THE DIFFUSION OF MICROFINANCE

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ABSTRACT. We examine how participation in a microfinance program diffuses through social networks, using detailed demographic, social network, and participation data from 43 villages in South India. 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 significantly higher when the injection points have higher eigenvector centrality. We also 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. However, information passing by non-participants is still substantial and significant, accounting for roughly one-third of informedness and participation. We also find that, once we have properly conditioned on an individual being informed, her decision to participate is not significantly affected by the participation of her acquaintances.

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1. Introduction

Information is constantly being passed on through social networks: friends get pure information from friends (for example, they might learn about the existence of a new product) as well as opinions (for example, on whether or not the the product works). While there are numerous studies documenting such phenomena,[1] few model the exact mechanics of information transmission and empirically distinguish between alternative models of transmission. However, understanding how information exchange takes place is crucial to the design of effective campaigns, for example in public health. In this paper, we use rich data that we collected and a combination of structural and reduced-form approaches to investigate the nature of information exchange.

The data include detailed information about social networks from 75 different rural villages in southern India as well as information on the subsequent diffusion of microfinance participation in 43 of those villages. The data are unique given the large number of different villages for which we have observations, the wealth of information on possible connections (we have data on 13 different types of relationships, from whether respondents go to the temple together to whether they borrow money or kerosene from one another), and the fact that the data are matched with administrative data on the take up of microfinance in 43 of these villages, collected over a period of more than a year.

Our analysis consists of two main components that differ in both the issues explored and techniques employed. The first is a reduced-form approach in which we take advantage of cross-village variation in network characteristics and initial contact nodes to identify what influences diffusion. The second is a structural modeling approach in which we explicitly model information passing from household to household within networks, and subsequent participation decisions. This allows us to infer the importance of pure information transmission about microfinance availability relative to opinion transmission and peer effects. Next, we describe each of the two approaches in more detail.

In our reduced-form analysis, we test which attributes of network structure are significantly related to microfinance diffusion. One of the main concepts that we analyze is the role of the initial injection points. Specifically, if only ten or twenty members of a village of a thousand people are initially informed about the opportunity to borrow from a microfinance institution, how does eventual participation depend on exactly which individuals

[1]The literature documenting diffusion in various case studies spans decades from Ryan and Gross (1943) on the diffusion of hybrid corn adoption, to Lazarsfeld et al. (1944) on word-of-mouth influences on voting behavior, to Katz and Lazarsfeld (1955) on the roles of opinion leaders in product choices, to Coleman et al. (1966) on connectedness of doctors and new product adoption. More recently the literature includes Foster and Rosenzweig (1995) and Conley and Udry (2010) on learning and agricultural technology, and Kremer and Miguel (2007) on deworming drugs; this literature includes both empirical and theoretical analyses. For background discussion and references, see Rogers (2003), Jackson (2008), and Jackson and Yariv (2010).

are initially contacted? The previous empirical literature is largely silent on this topic, although some case studies and theory speak to this.[2] The setting we examine is particularly suitable for studying this question because our microfinance partner always follows the same procedure for informing a village about microfinance opportunities: the partner identifies specific people in the village (teachers, shopkeepers, etc.) and calls them the "leaders" (irrespective of whether they are, in fact, opinion leaders in that particular village), informs them about the program, and asks them to tell other potentially interested villagers about the program. This fixed rule provides exogenous variation across villages in the network characteristics of the individuals who were initially contacted, which we show are uncorrelated with other attributes of the village. In some villages, those who were initially contacted are more centrally positioned in the network than in other villages. We show that eventual program participation is higher in villages where the first set of people to be informed are more important in a network sense. In particular, we show that a specific measure of the importance or position of the initially contacted individuals, their eigenvector centrality (explained below), is significantly related to eventual microfinance participation, while other measures of centrality are not.

We also examine 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 could play substantial roles in determining the nature of diffusion, we do not find significant evidence that they do in this setting (and explain why this might be).

The second major contribution of the paper is to develop and structurally estimate models that distinguish alternative mechanisms for the diffusion of information. Here, we move beyond the existing literature in two ways.

