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Abhijit Banerjee
Arun G. Chandrasekhar
Esther Duflo
Matthew O. Jackson

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ABSTRACT

We examine how participation in a microfinance program diffuses through social networks. We collected detailed demographic and social network data in 43 villages in South India before microfinance was introduced in those villages and then tracked eventual participation. We exploit exogenous variation in the importance (in a network sense) of the people who were first informed about the program, "the injection points". Microfinance participation is higher when the injection points have higher eigenvector centrality. We estimate structural models of diffusion that allow us to (i) determine the relative roles of basic information transmission versus other forms of peer influence, and (ii) distinguish information passing by participants and non-participants. We find that participants are significantly more likely to pass information on to friends and acquaintances than informed non-participants, but that information passing by non-participants is still substantial and significant, accounting for roughly a third of informedness and participation. We also find that, conditioned on being informed, an individual's decision is not significantly affected by the participation of her acquaintances.

Abhijit Banerjee
MIT
Department of Economics
E52-252d
50 Memorial Drive
Cambridge, MA 02142-1347
and NBER
banerjee@mit.edu

Arun G. Chandrasekhar
MIT Department of Economics
50 Memorial Drive, E52
Cambridge, MA 02142
agc2104@gmail.com

Esther Duflo
Department of Economics
MIT, E52-252G
50 Memorial Drive
Cambridge, MA 02142
and NBER
eduflo@mit.edu

Matthew O. Jackson
Department of Economics
Stanford University
Stanford, CA 94305-6072
and CIFAR
and also external faculty of the Santa Fe Institute
jacksonm@stanford.edu

1. Introduction

Information is constantly passed on through social networks: friends pass on both pure information (for example, about the existence of a new product) and opinions (whether it is valuable). While there are numerous studies documenting such phenomena,[1] few studies model the exact mechanics of information transmission and empirically distinguish between alternative models of transmission. This is what we do here, using rich data we collected and a combination of structural and reduced form approaches.

The data include detailed information on social networks from 75 different rural villages in southern India as well as the subsequent diffusion of microfinance participation in 43 of those villages. The data is unique for its high sampling rate (∼50% of households answered questions about their social relationships to everyone in the village), the large number of different villages for which we have observations, and the wealth of information on possible connections that it contains (we have data covering 13 different types of relationships, from going to the temple together to borrowing money or kerosene). The data is matched with administrative data on the take-up of microfinance in 43 of these villages at several points of time over a period of several months.

We begin with a reduced form approach, where we compare villages to see what influences the patterns of diffusion in different places. The first question we ask concerns the role of injection points in the diffusion of information. Specifically, if only ten or twenty members of a village of a thousand people are informed about microfinance opportunities, does eventual long-run participation depend on which individuals are initially contacted? While there are good reasons to think that this may be the case, the previous empirical literature is largely silent on this topic. Analyses are generally either case studies or theoretical analyses.[2] The setting we examine is particularly favorable to study this question

[1]The literature documenting diffusion in various case studies includes the seminal works of Ryan and Gross (1943) on the diffusion of hybrid corn adoption, of Lazarsfeld et al. (1944) on word-of-mouth influences on voting behavior, of Katz and Lazarsfeld (1955) on the roles of opinion leaders in product choices, of Coleman et al. (1966) on connectedness of doctors and new product adoption; and now is spanned by an enormous literature that includes both empirical and theoretical analyses. For background discussion and references, see Rogers and Rogers (2003), Jackson (2008), and Jackson and Yariv (2010).
[2]See Jackson and Yariv (2010) for references and background.

because our microfinance partner always follows the same method in informing a village about microfinance opportunities: they identify specific people in the village (teachers, self-help group leaders, etc.) and call these the "leaders" (irrespective of whether they are, in fact, opinion leaders in this particular village or not), inform them about the program, and ask them to spread the word to other potentially interested people about an information session. This fixed rule provides exogenous variation across villages in terms of the network characteristics of which individuals were initially contacted (we show that the network characteristics of the set of "leaders" are uncorrelated with other variables at the village level). For example, in some villages the initial people contacted are more centrally positioned in the network but in other villages, they are not. We show that eventual participation is higher in villages where the first set of people to be informed are more important in a network sense in that they have higher eigenvector centrality. Moreover, the importance of leaders with high eigenvector centrality goes up over time, as would be expected in a model of social network diffusion.

We also look at the effects of other village level measures of network connectivity, such as average degree, average path length, clustering, etc., which capture the characteristics of the network as a whole, rather than the network position of the injection points. While there are theoretical arguments suggesting that a number of these characteristics might matter for transmission, we do not find significant evidence of such relationships.

We thus go a step further and ask whether the data is consistent with a model of diffusion through the social network. The second major contribution of the paper is to model and structurally estimate a set of alternative mechanisms for the diffusion of information. In addition, from the setting and the use of the known, exogenously assigned injection points to aid identification, our contribution here is twofold.

First, the models that we introduce allow for information to be transmitted even by those who are informed but choose not to participate themselves, though not necessarily at the same rate as the participants. This contrasts with standard contagion-style diffusion models, where the diffusion occurs in an infection style: an individual needs to have infected neighbors to become infected him or herself. In our model, people who become informed and are either ineligible or choose not to participate can still tell their friends and acquaintances about the availability of microfinance; and, in fact, we find that the role of such non-participants is substantial and significant. We do find that there is a significant participation effect in information transmission: we estimate that people who do participate are more than four times as likely to pass information about microfinance on to their friends as non-participants. Even so, non-participants still pass a significant amount of information along, especially as there are many more non-participants in the village than participants. In fact, our estimates indicate that information passing by non-participants is responsible for a third of overall information level and participation.

Second, in our framework, whether a person participates in microfinance can depend both on whether they are aware of the opportunity (an information effect), and also, possibly, on whether their personal friends and acquaintances participate (what we call an endorsement effect). We use the term endorsement loosely as a catch-all for any interaction beyond basic information effects. Therefore, an endorsement effect may capture complementarities, substitution, imitation effects, etc. Diffusion models generally focus on one aspect of diffusion or the other, and we know of no previous study that empirically distinguishes these effects. Indeed, these effects can be a challenge to distinguish since they have similar reduced form implications (friends of informed people who take up microfinance will be more likely to take it up as well than friends of informed people who do not take up microfinance).

By explicitly modeling the communication and decision processes as a function of the network structure and personal characteristics, we estimate relative information and endorsement effects. We find that the information effect is significant. Once informed, however, an individual's decision is not significantly influenced by the fraction of her friends who participate. In this sense, we find no (statistical) evidence of an endorsement effect, once one allows for both effects in the same framework.[3]

[3]Note that this is quite different from distinguishing peer effects from homophily, where peer effects are diminished when one properly accounts for the characteristics of an individual and the correlation of those characteristics with his or her peers (e.g., see Aral et al. (2009). Here, the endorsement effects are disappearing when separating out information transmission from other influence.

Of course, we have to be careful in our analysis to deal with well-known problems of estimating diffusion: the social networks are endogenous and there tend to be strong similarities across linked individuals, which tend to correlate their decisions independently of any other factors. This is less of an issue for our non-finding of endorsement effects (as it would tend to bias the effects upward), but could conceivably also lead to patterns of behavior that bias estimated information transmission. To explore this, we compare our model of information transmission with a model where there is no information transmission. Instead, take-up is a function of the distance from the injection point, (say) because of similarities between the injection points and people close to them. We show that the model incorporating information transmission does significantly better in explaining observed behavior. Finally, we also show that the model does well in predicting aggregate patterns of diffusion over time, even though the data used for the estimation is only the final take-up.

The remainder of the paper is organized as follows. In Section 2 we provide background information about our data. Section 3 outlines our conceptual framework. Section 4 contains a reduced form analysis of how network properties and initial injection points correlate with microfinance participation. In Section 5 we present and structurally estimate a series of diffusion models to distinguish the effects of information transmission, endorsement, and simple distance on patterns of microfinance participation. Section 6 concludes.

2. Background and Data

2.1. **Background.** This paper studies the diffusion of participation in a program of Bharatha Swamukti Samsthe (BSS), a microfinance institution (MFI) in rural southern Karnataka.[4]

BSS operates a conventional group-based microcredit program: borrowers form groups of 5 women who are jointly liable for their loans. The starting loan is approximately 10,000 rupees and is reimbursed in 50 weekly installments. The interest rate is approximately

[4]The villages we study are located within 2 to 3 hours driving distance from Bangalore, the state's capital and India's software hub.

28% (annual). When BSS starts working in a village, it seeks out a number of predefined "leaders", who based on cultural context are likely to be influential in the village: teachers, leaders of self-help groups, and shop keepers. BSS first holds a private meeting with the leaders: at this meeting, credit officers explain the program to them, and then ask them to help organize a meeting to present information about microfinance to the village and to spread the word about microfinance among their friends. These leaders play an important part in our identification strategy, since they are known as "injection points" for microfinance in the village. After that, interested eligible people (women between 18 and 57 years) contact BSS, are trained and formed into groups, and credit disbursements start.

At the beginning of the project, BSS provided us with a list of 75 villages where they were planning to start their operations within about six months. Prior to BSS's entry, these villages had almost no exposure to microfinance institutions, and limited access to any form of formal credit. These villages are predominantly linguistically homogeneous, and heterogeneous in caste (the majority of the population is Hindu, with Muslim and Christian minorities). Households' most frequent primary occupations are in agriculture (finger millet, coconuts, cabbage, mulberry, rice) and sericulture (silk worm rearing).

We collected detailed data (described below) on social networks in these villages. Over time, BSS started its operations in 43 of them (BSS ran into some operational difficulties in the mean time and was not able to expand as rapidly as they had hoped). Across a number of demographic and network characteristics, BSS and non-BSS villages look similar.[5] Our analyses below focus on the 43 villages in which BSS introduced the program.

2.2. **Data.** Six months prior to BSS's entry into any village (starting in 2006), we conducted a baseline survey in all 75 villages. This survey consisted of a village questionnaire, a full census including some information on all households in the villages, and a detailed follow-up individual survey of a subsample of individuals, where information about social connections was collected. In the village questionnaire, we collected data on the village

[5]The main difference seems to be in the number of households per village: 223.2 households (56.17 standard deviation) and 165.8 households (48.95 standard deviation), respectively.

leadership, the presence of pre-existing NGOs and savings self-help groups (SHGs), as well as various geographical features (such as rivers, mountains, and roads). The household census gathered demographic information, GPS coordinates, amenities (such as roofing material, type of latrine, type of electrical access or lack thereof) for every household in the village.

