\ldots,k_t\in\{1,\ldots,n\}^t} g_{ik_1}g_{k_1k_2}\cdots g_{k_{t-1}j}\right] &\leq n^{t-1}p^t\left(1+\frac{t}{pn}+\left(\frac{t}{pn}\right)^2\ldots+\left(\frac{t}{pn}\right)^t\right) \\ &= n^{t-1}p^t\left(\frac{1-\left(\frac{t}{pn}\right)^t}{1-\left(\frac{t}{pn}\right)}\right).\end{aligned}$$

Thus,

$$\mathrm{E}\left[\mathbf{g}(n,p)^t\right]_{ij} \leq n^{t-1}p^t\frac{1}{1-\frac{T}{pn}}.$$

Since $T << pn$ it follows that (here $o(1)$ is with respect to n):

$$\begin{aligned}\mathrm{E}\left[DC\left(\mathbf{g}(n,p);q,T\right)\right]_i &= \sum_1^T q^t n \mathrm{E}\left[\mathbf{g}(n,p)^t\right]_{ij} \\ &\leq \sum_1^T q^t n^t p^t(1+o(1)) = npq\frac{1-(npq)^T}{1-npq}(1+o(1)).\end{aligned}$$

The theorem follows directly. ■

Proof of Theorem 2 . Recall that $\mathbf{H} = \sum_{t=1}^{T} (q\mathbf{g})^t$ and $DC = \left(\sum_{t=1}^{T} (q\mathbf{g})^t\right) \cdot \mathbf{1}$ and so

$$DC_i = \sum_j H_{ij}.$$

Additionally,

$$\mathrm{cov}(DC, H_{\cdot,j}) = \sum_i \left(DC_i - \sum_k \frac{DC_k}{n}\right)\left(H_{ij} - \sum_k \frac{H_{kj}}{n}\right).$$

Thus

$$\sum_j \mathrm{cov}(DC, H_{\cdot,j}) = \sum_i \left(DC_i - \sum_k \frac{DC_k}{n}\right)\left(\sum_j H_{ij} - \sum_k \frac{\sum_j H_{kj}}{n}\right),$$

implying

$$\sum_j \mathrm{cov}(DC, H_{\cdot,j}) = \sum_i \left(DC_i - \sum_k \frac{DC_k}{n}\right)\left(DC_i - \sum_k \frac{DC_k}{n}\right) = \mathrm{var}(DC),$$

which completes the proof. ■

Proof of Corollary 1 . To see (1), first note that $x\frac{1-x^T}{1-x} \to 0$ if $x \to 0$, and that $x\frac{1-x^T}{1-x} \to x\frac{x^T}{x} \to \infty$ if $x \to \infty$. Replacing x with npq and then applying Theorem 1 yields the result under (a) and (b), respectively.

To see (2), we consider the case in which $q > 1/(\mathrm{E}[\lambda_1])^{1-\varepsilon}$, which of course is equivalent to $npq > (np)^{\varepsilon}$. This is the case under which (b) applies. This also implies the result in (a), since if the conclusion of (a) holds for such a q it will also hold for all lower q, given that DC is monotone in q.

Again, since $npq > 1$, it follows that if T is growing, then

$$\mathrm{E}\left[DC\left(\mathbf{g}(n,p); q, T\right)\right]_i \to npq\frac{1-(npq)^T}{1-npq} \to (npq)^T.$$

So, to have

$$\mathrm{E}\left[DC\left(\mathbf{g}(n,p); q, T\right)\right]_i \geq kn$$

for some $k > 0$, it is sufficient that $(npq)^T \geq kn$, or

$$T \geq \frac{\log(n) + \log(k)}{\log np + \log(q)} \to \frac{\log(n)}{\log np} \sim \mathrm{E}[Diam\left(\mathbf{g}(n,p)\right)],$$

where the last comparison is a property of Erdos–Renyi random networks given that $\frac{1-\varepsilon}{\sqrt{n}} \geq p \geq (1+\varepsilon)\frac{\log(n)}{n}$, and so this establishes (b). From the analogous calculation, if T is below $\frac{\log(n)}{\log np}$, then $\mathrm{E}\left[DC\left(\mathbf{g}(n,p); q, T\right)\right]_i \leq kn$ for any k, and so (a) follows. ■

Proof of Theorem 3. Again, we prove the result for a positive diagonalizable **g**, noting that it then holds for any (nonnegative) **g**.