First, the models that we introduce allow for information to be transmitted even by those who are informed but choose not to participate themselves (and we allow non-participants to transmit information at a different rate from participants). This contrasts with standard contagion-style diffusion models, in which the diffusion is modeled as an infection: an individual needs to have infected neighbors to become infected. 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 also find that there is a significant participation effect in information transmission: people who do participate are estimated to be more than four times as likely to pass on information about microfinance to their friends as non-participants. Nonetheless, non-participants transmit a significant amount of information, especially since there are many more non-participants

[2]See Jackson and Yariv (2010) as well as the discussion in Section 3.2 for references and background.

in the village than participants. In fact, our estimates indicate that information passing by non-participants is responsible for one-third of overall information about the program and program participation.

Second, in our framework, whether a person participates in microfinance can depend on whether the person is aware of the opportunity (a pure information effect), as well as whether the person's friends and acquaintances themselves participate in the program (which we loosely deem an "endorsement effect"). Note that endorsement here is a catch-all for any interaction beyond basic information transmission: such effects might be driven by complementarities, by substitution, by imitation, by opinion transmission, etc. Diffusion models generally focus on one or the other of these effects, and we know of no previous study that empirically distinguishes between them. Indeed, without a structural model, these effects are difficult to distinguish since they have similar reduced-form implications. In both cases, friends of people who take up microfinance will be more likely to take it up themselves than friends of those who do not take up microfinance.

By explicitly modeling the communication and decision processes as a function of network structure and individual characteristics, we are able to separately estimate 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 differential information passing rates for takers and non-takers).[3]

Of course, the usual challenges of identifying diffusion models remain: the social networks are endogenous and there tend to be strong similarities across linked individuals, which could generate correlations in their decisions even when there is no diffusion. To explore the empirical importance of such correlations, we compare our model of information transmission with an extended version of the model in which there is an added component of correlation. In the extension, take up is also allowed to be a function of an individual's network distance from initially informed households who choose to participate, (say) because of similarities between individuals who are at similar distances from the leaders. We show that this extended model of information transmission that that incorporates distance from leaders does not substantively change our estimates of the information transmission parameters by participants and non-participants. Moreover, we estimate our main model on an alternative set of moments exploiting a different set of variation and show that our conclusions are not substantively altered. As a final check, we show that the model does well in predicting aggregate patterns of diffusion over time,

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

even though the data used for the estimation of the model are only the initial injections points and the final take-up patterns.

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 the reduced-form analysis of how network properties and initial injection points correlate with microfinance participation. In Section 5 we structurally estimate diffusion models that distinguish the impacts of information transmission, endorsement effects, and simple distance from injection points on patterns of microfinance participation. Section 6 concludes.

2. Background and Data

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

BSS operates a conventional group-based microcredit program: borrowers (women only) are formed into groups of 5 and are jointly liable for their loans. The starting loan is approximately 10,000 rupees (just over 200 dollars) and is repaid in 50 weekly installments. The annualized interest rate is approximately 28%.

When BSS starts working in a village, it seeks out a number of pre-defined leaders, who BSS expects to be well-connected within the village: teachers, leaders of self-help groups, and shopkeepers. BSS first holds a private meeting with the leaders. At this meeting, credit officers explain the program to the village leaders, and then ask them to help organize a meeting to present information about microfinance to the village, and to tell their friends about microfinance. These leaders play an important part in our identification strategy, since they function as injection points for microfinance in the village. After BSS meets with village leaders, interested, eligible villagers (women between the ages of 18 and 57) contact BSS, are trained and formed into groups, and credit disbursements begin.

At the beginning of the project, BSS provided us with a list of 75 villages in which they were planning to start operations within approximately six months. Prior to BSS's entry, these villages had almost no exposure to microfinance institutions, and limited access to any type of formal credit. These villages are, by and large, linguistically homogeneous but heterogeneous in terms of caste. The majority of the population in these villages is Hindu, but there are both Muslim and Christian minorities. The most common primary occupations are agricultural work (growing finger millet, coconuts, cabbage, mulberries and rice), sericultural work (silkworm rearing), and dairy production.

[4]The villages we study are located within two or three hours driving distance from Bangalore, the state's capital.