After the village and household modules were completed, a detailed individual survey was administered to a subsample of the individuals, stratified by religion and geographic sub-locations. Over half of the BSS-eligible households, those with females between the ages of 18 and 57, in each stratification cell were randomly sampled, and individual surveys were administered to eligible members and their spouses, yielding a sample of about 46% per village.[6] The individual questionnaire gathered information such as age, sub-caste, education, language, native home, occupation. So as to not prime the villagers or raise any possible connection with BSS (who would then enter the village some time later), we did not ask for explicit financial information.

Most importantly, these surveys also included a module which gathered social network data on thirteen dimensions, including which friends or relatives visit one's home, which friends or relatives the individual visits, with whom the individual goes to pray (at a temple, church, or mosque), from whom the individual would borrow money, to whom the individual would lend money, from whom the individual would borrow or lend material goods (kerosene, rice), from whom they obtain advice, and to whom they give advice.[7]

The resulting data set is unusually rich, including networks of full villages of individuals, including more than ten types of relationships, for a large number of villages, and in a developing country context. Other papers exploiting the data include Chandrasekhar et al. (2011a), which studies the interaction between social networks and limited commitment in informal insurance settings, Jackson et al. (2011), which establishes a model of favor exchange on networks using this data as its empirical example, Chandrasekhar et al.

[6]The standard deviation is 3%.

[7]Individuals were allowed to name up to five to eight network neighbors depending on the category. The data exhibits almost no top-coding in that nearly no individuals named the full individuals in any single category (less than one tenth of one percent).

(2011b), which analyzes the role of social networks in mediating hidden information in informal insurance settings, Breza et al. (2011), which examines the impact of social networks on behavior in trust games with third-party enforcement, and Chandrasekhar and Lewis (2011), which demonstrates the biases due to studying sampled network data using this data set as its empirical example. The data is publicly available from the `Social Networks and Microfinance project web page`.

Finally, in the 43 villages where they started their operations, BSS provided us with regular administrative data on who joined the program, which we matched with our demographic and social network data.

2.3. **Network Measurement Concerns and Choices.** Like in any study of social networks, we face a number of decisions on how to define and measure the networks of interest.

A first question is whether we should consider the individual or the household as the unit of analysis. In our case, because microfinance membership is limited to one per household, the household level is the correct conceptual unit.

Second, while the networks derived from this data could be, in principle, directed, in this paper we symmetrize the data and consider an undirected graph. In other words, two people are considered to be neighbors (in a network sense) if at least one of them mentions the other as a contact in response to some network question. This is appropriate since we are interested in communication: for example, the fact that one agent borrows kerosene and rice from another is enough to permit them to talk in either direction, regardless of whether the kerosene and rice lending is reciprocated.[8]

Third, the network data enables us to construct a rich multi-graph with many dimensions of connections between individuals. In what follows, unless otherwise specified, we

[8]entries of the aggregated adjacency matrix differ across the diagonal. The rate of failed reciprocation among relatives is similar to that of other categories. Because so much of the failed reciprocation could be simply due to measurement error, there is no obvious reason to take the relationships to be directional.

consider two people linked if they have any relationship.[9] Since we are interested in contact between households and any of the relationships mentioned permit communication, this seems to be the appropriate measurement.

Finally, our data involves partially observed networks, since only about half of the households were surveyed. This can induce biases in the measurement of various network statistics, and the associated regression, as discussed by Chandrasekhar and Lewis (2011). We apply analytic corrections proposed in their paper for key network statistics under random sampling, which are shown by Chandrasekhar and Lewis (2011) to asymptotically eliminate bias.[10]

2.4. **Descriptive Statistics.** Table 1 provides some descriptive statistics. Villages have an average of 223 households. The average take-up up rate for BSS is 18.5%, with a cross-village standard deviation of 8.4%. On average, 12% of each of the households have members designated as "leaders". Leaders take up microfinance at a rate of 25% with a standard deviation of 12.5% across villages.[11] About 21% of households are members of some SHG with a standard deviation of 8%. The average education is 4.92 standards with a standard deviation of 1.01. The average fraction of "general" (GM) caste or "other backward caste" (OBC) is 63% with substantial cross-village heterogeneity; the standard deviation is 10%.[12] About 39% have access to some form of savings with a standard deviation of 10%. Leaders tend to be no older or younger than the population (with a p-value of 0.415), though they do tend to have more rooms in their house (2.69 as compared to 2.28 with a p-value of 0.00).

Turning to network characteristics, the average degree (the average number of connections that each household has) is almost 15. The worlds are small, with an average

[9]See Jackson et al. (2011) for some distinctions between the structures of favor exchange networks and other sorts of networks in these data. Here, we work with all relationships since all involve contact that enable word-of-mouth information dissemination.

[10]Moreover, Chandrasekhar and Lewis (2011) apply a method of graphical reconstruction to estimate some of the regressions from this paper and correct the bias due to sampling. Their results suggest that our results in Table 3 underestimate the impact of leader eigenvector centrality on the microfinance take-up rate, indicating that we are presenting a conservative result.

[11]Take-up is measured as a percentage of non-leader households.

[12]Thus, the remaining 37% are scheduled caste/scheduled tribe: groups that historically have been relatively disadvantaged.

network path length of 2.2 between households. Clustering rates are 26%: just over a quarter of the time that some household i has connections to two other households j and k, do j and k have a connection to each other.[13]

Eigenvector centrality is a key concept in our analysis of the importance of injection points and is a recursively defined notion of centrality: A household's centrality is defined to be proportional to the sum of its neighbors' centrality.[14] While leader and non-leader households have comparable degrees, leaders are more important in the sense of eigenvector centrality: their average eigenvector centrality is 0.07 (0.018), as opposed to 0.05 (0.009) for the village as a whole. At the village level, the 25th and 75th percentiles of the average eigenvector centrality for the population are 0.0462 and 0.0609, while for the set of leaders they are 0.065 and 0.092. There is considerable variation in the eigenvector centrality of the leaders from village to village, a feature that we exploit below.

3. Conceptual Framework

Diffusion models may be separated into two primary categories.[15] In pure contagion models, the primary driver of diffusion is simply information or a mechanical transmission, as in the spread of a disease, a computer virus, or awareness of an idea or rumor. In what we call, for want of a better term, "endorsement effects models", there are interactive effects between individuals so that an individual's behavior depends on that of his or her neighbors, as in the adoption of a new technology, human capital decisions, and other decisions with strategic complementarities. The dependency may in principle be positive (for example, what other people did conveys a signal about the quality of the product, as in Banerjee (1992)) or negative (for example, because when an individual's neighbors take up microfinance, they may share the proceeds with the individual, as in Kinnan and Townsend (2010)).

[13]This is substantially higher than the fraction that would be expected in a network where links are assigned uniformly at random but with the same average degree, which in this case would be on the order of one in fifteen. Such a significant difference between observed clustering and that expected in a uniformly random network is typical of many observed social networks (e.g., see Jackson (2008)).

[14]It corresponds to the i^{th} entry of the eigenvector corresponding to the maximal eigenvalue of the adjacency matrix, normalized so that the entries sum to one across the vector.

[15]See Jackson and Yariv (2010) for a recent overview of the literature and additional background.

Little research incorporates both aspects of diffusion and distinguishes between them.[16] Because the reduced form implications of these different types of diffusion are quite similar, without explicit modeling of information transmission and participation decisions, it can be impossible to distinguish whether, for instance, an individual who has more participating friends is more likely to participate because they were more likely to hear about it or because they are influenced by the numbers of their friends who participate.

In this section, we propose simple models of the diffusion of microfinance that incorporate both the diffusion of information and the potential endorsement effects. We then discuss reduced from implications of such models, specifically, concerning the potential impacts of "injection points" (the first people who were informed about a program), and differences in take-up in some villages compared to others. The bulk of our analysis will, however, be a structural estimation of such models to disentangle basic information from endorsement effects.

In addition to separating information from endorsement effects, our base model also has another important and novel feature: distinguishing information passing by those who take up microfinance from those who do not. Thus, the model allows for diffusion by "non-infected nodes" and we can then estimate their role in diffusion.

3.1. **The models.** The models that we estimate have a common structure, illustrated in Figures 1 to 5. They are discrete time models, described as follows:

- BSS informs the set of initial leaders.
- The leaders then decide whether or not to participate. In Figure 1, one leader has decided to participate, and the other has not.
- In each period, households that are informed pass information to their neighbors, with some probability. This probability may differ depending on the household's decision of whether or not to participate. Just as an illustration, in Figure 2, the household that does not participate informs one link and the household that participates informs three.

[16]This is not to say that both of these aspects are not understood to be important in diffusion (e.g., see Rogers and Rogers (2003), Newman (2002)), but rather that there are no systematic attempts to model both at the same time and disentangle them.

- In each period, households who were informed in the previous period decide, once and for all, whether or not to participate, depending on their characteristics and potentially on their neighbor's choices as well (the endorsement effect). This is illustrated in Figure 3.
- The model then repeats itself. In Figure 4, all the informed households pass the information again to some of their contacts with some probability that depends on their participation status, and in Figure 5, the newly informed nodes decide again.
- The process repeats for a certain number of periods (which we will estimate in the data).

Specifically, let p_i denote the probability that an individual who was informed last period decides to adopt microfinance, as a function of the individual's characteristics and peers.

In the baseline model, termed the "information" model, $p_i(\alpha, \beta)$ is given by

$$p_i = \mathrm{P}(\text{participation}|X_i) = \Lambda(\alpha + X_i'\beta), \tag{1}$$

where we allow for covariates (X_i), but not for "endorsement effects."[17]

We then enrich the model to allow the decision to participate (conditional on being informed), to depend on what others have done. We call this the "information model with endorsement effects" (or sometimes the "endorsement model," for short), and then $p_i^E(\alpha, \beta, \lambda)$ refers to

$$p_i^E = \mathrm{P}(\text{participation}|X_i) = \Lambda(\alpha + X_i'\beta + \lambda F_i), \tag{2}$$

[17]Here, Λ indicates a logistic function so that

$$\log\left(\frac{p_i}{1-p_i}\right) = \alpha + X_i'\beta.$$

where F_i is a fraction where the denominator is the number of i's neighbors who informed i and the numerator is the number of these who have participated in microfinance, and where agents are weighed by their importance in the network.[18]

The other important parameters in these models are those that govern the per-period probability that a household informs another. We let q^N denote the probability that an informed agent informs a given neighbor about microfinance in a round, conditional on the informed agent choosing *not to* participate in microfinance, and q^P denote the probability that an informed agent informs a given neighbor in a round about microfinance, conditional on the agent having chosen *to* participate in microfinance.

We refer to the models in terms of the parameters that apply as follows:

(1) Information Model: $\left(q^N, q^P, p_i(\alpha, \beta)\right)$.
(2) Information Model with Endorsement Effects: $\left(q^N, q^P, p_i^E(\alpha, \beta, \lambda)\right)$.