Again, let **g** be written as

$$\mathbf{g} = \mathbf{V}\Lambda\mathbf{V}^{-1}.$$

Also, let $\tilde{\lambda}_k = q\lambda_k$. It then follows that we can write

$$\mathbf{H} = \sum_{t=1}^{T} (q\mathbf{g})^t = \sum_{t=1}^{T} \left(\sum_{k=1}^{n} v_i^{(R,k)} v_j^{(L,k)} \tilde{\lambda}_k^t \right).$$

By the ordering of the eigenvalues from largest to smallest in magnitude,

$$\begin{aligned} \mathbf{H}_{\cdot,j} &= \sum_{t=1}^{T} \left[v^{(R,1)} v_j^{(L,1)} \tilde{\lambda}_1^t + v^{(R,2)} v_j^{(L,2)} \tilde{\lambda}_2^t + O\left(\left| \tilde{\lambda}_2 \right|^t \right) \right] \\ &= \sum_{t=1}^{T} \left[v^{(R,1)} v_j^{(L,1)} \tilde{\lambda}_1^t + O\left(\left| \tilde{\lambda}_2 \right|^t \right) \right] \\ &= v^{(R,1)} v_j^{(L,1)} \sum_{t=1}^{T} \tilde{\lambda}_1^t + O\left(\sum_{t=1}^{T} \left| \tilde{\lambda}_2 \right|^t \right). \end{aligned}$$

So, since the largest eigenvalue is unique, it follows that

$$\frac{\mathbf{H}_{\cdot,j}}{\sum_{t=1}^{T} \tilde{\lambda}_1^t} = v^{(R,1)} v_j^{(L,1)} + O\left(\frac{\sum_{t=1}^{T} \left| \tilde{\lambda}_2 \right|^t}{\sum_{t=1}^{T} \tilde{\lambda}_1^t} \right).$$

Note that the last expression converges to 0 since $\tilde{\lambda}_1 > 1$, and $\tilde{\lambda}_1 > \tilde{\lambda}_2$. Thus,

$$\frac{\mathbf{H}_{\cdot,j}}{\sum_{t=1}^{T} \tilde{\lambda}_1^t} \to v^{(R,1)} v_j^{(L,1)}$$

for each j. This completes the proof since each column of **H** is proportional to $v^{(R,1)}$ in the limit, and thus has the correct ranking for large enough T.[38] Note that the ranking is up to ties, as the ranking of tied entries may vary arbitrarily along the sequence. That is, if $v_i^{(R,1)} = v_\ell^{(R,1)}$, then j's ranking over i and ℓ could vary arbitrarily with T, but their rankings will be correct relative to any other entries with higher or lower eigenvector centralities. ■

[38]The discussion in Footnote 37 clarifies why $q > 1/\lambda_1$ is required for the argument.

Appendix B. Extension of Phase 1 results

This section extends the descriptive analysis from the Phase 1 network data on 33 villages. We repeat all of our analyses with OLS specifications instead of Poisson specifications. Additionally, we include a Post-LASSO estimation which conducts a LASSO to select which variables best explain our outcome of interest (number of nominations) and then does a post-estimation to recover consistent parameter estimates.

Table B.1. Factors predicting nominations

	(1) Event	(2) Event	(3) Event	(4) Event	(5) Event
Diffusion Centrality	0.285				
	(0.060)				
Degree Centrality		0.250			
		(0.061)			
Eigenvector Centrality			0.283		
			(0.064)		
Leader				0.436	
				(0.168)	
Geographic Centrality					-0.025
					(0.038)
Observations	6,466	6,466	6,466	6,466	6,466

	(1) Loan	(2) Loan	(3) Loan	(4) Loan	(5) Loan
Diffusion Centrality	0.391				
	(0.071)				
Degree Centrality		0.367			
		(0.065)			
Eigenvector Centrality			0.378		
			(0.074)		
Leader				0.653	
				(0.224)	
Geographic Centrality					-0.045
					(0.029)
Observations	6,466	6,466	6,466	6,466	6,466

Notes: This table uses data from the Phase 1 dataset. It reports estimates of OLS regressions where the outcome variable is the expected number of nominations under the event question. Panel A presents results for the event question, and Panel B presents results for the loan question. Degree centrality, eigenvector centrality, and diffusion centrality, $DC\left(\mathbf{g}; 1/\mathrm{E}[\lambda_1], \mathrm{E}[Diam(\mathbf{g}(n,p))]\right)$, are normalized by their standard deviations. Standard errors (clustered at the village level) are reported in parentheses.