We collected detailed data (described below) on social networks in these villages. In 2007, after we finished data collection, BSS began operations in some of these villages. By the the time we finished collecting data for this paper at the end of 2010, BSS had entered 43 of the villages. Across a number of demographic and network characteristics, the villages they entered look similar to the ones they did not.[5] Our analyses below focuses on the 43 villages in which BSS introduced their program.

2.2. **Data.** In 2006, six months prior to BSS's entry into any village, we conducted a baseline survey in all 75 villages. This survey consisted of a village questionnaire, a full census that collected data on all households in the villages, and a detailed follow-up survey fielded to a subsample of individuals. In the village questionnaire, we collected data on the village leadership, the presence of pre-existing NGOs and savings self-help groups (SHGs), and various geographical features of the area (such as rivers, mountains, and roads). The household census gathered demographic information, GPS coordinates and data on a variety of amenities (such as roofing material, type of latrine, quality of access to electric power, etc.) for every household in each village.

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

Most importantly, these individual surveys also included a module that collected social network data along thirteen dimensions, including names of friends or relatives who visit the respondent's home, names of those friends or relatives the respondent visits, who the respondent goes to pray with (at a temple, church, or mosque), from whom the respondent would borrow money, to whom the respondent would lend money, from whom the respondent would borrow or to whom the respondent would lend material goods

[5]The main difference seems to be in the number of households per village: villages BSS entered had 223.2 households on average (56.17 standard deviation) and those it did not enter had 165.8 households on average (48.95 standard deviation).
[6]The standard deviation is 3%.

(kerosene, rice), from whom the respondent gets advice, and to whom the respondent gives advice.[7]

The resulting data are unusually rich, since the networks cover entire villages and 13 types of relationships between any two individuals, and since there are a large number of surveyed villages.[8] The data are publicly available from the `Social Networks and Microfinance project web page`.[9]

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.** As in any study of social networks, we face a number of questions regarding 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 member per household and borrowing decisions are often made at the household level, the household is the correct conceptual unit.

Second, while the networks derived from these 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 create an occasion for a conversation in which information could flow in either direction, regardless of whether the kerosene and rice flows are bi-directional.[10]

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

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

[8]Other papers exploiting this 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 and uses these data for an empirical example, Chandrasekhar et al. (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 that result from studying sampled network data and uses this data set for an empirical example.

[9]`http://economics.mit.edu/faculty/eduflo/social`

[10]The rate of failed reciprocation among questions asking people to name their relatives living outside of their household is similar to that of other categories. Because so much of the failed reciprocation could simply be due to measurement error, there is no clear justification for taking the relationships to be directional.

consider two people linked if they have a relationship along any dimension. Since we are interested in contact between households and all of the relationships mentioned permit communication, this seems to be an appropriate measure.[11]

Fourth, we treat the networks as closed societies even though there may exist ties across villages. The villages appear to have relatively few cross-ties (cross-marriages are rare) and the villages are mostly geographically well-separated, so this does not appear to be a major concern.

Finally, our data involve partially observed networks, since only about half of the households were surveyed. This can induce biases in the measurement of various network statistics, and in the associated regressions, as discussed in Chandrasekhar and Lewis (2011). We apply analytic corrections proposed in their paper for key network statistics calculated under random sampling, which are shown by Chandrasekhar and Lewis (2011) to asymptotically eliminate bias.[12]

2.4. **Descriptive Statistics.** Table 1 provides some descriptive statistics. Villages that BSS entered have an average of 223 households. The average take-up rate for BSS is 18.5%, with a cross-village standard deviation of 8.4%.[13] On average, 12% of households have a member designated as a leader. Leaders take up microfinance at a rate of 25%, with a standard deviation of 12.5% across villages. About 21% of households have members of some SHG (the standard deviation is 8% across households). The average education is 4.92 standards (i.e. school attended up to the end of fifth grade), with a standard deviation of .99. The fraction of respondents who belong to the "general" (GM) castes and "other backward castes" (OBC) is 63%, with substantial cross-village heterogeneity (the standard deviation is 9%).[14] About 39% of households have access to some form of savings (the standard deviation is 10%). Leaders tend to be no older or younger than the rest of the population (the p-value on the difference is 0.415), though they do tend to have more rooms in their houses (2.69 as compared to 2.28–the difference has 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. These are small worlds, with an average

[11]See Jackson et al. (2011) for some distinctions between the structures of favor exchange networks and other sorts of networks in these data. In further research, we are examining whether some networks appear better than others at predicting information transmission, and also whether incorporating the number of ties between individuals enhances predictive power, but these are substantial projects on their own.