Before fitting these models, we discuss the reduced form implications of the models at the aggregate level: what differences would we expect in the take up of microfinance between villages based on their network characteristics?

3.2. **Injection Points.** A first characteristic that may differentiate the villages are the "injection points", or the first villagers to be informed. The idea that injections points may matter has roots in the opinion leaders of Katz and Lazarsfeld (1955) (e.g., see Rogers and Rogers (2003) and Valente and Davis (1999)), as well as measurements of "key" individuals based on their influence of other's behaviors (e.g., Ballester et al. (2006)), and underlie some "viral marketing" strategies (e.g., see Feick and Price (1987); Aral and Walker (Forthcoming)).

Surprisingly, there is little theory explicitly modeling the role of injection points in information or endorsement effects models. However, it is clear that properties of the initially informed individuals could substantially impact diffusion. Regardless of the model (information or endorsement effect), a first obvious hypothesis is that if the set of initially informed individuals in one village have a greater number of connections relative to

[18] In what follows, we use eigenvector centrality as a measure of network importance, and weight the fraction accordingly. In a supplementary appendix we also discuss other weightings, including degree and neutral weightings, but the eigenvector is the best-performing weighting.

another village, then initial information transmission could be greater, and the chance of a sustained diffusion could be higher.[19] As time goes by, and the friends of the leaders have had time to inform their own friends, a second hypothesis is that another measure of the centrality of the initial leaders that captures their network reach, their eigenvector centrality, would start mattering more and more. This is in line with the ideas behind eigenvector centrality, which measures an individual's centrality by weighting his or her neighbors' centralities, instead of simply counting degree. Moreover, if there are endorsement effects beyond information diffusion, the participation decisions of these leaders may also affect participation in the village.

As described in detail below, BSS strategy of contacting the same category of people (the "leaders") when they first start working in a village provides village to village variation, which, we will argue, leads to plausibly exogenous variation in the degrees and the eigenvector centrality of the first people to be informed. We take advantage of this variation to identify the effect of the characteristics of the initial injection points on the eventual village level take-up. We examine the extent to which take-up correlates with the degree of the leaders, as well as their eigenvector centrality, and other measures of their influence. In addition, as we observe take-up over time, we can also see which characteristics of the leaders correlate with earlier versus later take-up.

3.3. **Network Characteristics.** While it is important to examine how the initial seeding affects diffusion in a social network, there are other aspects of social network structure that could also matter in diffusion. We therefore examine how take-up correlates with other network characteristics.

In particular, in most contagion models, adding more links increases the likelihood of non-trivial diffusion and its extent.[20] For instance, Jackson and Rogers (2007) examine a standard SIS infection model and show that if one network is more densely connected than another in a strong sense (i.e. its degree distribution stochastically dominates the other's),

[19]For example, working with a basic SIR model, the probability of the initially infected nodes' interactions with others would affect the probability of the spread of an infection. See Jackson (2008) for additional background on the concepts discussed in this section.

[20]See Chapter 7 in Jackson (2008) for additional discussion and theoretical background.

then the former network will be more susceptible to a non-trivial diffusion and have a higher infection rate if diffusion occurs. In addition, how varied the degrees (number of links) are across individuals in a network can affect diffusion properties, since highly connected nodes can serve as “hubs” that play important roles in facilitating diffusion (see Valente and Davis (1999), Pastor-Satorras and Vespignani (2000), Newman (2002), López-Pintado (2008), and Jackson and Rogers (2007)).

In addition to the distribution of degrees within a population, there are other networks characteristics that can also affect diffusion, such as how segregated the network is. Having a network that is strongly segregated can significantly slow information flow from one portion of the network to another. This can be measured via the second eigenvalue of a stochasticized adjacency matrix describing communication on the network, as shown by Golub and Jackson (2009).

To estimate the effects of variation in these aspects of network structure on take-up, we again take advantage of cross-village variation. However, for this analysis it is not entirely clear the extent to which we should expect significant effects of these characteristics on take-up. First, in much of the theory once one exceeds minimum connectivity thresholds the extent of the diffusion is no longer as significantly impacted by network structure per se, but by other characteristics of the nodes and their decision making.[21] Second, while there was exogenous variation in the injection points that allowed for identification and potentially some causal inference, any variation in network structure across villages could be endogenous and correlated with other factors influencing take-up.

Given these obstacles, we report the results of regressions of take-up on various network characteristics for the sake of completeness, but then we move on to our structural estimation, which allows us to identify and test effects that cannot be identified via a regression-style analysis.

[21] Diffusion thresholds in standard contagion models are around 1 effective contact per node. This is not simply one link per node, but at least one link through which an infection would be expected to pass in a given period. So if there is some randomness in contact through links, it is the effective contact that matters (e.g., see Jackson (2008)). This aspect will be picked up when we explicitly estimate information passing in our structural modeling, but might not turn out to be directly related to the average degree within a village.

4. Preliminary Evidence: Do Injection Points and/or Network Structure Matter?

4.1. **Injection points.**

4.1.1. *Identification strategy.* In general, identifying the impact of the network characteristics of the first people informed with a new idea (like microfinance) is difficult for two reasons: first, even when there is data on adoption over time, most data sets do not distinguish between information and adoption. The first people informed may not adopt, for example. Second, information that is first received by, for example, the most popular people in a network may also spread faster for other reasons (for example, a competent marketing strategist may both identify the most central people in a network and inform them first, and then also conduct an efficient generalized information campaign).

BSS methodology of spreading information about their program motivates our identification strategy to assess the causal effect of the network characteristics of the first people informed about microfinance. When entering a village, BSS gives instructions to its workers to contact people who fill a specific list of roles in a village (whom we have called "leaders"): saving self-help group (SHG) leaders, pre-school (*anganwadi*) teachers, and shop owners. The set of individuals they attempt to contact is fixed, and does not vary from village to village. Upon entering a village, BSS staff identify and rely on such individuals to disseminate information about microfinance and to help orchestrate the first village-wide meeting.

This methodology for spreading information helps in the identification of any causal effect of the network characteristics of the first people to be informed about the product for two reasons. First, we know that they are the injection point for microfinance in the village. Second, we know that they are not selected with any knowledge of their village's network characteristics or their position in the network, or with any consideration for the village's propensity to adopt microfinance.

Of course, there could still be some omitted variable bias: it could conceivably be the case that villages where "leaders" are, say, less important or less connected are also less likely to take up microfinance for other reasons. However, we show in Table 2 that neither the eigenvector centrality nor the degree of the leaders is correlated with other village variables. This is reassuring, as it suggests that the network characteristics of the leader sets may be considered to be exogenous. We thus regress microfinance take-up on the network characteristics of the "leaders" (degree, and eigenvector centrality).

Specifically, we estimate regressions of the form

$$y_r = \beta_0 + \beta_1 \cdot \xi_r^L + W_r'\delta + \epsilon_r \tag{3}$$

where y_r is the average village level microfinance take-up, ξ_r^L is a vector of network statistics for the leaders (we introduce, separately and together, degree and eigenvector centrality),[22] and W_r is a vector of village level controls.

Though it is likely to be endogenous, we also display specifications where we introduce the centrality of the leaders who have become microfinance members:

$$y_r = \beta_0 + \beta_1 \cdot \xi_r^L + \beta_2 \cdot \xi_r^{LM} + W_r'\delta + \epsilon_r \tag{4}$$

where ξ_r^{LM} is vector of the set of leaders who became microfinance members.

We also explore whether the correlation pattern changes over time. For this investigation, we exploit data provided by BSS about participation at several points in time since the introduction of the program (from 2/2007 to 12/2010 across 43 villages). As discussed above, a pattern that we might expect is that the degree of leaders matters more initially (because degree correlates with how many people they regularly interact with) while their importance (eigenvector centrality) would matter more later, after the information has had time to diffuse (because the people they contacted were themselves more influential). To test this hypothesis, we run regressions of the following form:

$$y_{rt} = \beta_0 + \beta_1 \cdot \xi_r^L \times t + (X_r \times t)'\delta + \alpha_r + \alpha_t + \epsilon_{rt} \tag{5}$$

[22] See the supplementary appendix for other regressions including betweenness centrality, which does not significantly matter.

where y_{rt} is the share of microfinance take-up in village r at period t, ξ_r^L is the average degree and/or the average eigenvector centrality for the set of leaders and X_r is a vector of village level controls, α_r are village fixed effects, and α_t are period fixed effects. The standard errors are clustered at the village level.

As before, we also include a specification where we introduce degree and eigenvector centrality over time.

This regression include village fixed effects, and is thus not biased by omitted village level characteristics. The coefficient β_1 will indicate whether degree (or eigenvector centrality) becomes less (more) correlated with take-up over time.

4.1.2. *Results.* The results are presented in Tables 3 and 4. Basic cross sectional results are presented in Table 3. The average degree of leaders is not correlated with eventual microfinance take-up. However, their eigenvector centrality is. The coefficient of 1.6, in column (1), implies that when the eigenvector centrality of the set of leaders is one standard deviation larger, microfinance take-up is 2.7 percentage points (or 15%) larger. The results are robust to introducing degree and eigenvector centrality at the same time. They are also robust to the introduction of control variables. Interestingly, we do not find that, conditional on the centrality of the leaders as a whole, the centrality of the leaders who become members themselves is more strongly correlated with eventual take-up. A potential intuition for this result is that leaders are conduits of information regardless of their eventual participation.

Table 4 presents evidence on how the impacts of degree and eigenvector centrality of leaders vary over time, where a period is a four-month block. In all specifications, we find that the eigenvector centrality of the set of leaders matters significantly more over time. The point estimate in column (1), for example, suggest that, in each period, a one standard deviation increase in the centrality of the leader set is associated with an increase in the take-up rate which is 0.35 percentage points greater. The point estimate of the interaction between degree and time is always negative, although it is not significant. As before, we find a perhaps counterintuitive result for the centrality of the the subset of leaders who take up: if anything, it seems that their centrality matters less over time (relative to that of the other leaders). This could be explained by the microfinance take-up decisions of the leaders–it is possible that the leaders who don't take up are more important and busy people and therefore have more influence.

Overall, these results strongly suggest that social networks play a role in the diffusion of microfinance and the people chosen by BSS to be the first to be informed are indeed important in the diffusion process. However, these reduced-form results cannot shed light on the specific form that diffusion takes in the village. The theoretical models only provide partial guidance on what reduced form pattern should be expected. Even the result that the centrality of the leaders who take up microfinance more does not seem to matter more than that of the average leaders is not necessarily proof that the model of diffusion is a pure information model. To distinguish between models, we exploit individual data and our knowledge of the initial "injection point" (BSS leaders) to estimate structural models of information diffusion.