Table B.2. Factors predicting nominations

	(1) Event	(2) Event	(3) Event	(4) Event	(5) Event	(6) Event
Diffusion Centrality	0.303	0.161	0.269	0.285	0.173	0.285
	(0.091)	(0.087)	(0.061)	(0.060)	(0.107)	(0.060)
Degree Centrality	-0.020				-0.013	
	(0.066)				(0.068)	
Eigenvector Centrality		0.138			0.137	
		(0.095)			(0.095)	
Leader			0.294			
			(0.174)			
Geographic Centrality				-0.026		
				(0.039)		
Observations	6,466	6,466	6,466	6,466	6,466	6,466
Post-LASSO						✓

	(1) Loan	(2) Loan	(3) Loan	(4) Loan	(5) Loan	(6) Loan
Diffusion Centrality	0.310	0.266	0.366	0.391	0.175	0.310
	(0.112)	(0.089)	(0.071)	(0.071)	(0.124)	(0.112)
Degree Centrality	0.091				0.098	0.091
	(0.079)				(0.079)	(0.079)
Eigenvector Centrality		0.138			0.144	
		(0.089)			(0.087)	
Leader			0.461			
			(0.229)			
Geographic Centrality				-0.045		
				(0.030)		
Observations	6,466	6,466	6,466	6,466	6,466	6,466
Post-LASSO						✓

Notes: This table uses data from the Phase 1 dataset. It reports estimates of OLS regressions where the outcome variable is the expected number of nominations. Panel A presents results for the event question, and Panel B presents results for the loan question. Degree centrality, eigenvector centrality, and diffusion centrality, $DC\left(\mathbf{g}; 1/\mathrm{E}[\lambda_1], \mathrm{E}[Diam(\mathbf{g}(n,p))]\right)$, are normalized by their standard deviations. Column (6) uses a post-LASSO procedure where in the first stage LASSO is implemented to select regressors and in the second stage the regression in question is run on those regressors. Omitted terms indicate they were not selected in the first stage. Standard errors (clustered at the village level) are reported in parentheses.

Appendix C. Extension of experiment analysis

This section extends the analysis of the experiment results to using four instruments.

Table C.1. Calls received by treatment

	(1) RF Calls Received	(2) OLS Calls Received	(3) IV 1: First Stage At least 1 Gossip	(4) IV 2: First Stage At least 1 Elder	(5) IV: Second Stage Calls Received
Gossip Treatment	4.559		0.795	0.430	
	(3.121)		(0.0753)	(0.108)	
5 Gossip Seeds	-1.785		-0.303	-0.206	
	(5.290)		(0.110)	(0.153)	
Elder Treatment	2.279		0.370	0.872	
	(2.424)		(0.106)	(0.0685)	
5 Elder Seeds	-6.798		-0.272	-0.0578	
	(3.487)		(0.149)	(0.100)	
At least 1 Gossip		3.786			8.063
		(1.858)			(3.845)
At least 1 Elder		0.792			-3.684
		(2.056)			(2.266)
Observations	212	212	212	212	212
Control Group Mean	8.019	5.846	0.389	0.183	5.496

	(1) RF Calls Received / Seeds	(2) OLS Calls Received / Seeds	(3) IV 1: First Stage At least 1 Gossip	(4) IV 2: First Stage At least 1 Elder	(5) IV: Second Stage Calls Received / Seeds
Gossip Treatment	1.593		0.795	0.430	
	(1.030)		(0.0753)	(0.108)	
5 Gossip Seeds	-1.083		-0.303	-0.206	
	(1.348)		(0.110)	(0.153)	
Elder Treatment	0.622		0.370	0.872	
	(0.770)		(0.106)	(0.0685)	
5 Elder Seeds	-1.430		-0.272	-0.0578	
	(0.912)		(0.149)	(0.100)	
At least 1 Gossip		0.952			2.169
		(0.501)			(1.043)
At least 1 Elder		0.309			-0.676
		(0.511)			(0.578)
Observations	212	212	212	212	212
Control Group Mean	1.953	1.451	0.389	0.183	1.186

Notes: This table uses data from the Phase 2 experimental dataset. Panel A uses the number of calls received as the outcome variable. Panel B normalizes the number of calls received by the number of seeds, 3 or 5, which is randomly assigned. For both panels, Column (1) shows the reduced form results of regressing number of calls received on dummies for gossip treatment and elder treatment. Column (2) regresses number of calls received on the dummies for if at least 1 gossip was hit and for if at least 1 elder was hit in the village. Columns (3) and (4) show the first stages of the instrumental variable regressions, where the dummies for "at least 1 gossip" and "at least 1 elder" are regressed on the exogenous variables: gossip treatment dummy, 5 gossip seeds dummy, elder treatment dummy, 5 elder seeds dummy. Column (5) shows the second stage of the IV; it regresses the number of calls received on the dummies for if at least 1 gossip was hit and if at least 1 elder was hit, both instrumented by treatment status of the village (gossip treatment or not, elder treatment or not) and seed number dummies for the village (5 gossip seeds or not, 5 elder seeds or not). All columns control for number of gossips, number of elders and number of seeds. For columns (1), (3), and (4) the control group mean is calculated as the mean expectation of the outcome variable when the treatment is "random". For columns (2) and (5), the control group mean is calculated as the mean expectation of the outcome variable when no gossips or elders are reached. The control group mean for the second stage IV is calculated using IV estimates. Robust standard errors are reported in parentheses.