[12]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, if anything, our results in Table 3 underestimate the impact of leader eigenvector centrality on the microfinance take-up rate. This indicates that we are presenting conservative estimates.

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

[14]Thus, the remaining 37% are from the scheduled castes and scheduled tribes: groups that historically have been relatively disadvantaged.

network path length of 2.3 between households, and a clustering rate of 26%: when household i has a connection with two other households j and k, j and k also have a connection to each other just over a quarter of the time.[15]

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' centralities.[16] 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 (with a standard deviation of 0.017), as opposed to 0.05 (standard deviation of 0.009) for the village as a whole. At the village level, the 25th and 75th percentiles of average eigenvector centrality are 0.0462 and 0.0609 for the population as a whole, versus 0.065 and 0.092 for the set of leaders. There is, however, considerable variation across villages in the eigenvector centrality of leaders, a feature of the sample that we exploit below.

3. Conceptual Framework

Diffusion models may be separated into two primary categories.[17] In pure contagion models, the diffusion happens through mechanical transmission, as in the spread of a disease, a computer virus, or awareness of an idea or rumor. In what we call the endorsement effects models, there are interactive effects between individuals. In that case, an individual's behavior depends on that of his or her neighbors, as in the adoption of a new technology, human capital investment decisions, and other decisions with strategic complementarities or substitution effects. The dependency may in principle be positive (for example, what other people do conveys opinions or a signal about the quality of a 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).

However, we are not aware of models aimed at distinguishing these types of diffusion, nor research that empirically distinguishes between them.[18] The reduced-form implications of

[15]This is substantially higher than the clustering rate that would be expected in a network in which links are assigned uniformly at random but such that nodes have the same average degree. In this case, the clustering rate 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 Watts and Strogatz, 1998 and the references in Jackson, 2008).

[16]Household centrality corresponds to the i^{th} entry of the eigenvector corresponding to the maximal eigenvalue of the adjacency matrix. So, it solves $aC_i = \sum_j g_{ij} C_j$, where $g_{ij} = 1$ if i and j are linked and 0 otherwise. This is expressed as $a\mathbf{C} = \mathbf{gC}$, where a is the eigenvalue and C is the eigenvector of centralities, which is nonnegative for the largest eigenvalue. Extensive discussion of this and other centrality measures appears in Jackson (2008).

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

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

these different types of diffusion are similar. Consequently, without explicit modeling of information transmission and participation decisions, it may be impossible to tell whether, for instance, an individual who has more participating friends participates with greater likelihood because she has more chances to find out about the program or because she feels more pressure to participate when more of her friends participate.

In this section, we propose network-based models of diffusion that incorporate both information effects and potential endorsement/peer effects. We then discuss reduced-form implications of network structure for diffusion. Specifically, we evaluate the potential impacts of injection points and other network characteristics that vary across villages.

In addition to separating information from endorsement effects, our base model also has another important and novel feature: it distinguishes information passing by those who take up microfinance from information transmission by those who do not. Thus, the model allows for diffusion by non-infected nodes.

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 about its operating plans.
- The leaders then decide whether or not to participate.
  - As an illustration, in Figure 1, one leader has decided to participate, and the other has decided not to participate.
- In each period, households that are informed pass information to their neighbors with some probability.[19] This probability may differ depending on the household's decision regarding whether or not to participate.
  - As an illustration, in Figure 2, the household that does not participate informs one adjacent node and the household that participates informs three.
- In each period, households who were informed in the previous period decide, once and for all, whether 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 process then repeats itself.
  - In Figure 4, all of the informed households again pass information to some of their contacts with a probability that depends on their own participation status. In Figure 5, the newly informed nodes decide whether to participate.

[19] The notion of a period here captures iterations or waves of communication, allowing individuals to inform their friends, who can then inform their friends and so forth. These communication waves might happen quite quickly and somewhat sporadically, so periods in the model might not correspond neatly to calendar time. Nonetheless, they are a useful modeling device for capturing iterations of communication.