4.2. **Variation in Network Structure and Diffusion.** Before turning to the structural model, we next examine the correlation between village-level participation rates (measured after about a year) on a set of variables that capture network structure including: number of households, average degree, clustering, average path length, the first eigenvalue of the adjacency matrix, and the second eigenvalue of the stochasticized adjacency matrix. We include the variables both one by one and together.[23]

Table 5 presents the results of running regression of the form

$$y_r = W_r'\beta + X_r'\delta + \epsilon_r \tag{6}$$

where y_r is the fraction of households joining microfinance, W_r is a vector of village-level network covariates and X_r is a vector of village-level demographic covariates.

While there is some correlation between the network statistics and average participation in the microfinance program when they are introduced individually (some of them counter-intuitive; for example, average degree appears negatively correlated with take-up), no

[23]We present here the regression without control variables, but the results are similar when we control for two variables that seem to be strongly correlated with microfinance take-up, namely participation in self-help groups and caste structure.

variable is significant when we introduce them together. However, as discussed above, it could be that variation in average degree is not really capturing variations across villages in actual information passing. Also, it is important to note that the correlations are at best suggestive: villages with particular network characteristics may also be more likely to take up microfinance for reasons that have nothing to do with the network, leading to downward or upward bias. There is also a strong degree of correlation between some of the network variables (see Appendix Tables A-1 and A-2), so that they cannot be examined independently, but, given the small number of villages, multicollinearity may obscure relevant patterns. This may be an artifact of the lack of a well-specified functional form: theory does not offer much guidance beyond the general prediction that there should be a correlation between some of these network characteristics and diffusion. As we show next, a more structured approach sheds much more light on the transmission mechanism in the network.

5. Structural Estimation

5.1. **Estimation method.** As a reminder, we are seeking to estimate the following models:

(1) Information Model: $\left(q^N, q^P, p_i(\alpha, \beta)\right)$.
(2) Information Model with Endorsement Effects: $\left(q^N, q^P, p_i^E(\alpha, \beta, \lambda)\right)$.

The formulation of these models is as was described in equations 1 and 2 and the full algorithm of how we fit these is described in Appendix B. We begin with a non-technical discussion of our estimation method. We use the method of simulated moments (MSM), where we match key moments (where $m_{emp,r}$ denotes the vector of empirical moments for village r). We work with two sets of moments. The first set of moments exploits most of the available variation in microfinance take-up:

(1) Share of leaders who take up microfinance (to identify β).
(2) Share of households with no neighbors taking up who take up.
(3) Share of households that are in the neighborhood of a taking leader who take up.

(4) Share of households that are in the neighborhood of a non-taking leader who take up.
(5) Covariance of the fraction of households taking up with the share of their neighbors who take up microfinance.
(6) Covariance of the fraction of household taking up with the share of second-degree neighbors that take up microfinance.

For each set of moments, we first estimate β using take-up decision among the set of leaders (who are known to be informed). To estimate q^N, q^P, and λ (or any subset of these in the restricted models), we proceed as follows. The parameter space Θ is discretized (henceforth we use Θ to denote the discretized parameter space) and we search over the entire set of parameters. For each possible choice of $\theta \in \Theta$, we simulate the model 75 times, each time letting the diffusion process run for the number of periods from the data. (On average, it runs 5 to 8 periods). For each simulation, the moments are calculated, and we then take the average over the 75 runs, which gives us the vector of average simulated moments, which we denote $m_{sim,r}$ for village r. We then chose the set of parameters that minimize the criterion function, namely

$$\widehat{\theta} = \underset{\theta \in \Theta}{\operatorname{argmin}} \left(\frac{1}{R} \sum_{r=1}^{R} m_{sim,r}(\theta) - m_{emp,r} \right)' \left(\frac{1}{R} \sum_{r=1}^{R} m_{sim,r}(\theta) - m_{emp,r} \right).$$

To estimate the distribution of $\widehat{\theta}$, we use a simple Bayesian bootstrap algorithm, formally described in Appendix C. The bootstrap exploits the independence across villages. Specifically, for each grid point $\theta \in \Theta$, we compute the divergence for the r^{th} village, $d_r(\theta) = m_{sim,r}(\theta) - m_{emp,r}$ and interpolate values between grid points. We bootstrap the criterion function by resampling, with replacement, from the set of 43 villages. For each bootstrap sample $b = 1, ..., 1000$ we estimate a weighted average, $D_b(\theta) = \frac{1}{R} \sum_{r=1}^{R} \omega_r^b \cdot d_r(\theta)$. Note that our objective function uses a weight of 1 for every village. Here, the weights are drawn randomly to simulate resampling with replacement. Then $\widehat{\theta}^b = \operatorname{argmin}_{\theta \in \Theta} D_b(\theta)' D_b(\theta)$.

In order to compare the fit of some of the models which are not nested, but which are estimated on the same criterion function, we study which model best fits the criterion function determined by the same moments. We bootstrap the criterion function value, evaluated at the estimated parameter $\widehat{\theta}$, and look at the distribution of the difference between the criterion functions of two models. The procedure is formally described in Appendix C.

5.2. **Discussion of identification.** The first set of moments combined with the assumption that all leaders are known injection points allow us to identify the parameters of the model, but only under quite demanding assumptions.

The intuition behind the identification of endorsement effects and differential information effects in our application can be clarified by a simple two by two example. Imagine, for example, that $q^N = 0.10$ and $q^P = 0.5$ (these are the parameters that we estimate below). Consider four individuals: one of them has one friend who is a leader, and this leader takes up microfinance; the second one has one friend who is a leader but does not take up microfinance; the third has four friends who are leaders, and all take microfinance; the fourth has four friends who are leaders, and none of them take up microfinance. On average, if the model runs for 6 periods (which is what we estimate as the average number of periods), the probability that the first person is informed is 98%.[24] The probability that the second person is informed is 41%. The probability that the third person is informed is essentially 1 and the probability that the fourth person is informed is 92%. Therefore, in a pure information model, the difference in take-up between persons 1 and 2 would be much larger than the difference in take-up between persons 3 and 4. However, the endorsement effects for an informed person is a function of the average fraction of informed friends who decide to take on microfinance: in an endorsement effects model, there would be a difference between the take-up of persons 3 and 4, which we would not see in a pure information model, even with different probabilities to inform.

This discussion clarifies a potential weakness in our identification strategy of endorsement effects' with this set of moments: we compare the behavior of different households

[24]This is simply $(1 - 0.5^6)$.

located at different positions in the network who both end up informed, as a function of their neighbors' decisions to take up microfinance, in order to estimate the endorsement effect. However, it is possible, for example, that households who are neighbors of people who take up are themselves more likely to need microfinance (in ways beyond our ability to measure from all of our demographic information). We might end up attributing this to endorsement in our estimation. For example, they may share a common activity, or a common access to finance. Thus, the traditional pitfalls of the identification of peer effects apply here as well.

We implement several robustness checks to address this concern.

First, an advantage of the structural approach is that the structure imposes more specific patterns on the moments than the simple intuition that people who are closer to people who take up microfinance should be more likely to take up themselves. To distinguish the specific predictions from a simple prediction that people who are close to each other should behave similarly, we compare these models to a more mechanical "distance model", which has no structural interpretation:

$$\mathrm{P}(\text{participation}|d_i) = \Lambda(\alpha + d(i, L^P)\rho + X_i'\beta).$$

Here $d(i, L^P)$ is the distance of agent i to the set of participating leaders, so it is the shortest path between i and the nearest leader who participates in microfinance.

We include this model as a (negative) benchmark: if it were to fit the data better than our richer model, it would be worrisome, since then the fact that people closer to participating leaders participate more may be due to omitted characteristics (those close to participating leaders may have similar preferences, for example). To the extent that the structural models do better in explaining the moments than a mechanical distance model, there is some assurance that the results of the structural equation are indeed capturing parameters of the structural model. In addition, we nest this model within our main model to study how our findings hold.

Second, we use an entirely different set of moments to re-estimate the model. This set of moments is directly inspired by the spirit of the reduced form regression we presented in Section 4: it only exploits proximity to the sets of injection points.

This second set of moments is:

(1) Share of leaders who take up microfinance (to identify β).
(2) Covariance of take-up and minimum distance to leader.
(3) Variance of take-up among those who are at distance one from leader.
(4) Variance of take-up among those who are at distance two from leader.

Although, as we discuss below, these moments have different shortcomings, because they are entirely different from those used in the first estimation (with the exception of the first moment) and they make no use of the take-up decision, they are immune to some of the potential homophily problems of the first strategy, and to the extent that the results are similar, this provides reassurance that the results are valid.

Finally, we investigate the ability of the model to replicate time-series patterns in the data (Table 4). Since the estimation of the structural model only exploits take-up in the final period, the ability of the model to replicate the time series pattern (with the eigenvector centrality of the leaders mattering increasingly over time) is a useful "out of sample" test for the model.

5.3. **Results.** Table 6 presents the result of the estimation (using the first set of moments) and Table 7 presents the result of the model selection with the quantiles of bootstrapped values of the difference in information functions (a negative value at all quantiles represented means that model A fits the data better).

Panel A.1 presents the parameters of the information model. q^N is 0.10, and q^P is 0.50, and both of these are significantly different from 0. What this suggests is that in every round informed people who are themselves participating in the program inform any given neighbor with probability .5, and those who are not participating inform any given neighbor with probability .1. We are able to reject equality of the two parameters: people who take up microfinance themselves are more likely to inform their neighbors than people who do not.

Panel A.2 presents estimates of the endorsement model, where the agent gives different weights to the decision of their informed neighbors.[25] There does not appear to be an extra endorsement effect over and above the information effect: conditional on being informed, an agent's decision to take up microfinance is not affected by what their neighbors chose to do themselves.

The information model where the probability that someone passes information to a neighbor is affected by whether they are informed or not, but where there are no additional endorsement effect is thus the structural model that fits the data the best. Moreover, as we show in Table 7, this model provides a better fit for the key moments in the model than a mechanical "distance to the leaders who take microfinance model". We can reject (at the 5% level) that the distance model fits the data better than the information model.

Finally, we can also check to see how substantial the role of non-participants is in passing information. Even though they pass information at a much lower rate than participants, there are many more non-participants in a village than participants. In fact, our estimates indicate that information passing by non-participants is responsible for a third of overall informedness and participation. We find this by comparing the model as fit above to what would happen if only participants spread information. That is, holding all else constant, we can then simulate the model when we set q^N to 0, and see how the fraction of informed households changes and how the take-up rate changes. We estimate that there would be a decline of roughly one-third in overall participation, from more than 20.2 percent to 13.7 percent, and a similar decline in the fraction of informed agents, from over 81 percent to 57 percent. Thus, not only is the level of information passing by non-participants statistically significant (and different from that of participants), but it also appears to play a substantial role in the spread of information passing and eventual take-up.