Appendix D. Experiment Analysis with Broadcast Village

This section repeats our main experimental analyses but includes the broadcast village where the poster was made by one of the seeds.

Table D.1. Calls received by treatment

	(1) RF Calls Received	(2) OLS Calls Received	(3) IV 1: First Stage At least 1 Gossip	(4) IV 2: First Stage At least 1 Elder	(5) IV: Second Stage Calls Received
Gossip Treatment	2.266		0.636	0.331	
	(3.116)		(0.0660)	(0.0821)	
Elder Treatment	-2.809		0.220	0.846	
	(2.577)		(0.0807)	(0.0502)	
At least 1 Gossip		5.005			6.122
		(2.210)			(4.532)
At least 1 Elder		-0.619			-4.914
		(2.472)			(2.628)
Observations	213	213	213	213	213
Control Group Mean	9.534	6.277	0.400	0.180	7.971

	(1) RF $\frac{\text{Calls Received}}{\text{Seeds}}$	(2) OLS $\frac{\text{Calls Received}}{\text{Seeds}}$	(3) IV 1: First Stage At least 1 Gossip	(4) IV 2: First Stage At least 1 Elder	(5) IV: Second Stage $\frac{\text{Calls Received}}{\text{Seeds}}$
Gossip Treatment	0.591		0.636	0.331	
	(0.841)		(0.0660)	(0.0821)	
Elder Treatment	-0.646		0.220	0.846	
	(0.738)		(0.0807)	(0.0502)	
At least 1 Gossip		1.359			1.535
		(0.644)			(1.179)
At least 1 Elder		-0.162			-1.164
		(0.691)			(0.748)
Constant				0.109	
				(0.160)	
Observations	213	213	213	213	213
Control Group Mean	2.452	1.595	0.400	0.180	2.048

Notes: This table uses data from the Phase 2 experimental dataset. Panel A uses the number of calls received as the outcome variable. Panel B normalizes the number of calls received by the number of seeds, 3 or 5, which is randomly assigned. For both panels, Column (1) shows the reduced form results of regressing number of calls received on dummies for gossip treatment and elder treatment. Column (2) regresses number of calls received on the dummies for if at least 1 gossip was hit and for if at least 1 elder was hit in the village. Columns (3) and (4) show the first stages of the instrumental variable regressions, where the dummies for "at least 1 gossip" and "at least 1 elder" are regressed on the exogenous variables: gossip treatment dummy and elder treatment dummy. Column (5) shows the second stage of the IV; it regresses the number of calls received on the dummies for if at least 1 gossip was hit and if at least 1 elder was hit, both instrumented by treatment status of the village (gossip treatment or not, elder treatment or not). All columns control for number of gossips, number of elders, and number of seeds. For columns (1), (3), and (4) the control group mean is calculated as the mean expectation of the outcome variable when the treatment is "random". For columns (2) and (5), the control group mean is calculated as the mean expectation of the outcome variable when no gossips or elders are reached. The control group mean for the second stage IV is calculated using IV estimates. Robust standard errors are reported in parentheses.

Table D.2. Calls received by seed type

	(1) Calls Received	(2) Calls Received	(3) Calls Received	(4) $\frac{\text{Calls Received}}{\text{Seeds}}$	(5) $\frac{\text{Calls Received}}{\text{Seeds}}$	(6) $\frac{\text{Calls Received}}{\text{Seeds}}$
At least 1 Gossip	12.89	13.02		3.751	3.871	
	(7.225)	(8.157)		(2.282)	(2.584)	
At least 1 Elder	-3.371	-3.321		-1.012	-0.962	
	(5.155)	(4.946)		(1.547)	(1.456)	
At least 1 High *DC* Seed		-0.485	2.262		-0.478	0.342
		(4.803)	(3.834)		(1.515)	(1.189)
Observations	69	69	69	69	69	69
Control Group Mean	4.840	4.840	8.828	1.101	1.101	2.433

Notes: This table uses data from the Phase 2 experimental and network dataset. The table presents OLS regressions of number of calls received (and number of calls received normalized by the number of seeds, 3 or 5, which is randomly assigned) on characteristics of the set of seeds. High *DC* refers to a seed being above the mean by one standard deviation of the centrality distribution. All columns control for total number of gossips, number of elders, and number of seeds. For columns (1), (2), (4), and (5), the control group mean is calculated as the mean expectation of the outcome variable when no gossips or elders are reached. For columns (3) and (6), the control group mean is calculated as the mean expectation of the outcome variable when no high *DC* seeds are reached. Robust standard errors are reported in parentheses.