- The process repeats for a given number of periods (based on the number of trimesters over which each village is exposed to microfinance in our data).[20]

Specifically, let p_i denote the probability that an individual who was informed last period decides to adopt microfinance, where p_i is a function of the individual's characteristics X_i and peer decisions.

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 the person's covariates (X_i) to influence take up, but not for endorsement effects.Here, Λ indicates a logistic function so that

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

We next 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). In this case $p_i^E(\alpha, \beta, \lambda)$ refers to

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

where F_i is a fraction in which the denominator is the number of i's neighbors who informed i about the program and the numerator is the number of these individuals who have participated in microfinance (with each person being weighted by their importance in the network).[21]

The other important parameters in these models are those that govern the per-period probability that a household informs another about the program. We let q^N denote the probability that an informed agent who does not herself participate informs any given neighbor about microfinance in a single round, and q^P denote the probability that an informed participating agent informs any given neighbor.

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

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

[20] The choice of time periods is fairly inconsequential since the probability of information passing rescales with the length of a period. So, provided there are sufficient iterations for information to travel three or four links outward from the injection points (the diameter of the typical village), the long-run participation rates can be approximated. Indeed, we find very similar estimates for the models if we endogenize the number of iterations.

[21] We use eigenvector centrality as the measure of network importance and weight the fraction of neighbors accordingly. So, neighbors with higher eigenvector centrality receive higher weight in a given node's decision. (For evidence that individuals disproportionately weight their neighbors by status when making decisions, see Henrich and Broesch, 2011.) We also discuss other weightings, including degree and neutral weightings which yield substantively similar results.

The algorithms for fitting the models are described in more detail in Appendix B.

Group Lending and Endorsement Effects. We emphasize that the endorsement effects are a catch-all for any peer effects or other effects beyond basic information transmission. For instance, it might be that people transmit opinions about microfinance, and participants tend to be more positive about microfinance than non-participants. In our model, that sort of opinion transmission would appear in the endorsement model as a positive λ. It could also be that there are substitution effects. For instance, borrowing from a household that has taken a loan might substitute for taking a loan directly, leading to a negative λ.

It might also be that there are complementarities in participation. If individuals prefer to participate with friends, then we would find a positive λ.[22] More generally, correlated borrowing would be picked up by λ.

We do not model group formation explicitly because doing so would substantially complicate the model. Further, although formation may be important in determining repayment incentives, it does not appear to be a significant driver of diffusion. In particular, anyone can show up and ask to participate and *it is BSS who forms them into groups* (i.e. whole groups do not have to show up together to be able to join). Thus, an individual need not convince others to join or to have friends who join.

3.2. **Injection Points.** Before fitting these models, we discuss the village-level reduced-form implications of the models: what differences would we expect in the take up of microfinance across villages based on their network characteristics?

First, characteristics of injection points may drive differences across villages. The idea that injections points may matter has roots in the opinion leaders of Katz and Lazarsfeld (1955) (also, see Rogers, 2003, and Valente and Davis, 1999), as well as the identification of key individuals based on their influence on others' behaviors (e.g., Ballester et al., 2006), and underlies some "viral marketing" strategies (e.g., see Brown and Reingen, 2009, Feick and Price, 1987, and Aral and Walker, Forthcoming).

There is little theory explicitly modeling the role of injection points in information transmission, as it is difficult to do so.[23] However, it is clear that properties of the initially informed individuals can substantially impact diffusion.[24] Regardless of the model (information or endorsement), an obvious initial hypothesis is that if the initially informed

[22]For additional background and modeling of incentives in group lending, see, for instance, Ghatak and Guinnane (1999), Ghatak (1999), Besley and Coate (1995), Rai and Sjöström (2004), and Bond and Rai (2008).

[23]For example, Kempe et al. (2003) show that it is a hard (NP-hard) problem to find the k injection points that maximize diffusion in a probabilistic diffusion model.