5.4. **Robustness Checks and Alternative Specification.** As we discussed, one potential concern with these results is that the structural estimation approach inherits the traditional correlated effects and endogeneity problems that plague any effort to estimate

[25]We present results where the weight given to a node is proportional to its eigenvector centrality, which fit the data better than other weighting schemes in our estimations, but those models gave similar results.

peer effects from observational data. One reassuring aspect is that these problems tend to bias such estimates upwards and we are not finding such effects. Nonetheless, it is still useful to perform robustness checks as the possible biases in information parameter estimates are less obvious. The model makes a much more specific prediction about the diffusion of microfinance than "people close to people who take up will take up themselves", so it is encouraging that it fits the data better than the mechanical "distance to taking leader model". But there remains a concern that the pattern we identify may be spurious. To address this, we perform several robustness and specification checks, which we apply to the model that is found to fit the data better, namely the pure information model.

5.4.1. *A different set of moments.* Our first strategy is to estimate the model with an entirely different set of moments. These alternative moments take advantage of the specificity of our setting, where BSS identity a specific set of "leaders" that are known to be informed. The moments are as follows:

(1) Share of leaders who take up microfinance (to identify β).
(2) Covariance of take-up and minimum distance to leader.
(3) Variance of take-up among those who are at distance one from leader.
(4) Variance of take-up among those who are at distance two from leader.

What we are exploiting here is the difference in behavior between people who are more or less directly connected to the leaders (and hence more or less likely to be informed). The second moment (covariance of take-up and minimum distance to leader) is intuitive: people closer to the leaders are more likely to be informed, and therefore should take up more to the extent that take-up depends on information. The last two moments allow us to separately identify q^N and q^P: if they are equal, the variance in take-up should increase less between distance 1 and distance 2 than if they are different.

The identification assumption in this case is that friends of leaders are similar to other people in the network in terms of their propensity to take up microfinance. In Appendix D Table A-3, we investigate whether these people are different from others in the network. We show that people who are further from leaders have fewer friends and are less central.

They are, however, no less likely to be part of an SHG, which is encouraging since SHG membership could indicate an underlying demand for a microcredit product. There is no clear pattern concerning other individual and household characteristics: people further away from leaders have smaller homes and less education, but are more likely to have a latrine and electricity.

To partially address this, we control for individual characteristics. We also recognize that there could still be potential biases. But because the source of variation is completely different than that for the first set of moments, and the source of potential biases is also different (we worry more about the heterogeneity of people who are close to leaders, but not about correlated effects), if the effects are the same, it will be nevertheless be encouraging (as a form of an over-identification test), since the biases have no reason to give us the same results. The results are presented in Panel B of Table 6. They are similar to the first set of results: we find $q^N = 0.10$ and $q^P = 0.60$, and the difference between the two remains significant.

5.4.2. *A Placebo Test: Does the model predict tile roof adoption?* Our second robustness check is a placebo test. If we are really missing some unobservable correlated effects that end up biasing our model, then they would also end up biasing the model relative to a decision which would have the same correlated effects but would clearly not be dependent on information passing. Thus, instead of using microfinance participation as the predicted variable, we use a "placebo" outcome: does a household have a tiled roof? The share of households who have such a roof is 32%, and having one may be correlated with wealth, which is probably correlated among people who are neighbors in the network, and so the potential biases will be present. On the other hand, there should no role for information passing when we fit our model. Thus, if our model technique is biased, then it would appear as if there is a critical role for information passing when there is not.

The model is estimated with the same set of moments as the main model by simply replacing microfinance participation with type of roof. The results, presented in Panel C of Table 6, are interesting: we find a much greater estimated q^N and q^P (0.90 and 0.80 respectively, with q^N actually greater than q^P, although the difference is not statistically significant). Overall, these estimates are different from the ones we obtain with microfinance, suggesting that the results may not be driven by selection bias. It is important to note that the estimated parameters in the model must be high in order to permit decisions to not be affected by information. If the parameters were low, then nobody would be informed and nobody could choose to have a tiled roof. Thus, if there is no effect, the parameters should be close to 1 and no different from each other, exactly as we find.

5.4.3. *Controlling for social distance to leaders who took up microfinance.* Our third check is to control for the most direct source of possible bias in our main estimate, which is that people who are close to leaders who chose to take up microfinance may themselves have a greater need for microfinance. We saw that the mechanical "distance to leaders who take up" model fits the data less well than our information model. However, can we go further and add a linear control for the social distance to leaders who chose to take up microfinance in our main MSM simulation. This nested specification ensures that our estimation relies on the specific functional form implied by the model, rather than by correlation in behavior.

The result of introducing the nearest distance to a leader who took up microfinance in the information model is presented in Panel D of Table 6. Both estimates are higher than before, particularly q^P, which is 0.90. The difference between the two stays significant, however.

5.5. **How well does the model predict the aggregate patterns?** Finally, to provide a test of the fit of the model, we attempt to replicate the basic cross-village patterns that we presented in the beginning of the paper. We do this for the information model, without enforcement, and set $q^N = 0.1$ and $q^P = 0.5$. To do so, we simulate the information model in each of our networks, construct the basic statistics that we had constructed in the real data for the simulated data, and run exactly the same regressions. The basic cross-sectional pattern are not interesting to replicate, since village level take up of microfinance is one of the moment we match. However, we make no use of the time-series structure of the data in the structural estimation. Thus, the ability of the simulated data over time to match the pattern observed in the data over time is a useful cross-validation of our structural model.

Table 8 presents results regarding whether the model is able to replicate time series patterns found in the data, where the average eigenvector centrality of the leaders was found to matter increasingly over time. Consistent with the real data, we find, in the simulated data that the average eigenvector centrality of the leaders matters increasingly over time. Although, the point estimate in the simulated data is smaller, if we restrict the regression to time periods 2 and onward then the model also produces quantitatively similar coefficients. Therefore, the model better replicates later periods of the diffusion process, only partially replicating first period dynamics.[26]

6. Conclusion

Taking advantage of arguably exogenous variation in initially informed individuals across villages induced by BSS strategy, we show that the eigenvector centralities of initially informed individuals are significant determinants of the eventual participation rate in a village; in contrast, other variations in social network characteristics across villages are relatively insignificant determinants of diffusion.

Motivated by these patterns, we have used the micro-data to estimate a structural model of the diffusion of information in the social network. While this estimation requires some stronger identification assumptions, it allows us to distinguish between different models of information transmission. We find that the data appears to be well-characterized by a model where participants pass information with much higher likelihood than non-participants, but nonetheless that both forms of information passing are important. The estimation also suggests that once informed, an individual's decision is not significantly affected by the participation of her acquaintances, suggesting no extra endorsement effects over and above information transmission.

[26] As periods in the model are rounds of communication, they may not correspond to either calendar time or rounds of sign-ups, and so we might expect better matching of long-run than short run dynamics.

The information model fits the data better than a mechanical "distance" model (where adoption is a function of distance to a participating leader), and does a good job replicating the aggregate cross sectional pattern in the data (including the lack of prediction concerning any of the social network characteristics and the eventual participation). The results hold up under several robustness checks: in particular, when we re-estimate the model using an entirely different set of moments, and when we re-estimate the model with a different participation variable where we know the information effect should not be present.

Our findings not only shed light on microfinance, but also suggest that further research is important. First, the fact that the initial injection points are a major predictor of diffusion in our setting suggests that more attention should be paid to initial conditions in both the theoretical and empirical analysis of diffusion. Second, the fact that we find differences in the role of pure information versus endorsement effects in this setting suggests that it will be useful to develop richer models of peer effects and diffusion that further disentangle the various roles that interactions can play, and to investigate this dichotomy across a wider range of applications. Finally, the role of non-participants in diffusion is also noteworthy and deserving of further attention in other settings.

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Table 1: Descriptive Statistics

	BSS Villages		Non-BSS Villages	
	Mean	Std. Dev.	Mean	Std. Dev.
	(1)	(2)	(3)	(4)
Panel A: Network Characteristics				
Number of Households	223.209	56.170	165.813	48.945
Degree (Corrected)	14.827	2.558	13.355	2.443
Graph Clustering (corrected)	0.259	0.046	0.290	0.063
Eigenvector Centrality	0.051	0.009	0.061	0.012
Betweenness Centrality	0.008	0.002	0.010	0.002
Path Length (Corrected)	2.293	0.137	2.285	0.170
Fraction in Giant Component	0.951	0.026	0.951	0.030
First Eigenvalue of Adjacency Matrix	15.080	2.563	13.553	2.491
Second Eigenvalue of Stochastized Matrix	0.802	0.079	0.751	0.302
Spectral Gap of Network	0.198	0.079	0.194	0.058
Degree of Leader (Corrected)	18.101	3.784	16.120	3.190
Degree from Leaders to Non-Leaders	10.486	2.071	9.591	2.039
Eigenvector Centrality of Leader	0.073	0.017	0.088	0.020
Betweenness Centrality of Leader	0.013	0.004	0.018	0.006
Degree of Taking Leader (Corrected)	15.933	6.896	--	--
Eigenvector Centrality of Taking Leader	0.066	0.030	--	--
Betweenness Centrality of Taking Leader	0.011	0.008	--	--
Panel B: Outcome Variables				
Microfinance take-up rate	0.185	0.084	--	--
Microfinance take-up rate of leaders	0.248	0.125	--	--
Panel C: Demographic Characteristics				
Average Age	47.130	2.139	47.985	2.186
Average Education Level	4.920	0.993	5.157	0.935
Average Number of Rooms	2.288	0.404	2.413	0.241
Average Number of Beds	0.867	0.449	0.852	0.449
Self-help Group Participation Rate	0.207	0.084	0.227	0.124
Fraction with Savings	0.387	0.098	0.418	0.117
Fraction GM or OBC	0.627	0.093	0.653	0.099

Note: Sample includes 43 BSS villages and 32 non-BSS villages. Network statistics used are described in Appendix A. Fraction GM or OBC refers to share of households that are not SC/ST.

Table 2: Explaining Leader Eigenvector Centrality and Degree

	Dependent Variable: Eigenvector Centrality of Leaders				Dependent Variable: Degree of Leaders			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	0.000353	0.000225		-0.000304	-0.299	-0.324		-0.402
	(0.00118)	(0.00124)		(0.00148)	(0.317)	(0.320)		(0.371)
Education	0.00126	0.00205		0.00400	0.944	0.988		1.771*
	(0.00328)	(0.00299)		(0.00386)	(0.766)	(0.829)		(0.990)
Fraction GM	-0.0149**	-0.0138*		-0.0128	0.978	0.997		0.724
	(0.00699)	(0.00717)		(0.00943)	(2.184)	(2.107)		(2.437)
Savings		0.0268		0.0215		4.067		1.588
		(0.0266)		(0.0409)		(7.395)		(8.785)
SHG Participation		0.0430		0.0414		-2.893		-2.116
		(0.0428)		(0.0418)		(9.808)		(10.93)
No. Beds			0.00737	0.00718			0.281	1.297
			(0.00816)	(0.0108)			(1.431)	(1.892)
Electricity			0.0176	0.0147			-0.966	2.282
			(0.0220)	(0.0240)			(5.068)	(5.763)
Latrine			0.0120	0.0163			3.279	6.382*
			(0.0143)	(0.0156)			(3.685)	(3.603)
Constant	0.0879*	0.0353	0.0117	-0.0110	25.12*	20.04	11.30	4.323
	(0.0520)	(0.0761)	(0.0380)	(0.117)	(13.89)	(19.49)	(7.317)	(22.30)
Observations	43	43	43	43	43	43	43	43
R-squared	0.087	0.113	0.068	0.169	0.099	0.122	0.064	0.266

Note: The dependent variable in columns (1)-(4) is the eigenvector centrality of the leaders. The dependent variable in (5)-(8) is the degree of leaders. Fraction GM refers to the fraction of households that are not SC/ST. Savings is a dummy for whether the household engages in formal savings. SHG participation is a dummy for whether the household has a member who participates in a self-help group.

Table 3: Leaders/Injection points

	Take-up Rate	Take-up Rate	Take-up Rate	Take-up Rate	Take-up Rate	Take-up Rate
	(1)	(2)	(3)	(4)	(5)	(6)
Eigenvector Centrality of Leaders	1.634*		1.934**	1.843	1.254*	1.332*
	(0.904)		(0.967)	(1.101)	(0.735)	(0.782)
Number of Households	-0.000382	-0.000704***	-0.000270	-0.000273	-0.000305	-0.000299
	(0.000247)	(0.000188)	(0.000270)	(0.000280)	(0.000216)	(0.000226)
Degree of Leaders		-0.00111	-0.00324	-0.00287		
		(0.00231)	(0.00259)	(0.00276)		
Fraction of Taking Leaders					0.323***	0.317***
					(0.101)	(0.105)
Eigenvector Centrality of Taking Leaders					-0.175	-0.253
					(0.428)	(0.427)
Savings				-0.0568		-0.0523
				(0.0940)		(0.0854)
Fraction GM				-0.0151		-0.00792
				(0.0363)		(0.0302)
Constant	0.150	0.362***	0.162	0.292	0.0924	0.0924
	(0.112)	(0.0573)	(0.106)	(0.202)	(0.0915)	(0.186)
Observations	43	43	43	43	43	43
R-squared	0.293	0.235	0.311	0.319	0.502	0.502

Note: Dependent variable is the microfinance participation rate of non-leader households and report heteroskedastic robust standard errors.

Table 4: Leader Characteristics that Matter Over Time

	Take-Up Rate	Take-Up Rate
	(1)	(2)
Eigenvector Centrality of Leaders	0.3511***	0.3491**
	(0.128)	(0.1635)
Degree of Leaders	-0.00075	-0.00063
	(0.00082)	(0.00088)
Number of Households		-0.000016
		(0.00003)
Savings		0.0082
		(0.0109)
Fraction GM		0.0049
		(0.0031)
Observations	239	239
R-squared	0.943	0.944

Note: The dependent variable is the microfinance take-up rate in a village in a time period. Every covariate is interacted with time. Regressions include village fixed effects and time fixed effects. Standard errors are clustered at the village level.

Table 5: Network Characteristics and Participation

	Take-up Rate	Take-up Rate	Take-up Rate	Take-up Rate	Take-up Rate	Take-up Rate	Take-up Rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of Households	-0.000721***						-0.000278
	(0.000185)						(0.000737)
Degree		-0.00779*					-0.0231
		(0.00443)					(0.0264)
Clustering Coefficient			0.0693				0.348
			(0.304)				(0.684)
Path Length				-0.100			-0.219
				(0.0848)			(0.364)
First Eigenvalue of Adjacency Matrix					-0.00851*		0.00718
					(0.00455)		(0.0205)
Second Eigenvalue of Stochastized Matrix						-0.156	-0.0179
						(0.188)	(0.304)
Constant	0.346***	0.300***	0.167**	0.414**	0.313***	0.310**	0.906
	(0.0469)	(0.0712)	(0.0785)	(0.193)	(0.0737)	(0.152)	(0.839)
Observations	43	43	43	43	43	43	43
R-squared	0.232	0.056	0.001	0.027	0.067	0.021	0.267

Note: Dependent variable is the microfinance participation rate of non-leader households.

Table 6: Structural Estimates

	(1)	(2)	(3)	(4)
Panel A: Standard Moments				
Panel A.1	q^N	q^P		$q^N - q^P$
Information Model	0.10	0.50		-0.40
	[0.0481]	[0.1693]		[0.1718]
Panel A.2	q^N	q^P	λ	$q^N - q^P$
Information Model w/ Endorsement	0.10	0.45	0.15	-0.40
(Eigenvector weighted)	[0.0382]	[0.1544]	[0.1227	[0.1635]
Panel A.3	ρ			
Distance from Taking Leader Model	-0.25			
	[0.0404]			
Panel B: Alternative Moments	q^N	q^P		$q^N - q^P$
	0.05	0.60		-0.55
	[0.0318]	[0.1444]		[0.1449]
Panel C: Tiled Roofing	q^N	q^P		$q^N - q^P$
	0.90	0.80		0.10
	[0.0336]	[0.0763]		[0.0766]
Panel D: Nested Model	q^N	q^P	ρ	$q^N - q^P$
	0.15	0.90	-0.05	-0.75
	[0.2558]	[0.1247]	[0.0620]	[0.2784]

Note: q^N represents the probability that a household that is informed about microfinance but has decided not to participate transmits information to a neighbor in a given period and q^P represents the probability that a household that is informed and has decided to participate transmits information to a neighbor in a given period. ρ is the coefficient on the social distance to the set of participating leader households. λ is the coefficient in the participation decision equation on the fraction of neighbors that informed a household about microfinance who themselves decided to participate. Panel A uses the moments described in Section 5.1. Panel B uses the moments described in Section 5.4.1. Panel C conducts a placebo test, estimating the diffusion model where whether a household has tiled roofing is the outcome variable of the diffusion process. Panel D includes the social distance from participating leaders in the participation equation, nesting the models of A.1 and A.3. Standard errors are as in Appendix C. We use village-level Bayesian bootstrap estimates of the model parameters with 1000 draws to produce the distribution of the parameter estimates.

Table 7: Model Selection

	5th Percentile	Median	95th Percentile
	(1)	(2)	(3)
Information Mode	-0.058	-0.037	-0.004

Note: The test statistic for Model A vs Model B is $42^{1/2}$(Criterion

Table 8: Leader Characteristics that Matter Over Time

	Simulated Data			*Empirical Data*
	Take-Up Rate	Take-Up Rate	Take-Up Rate	Take-Up Rate
	(1)	(2)	(3)	(4)
Eigenvector Centrality of Leaders	0.1069**	0.0781	0.1052*	0.1148*
	(0.0471)	(0.0640)	(0.1635)	(0.0593)
Degree of Leaders	0.00048**	0.00058	0.00014	0.00016
	(0.00022)	(0.00018)	(0.000298)	(0.00042)
Number of Households		0.000003		
		(0.000018)		
Savings		0.00196		
		(0.0060)		
Fraction GM		-0.0064		
		(0.0015)		
Observations	239	239	196	196
R-squared	0.983	0.986	0.983	0.977

Note: The dependent variable is the microfinance take-up rate in a village in a time period. Every covariate is interacted with time. Regressions include village fixed effects and time fixed effects. Standard errors are clustered at the village level. Columns (3) and (4) restricts the sample to time periods $t > 1$.

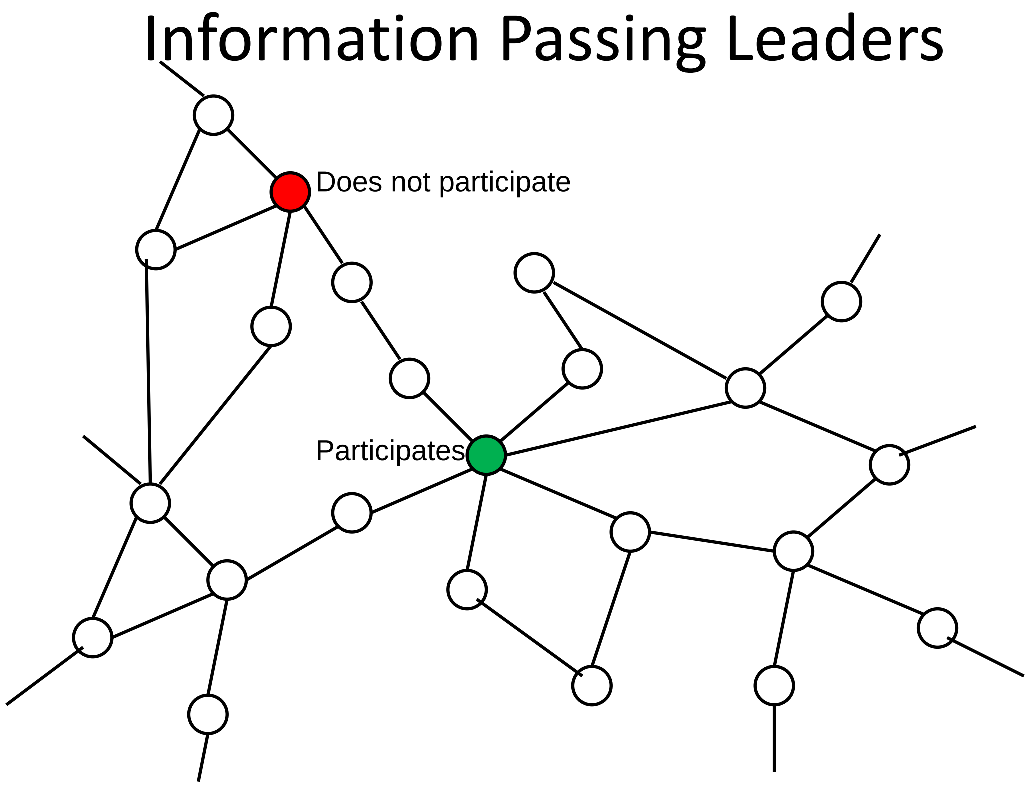

FIGURE 1. Leaders are initially informed and decide whether to participate or not.

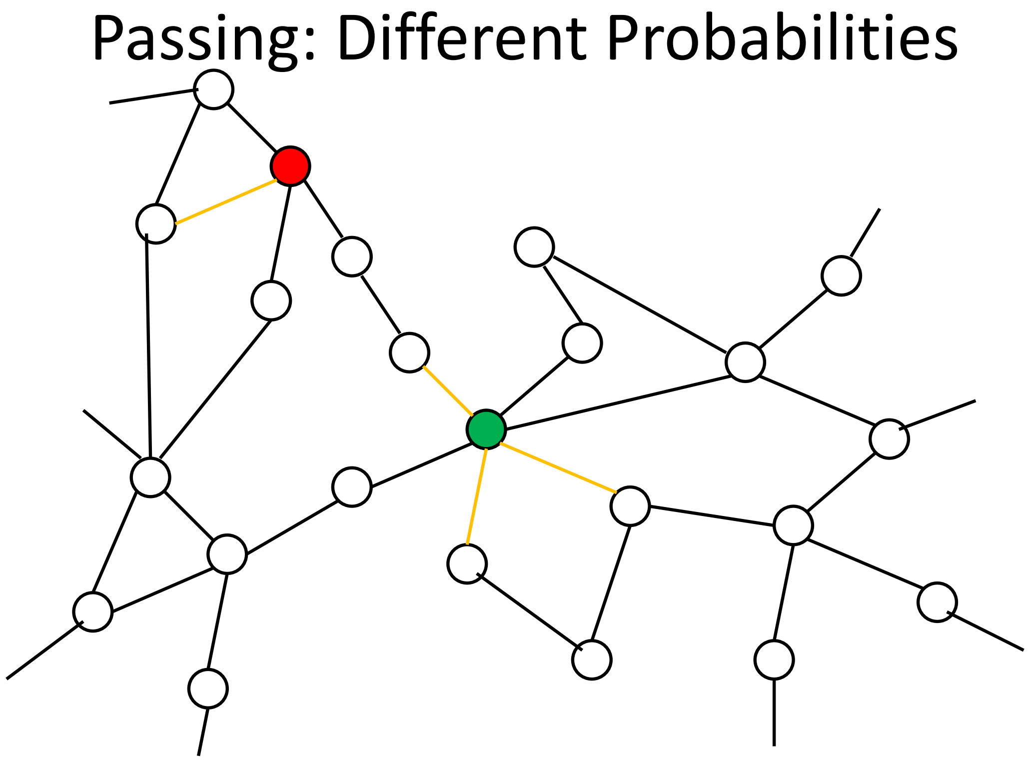

Figure 2. Nodes that participate have a higher probability of passing on information.

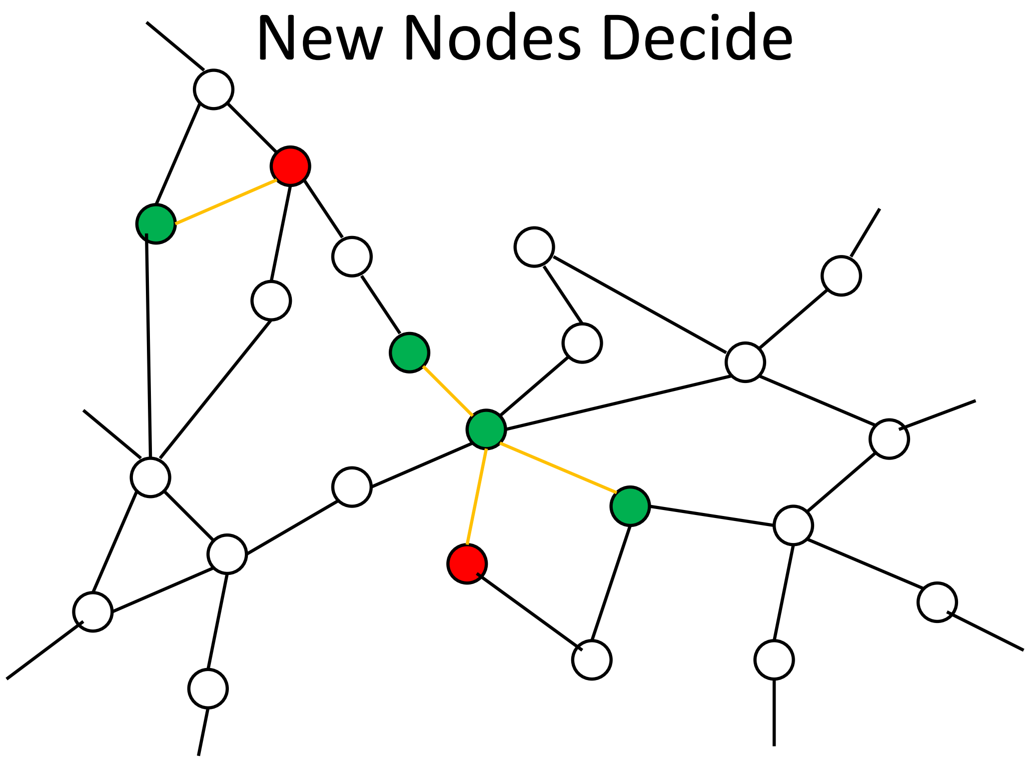

FIGURE 3. Newly informed nodes decide whether to take up microfinance or not.

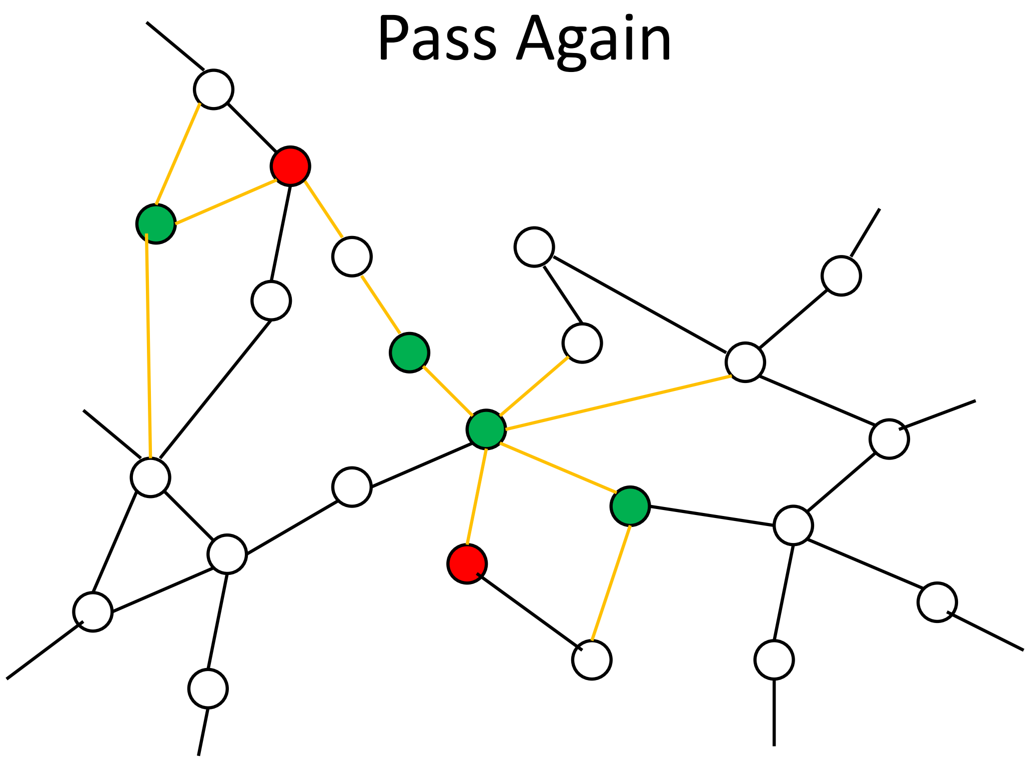

FIGURE 4. Informed nodes pass on information again.

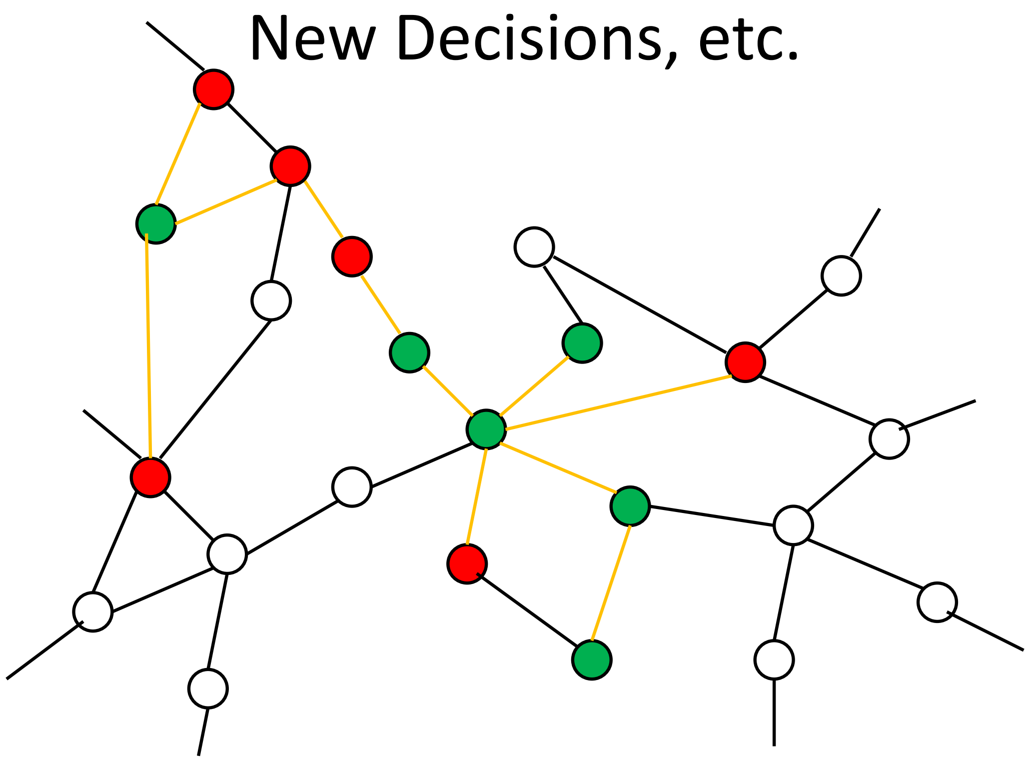

Figure 5. New decisions are made by the newly informed nodes.

Appendix A. Glossary of network terminology

In this section, we provide brief background definitions of some terms and variables with respect to how they are measured in our data.[27]

- Degree: the number of links that a household has.
  - This is a measure of how well-connected a node is in a graph.
- Clustering coefficient: the fraction of pairs of a household's neighbors who are neighbors of each other.
  - This is a measure of how interwoven a household's neighborhood is.
- Eigenvector centrality: a recursively defined notion of importance. A household's centrality is defined to be proportional to the sum of its neighbors' centralities. It corresponds to the i^{th} entry of the eigenvector corresponding to the maximal eigenvalue of the adjacency matrix.
  - This is a measure of how important a node is in the sense of information flow.
- Average path length: the mean length of the shortest path between any two households in the village.
  - Shorter average path length means information has to travel less (on average) to get from household i to household j.
- First eigenvalue: the maximum eigenvalue of the adjacency matrix representing the network.
  - This is a measure of how diffusive the network is. A higher first eigenvalue implies that information is generally more transmitted.
- Fraction of nodes in the giant component: the share of nodes in the graph that are in the largest connected component.
  - Typically, realistic graphs have a giant component with almost all nodes in it. Thus, the measure should be approaching one. For a network that is sampled, this number can be significantly lower. In particular, networks which were tenuously or sparsely connected to begin with may "shatter" under sampling and therefore the giant component may no longer be giant after sampling. In

[27]Detailed descriptions can be found in Jackson (2008).

turn, it becomes a useful measure of how interwoven the underlying network is.

- Second eigenvalue of the stochastized adjacency matrix: the stochastized adjacency matrix is defined by person i putting $1/d_i$ weight on each of her d_i-neighbors and 0 weight on the rest of the individuals in the network. The second eigenvalue is the second largest eigenvalue (in magnitude) of this matrix. The largest is mechanically one.
  - It captures a communication flow in a network. It provides bounds on the rate of convergence of beliefs in some models (e.g., see Golub and Jackson (2009)). Lower second eigenvalue means information convergence approaches faster; that is, the network has a lower consensus time.

Appendix B. Model structure

We formally describe the model in this section. The model is simulated in discrete time periods $t \in \mathbb{N}$. At each point in time, a node (household) has two states that we track:

- node i's information status: $s_{it}^{I} \in \{0,1\}$, with 0 indicating uninformed and 1 indicating informed,[28]
- node i's participation status: $m_{it} \in \{0,1\}$. Note that if $m_{it} = 1$ then $s_{it} = 1$ as one cannot participate without being informed.

Let I_t be the set of newly informed nodes at time t.[29] Define I^t be the historical stock of those informed.

The Basic Algorithm

(1) t=0
   (a) At the beginning of the period, the initial set of nodes (leaders) are informed. $s_{i0} = 1 \ \forall i \in L$ and $s_{i0} = 0$ if $i \notin L$, where $L = \{i \in N : \ i \text{ is a leader}\}$.
   (b) Next, those newly informed agents decide whether or not to participate: m_{i0} are distributed as Bernoulli with $p_i(\alpha, \beta)$ or $p_i^E(\alpha, \beta, \lambda)$, for each $i \in I_1$. In the case of p_i^E, for the initial period $F_i = 0$.
   (c) Next, each $i \in I^0$ transmits to $j \in N_i$ with probability $m_{i1} q^P + (1 - m_{i1})\, q^N$. This is independent across i and j. Let I_1 be the set of j's informed via this process who were not members of I^0, and let $I(j)$ be the set of i's who informed j.

(2) Iteration at time t:
   (a) The newly informed agents are now I_t.
   (b) Those newly informed agents decide whether or not to participate: m_{it} are distributed as Bernoulli with $p_i(\alpha, \beta)$ or $p_i^E(\alpha, \beta, \lambda)$, for each $i \in I_t$. In the case of p_i^E, for the initial period $F_i = |\{j | j \in I(i,t), m_{jt} = 1\}| / |I(i,t)|$ where $I(i,t)$ is the set of i's who informed j.

[28] So, note that $s_{i,t+1} \geq s_{it}$ for all t.

[29] That is $I_t = \{i : s_{it} = 1, s_{it-1} = 0\}$.

(c) Next, for all nodes $i \in I^t$ each i transmits to $j \in N_i$ with probability $m_{it} q^P + (1 - m_{it})\, q^N$. This is independent across i. Let I_{t+1} be the set of j's informed via this process who are not in I^t, let $I(j, t+1)$ be the set of i's who informed j, and the process repeats.

Appendix C. Structural estimation

Bootstrap Algorithm Let Θ be the parameter space and Λ a grid on Θ. Put $\psi(\cdot)$ as the moment function and let $z_r = (y_r, x_r)$ denote the empirical data with a vector of microfinance take-up decisions, y_r, and covariates x_r, including leadership status and other covariates included in the model, for village r. Define $m_{emp,r} := \psi(z_r)$ as the empirical moment for village r and $m_{sim,r}(s, \theta) := \psi(z_r^s(\theta)) = \psi(y_r^s(\theta), x_r)$ as the sth simulated moment for village r at parameter value θ. Also, put B as the number of bootstraps and S as the number of simulations used to construct the simulated moment.

(1) Pick lattice $\Lambda \subset \Theta$.
(2) For $\lambda \in \Lambda$ on the grid:
   (a) For each village $r \in [R]$, compute
   $$d(r, \lambda) := \frac{1}{S} \sum_{s \in [S]} m_{sim,r}(s, \theta) - m_{emp,r}.$$
   (b) For each $b \in [B]$, compute
   $$D(b) := \frac{1}{R} \sum_{r \in [R]} \omega_r^b \cdot d(r, \lambda)$$
   where $\omega_r^b := e_{br}/\bar{e}_r$ with e_{br} iid $\exp(1)$ random variables and $\bar{e}_r := \frac{1}{R} \sum e_{br}$.
   (c) Find $\lambda^{\star b} = \arg\min Q^{\star b}(\lambda)$, with
   $$Q^{\star b}(\lambda) := \| D(b) \|_{\ell_{2,R}}.$$
(3) Obtain $\{\lambda^{\star b}\}_{b \in B}$.
(4) For conservative inference, consider the $1 - \alpha/2$ and $\alpha/2$ quantiles of the $\lambda_j^{\star b}$ marginal empirical distribution.

Specifically, we consider for the information model $\Theta = [0,1]^2$, $\Lambda = [0.05 : 0.05 : 0.95] \times [0.05 : 0.05 : 0.95]$, $B = 1000$, $S = 75$; for the endorser model $\Theta = [0,1]^2 \times \mathbb{R}$, $\Lambda = [0.05 : 0.05 : 0.95]^2 \times [-5 : 0.05 : 1]$, $B = 1000$, $S = 75$.

Appendix D. Misc. Tables

Table A-1: Correlation of Network Characteristics

	No. of HH	Degree	Clustering	Eig. Cent.	Bet. Cent.	Path Length	Fraction	First Eig	Second Eig	Spectral Gap
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Number of Households	1.000									
Degree (Corrected)	0.177	1.000								
Clustering (Corrected)	-0.162	0.362	1.000							
Eigenvector Centrality	-0.873	0.006	0.054	1.000						
Betweenness Centrality	-0.843	-0.483	0.155	0.712	1.000					
Path Length (Corrected)	0.535	-0.598	-0.018	-0.713	-0.181	1.000				
Fraction in Giant Comp.	0.250	-0.107	0.135	0.086	-0.271	1.000				
First Eig	0.254	0.968	0.333	-0.118	-0.547	-0.510	0.240	1.000		
Second Eig	0.389	-0.242	0.406	-0.480	-0.062	0.711	-0.098	-0.230	1.000	
Spectral Gap	-0.389	0.242	-0.406	0.480	0.062	-0.711	0.098	0.230	-1.000	1.000

Table A-2: Principal Components

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Eigenvalues										
Component	Eigenvalue	Difference	Proportion	Cumulative						
Comp1	3.863	0.907	0.386	0.386						
Comp2	2.955	1.209	0.296	0.682						
Comp3	1.747	0.755	0.175	0.857						
Comp4	0.992	0.730	0.099	0.956						
Comp5	0.262	0.178	0.026	0.982						
Comp6	0.084	0.030	0.008	0.990						
Comp7	0.054	0.026	0.005	0.996						
Comp8	0.028	0.014	0.003	0.999						
Comp9	0.014	0.014	0.001	1.000						
Comp10	0.000	.	0.000	1.000						
Panel B: Eigenvectors										
	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9	Unexplained
Number of Households	-0.374	0.325	-0.233	0.089	-0.082	0.499	0.645	-0.006	-0.142	0.000
Degree (Corrected)	0.154	0.517	0.242	-0.031	-0.152	-0.010	0.081	-0.070	0.784	0.000
Clustering (Corrected)	-0.048	0.072	0.699	-0.218	0.482	0.366	-0.046	-0.235	-0.181	0.000
Eigenvector Centrality	0.427	-0.224	0.185	0.017	-0.457	0.592	-0.095	0.406	-0.028	0.000
Betweenness Centrality	0.217	-0.466	0.255	0.139	0.195	-0.261	0.699	0.169	0.169	0.000
Path Length (Corrected)	-0.465	-0.174	-0.097	0.003	0.398	0.184	-0.218	0.593	0.391	0.000
Fraction in Giant	0.125	0.125	0.051	0.939	0.210	0.097	-0.158	-0.069	-0.034	0.000
lambda1	0.116	0.538	0.197	-0.034	0.053	-0.336	0.060	0.625	-0.384	0.000
lambda2	-0.424	-0.098	0.353	0.143	-0.379	-0.144	-0.032	0.001	-0.027	0.000
Spectral Gap	0.424	0.098	-0.353	-0.143	0.379	0.144	0.032	-0.001	0.027	0.000

Table A-3: Distance to Leader Set on Characteristics

	dist	dist	dist	dist	dist	dist	dist	dist	dist	dist	dist	dist	dist
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
degree	-0.0301***												
	(0.00114)												
clustering		-0.162***											
		(0.0366)											
betweenness			-9.473***										
			(0.774)										
ecen				-3.523***									
				(0.194)									
room_no					-0.0688***								
					(0.00645)								
bed_no						-0.0170***							
						(0.00597)							
electricity							0.158***						
							(0.0129)						
latrine								0.0681***					
								(0.00940)					
educ									-0.00895***				
									(0.00217)				
ownrent										-0.0130			
										(0.00964)			
GMOBC											-0.0123		
											(0.0206)		
savings												-0.0605***	
												(0.0202)	
shgparticipate													0.0465
													(0.0454)
Constant	1.259***	1.021***	1.045***	1.152***	1.137***	0.994***	0.746***	0.812***	0.845***	0.991***	0.810***	0.825***	0.801***
	(0.0133)	(0.0125)	(0.00987)	(0.0125)	(0.0169)	(0.00981)	(0.0208)	(0.0246)	(0.0140)	(0.0150)	(0.0167)	(0.0122)	(0.00999)
Observations	7,986	7,986	7,986	7,986	7,986	7,986	7,983	7,985	3,659	7,839	3,646	3,659	3,659
R-squared	0.080	0.002	0.018	0.040	0.014	0.001	0.019	0.007	0.005	0.000	0.000	0.002	0.000

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
The dependent variable is the minimal distance to the set of leaders.