[24]For example, Ballester et al. (2006) suggests that a recursively-defined centrality measure can identify a most-influential individual in a setting with complementarities. Eigenvector-based measures are also important in determining how individuals initial beliefs matter in iterative updating models such as the DeGroot (1974) model, among others.

individuals in one village have a greater number of connections than those in another village, then initial information transmission will be higher in the first village, and the chance of sustained diffusion will be higher.[25] As time goes by, the friends of leaders will have time to inform their own friends about the program. So, a second hypothesis is that the leaders' eigenvector centrality should start mattering more over time, because what matters is how effective the leader's neighbors are in passing on the message (this in turn depends on how connected they are, which is precisely what eigenvector centrality measures). Finally, a third hypothesis is that if there are endorsement effects that go beyond information diffusion, the participation decisions of these leaders may also affect participation in the village.

As described in detail below, BSS's strategy of contacting the same category of people (the leaders) when they first start working in each village leads to plausibly exogenous variation in the degree and the eigenvector centrality of the first people to be informed about the program in each village. 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 rate. In addition, as we observe take up over time, we are able to to identify the characteristics of leaders that 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 matter for diffusion. We therefore examine how take up correlates with a number of other network characteristics.

In particular, in most contagion models, adding more links increases the likelihood of non-trivial diffusion and its extent.[26] 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), then the former network will be more susceptible to a non-trivial diffusion pattern and have a higher infection rate if diffusion occurs. The variance in degree (i.e. number of links) across individuals in a network can also affect diffusion properties, because 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 degree distribution within a population, there are other network characteristics, such as how segregated a network is, that also affect diffusion. Having a network that is strongly segregated can significantly slow information flow from one

[25]For example, working with a basic contagion model, such as the SIR model, the probability that the initially infected nodes interact 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.
[26]See Chapter 7 in Jackson (2008) for additional discussion and theoretical background.

portion of the network to another. The second eigenvalue of a stochasticized adjacency matrix describing communication on the network is a measure of the extent of such segregation, as shown by Golub and Jackson (2009).

To estimate the effect of these network characteristics on take up, we again take advantage of cross-village variation. However the extent to which we should expect significant impacts of these characteristics on take up is not entirely clear for two reasons. First, in much of the related theory, once one exceeds a minimum connectivity threshold, the extent of diffusion is no longer as significantly impacted by network structure per se, but is instead impacted by other node characteristics and their decision making.[27] Second, while exogenous variation in the injection points allows for identification and potentially for causal inference, the variation in network structure across villages could be endogenous and correlated with other factors that influence take up.

While recognizing these limitations, we nonetheless report the results of cross-sectional regressions of take up on various network characteristics for the sake of completeness. However, after doing so, we move on to our structural estimation, which allows us to identify and test specific hypotheses that cannot be identified via a regression-style analysis.

4. Reduced-Form Analysis: Do Injection Points and/or Network Characteristics Matter?

4.1. **Injection points.**

4.1.1. *Identification strategy.* BSS's procedure for spreading information about their program motivates the identification strategy we employ to assess the causal effect of the network characteristics of the first people informed about microfinance in a village on program take up. When entering any village, BSS gives instructions to its workers to contact the following groups of villagers (whom we have called leaders): self-help group (SHG) leaders, pre-school (*anganwadi*) teachers, and shop owners. This set of initially contacted villagers does not vary from village to village. BSS staff rely on these leaders to disseminate information about microfinance and to help orchestrate a village-wide meeting.

This procedure aids in the identification of the causal effect of leaders' network characteristics on program take up for two reasons. First, we know that the leaders are the injection points for microfinance information dissemination in the village. Second,

[27]Diffusion thresholds in standard contagion models are around one 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 notion of effective contact will be considered 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.

we know that the leaders are not selected with any knowledge of their villages' network characteristics or their positions in the network, or with any consideration for village propensity to adopt microfinance.

Of course, there could still be omitted variable bias: it might be that villages where leaders are less important or less connected, for example, 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 characteristics. This is reassuring, as it suggests that the network characteristics of the leaders are plausibly exogenous. This, given the exogenous variation introduced by BSS's strategy, then helps justify regressing 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 rate, ξ_r^L is a vector of network statistics for the leaders (we introduce, separately and jointly, degree and eigenvector centrality), and W_r is a vector of village level controls.[28]

Though they are likely to be endogenous, we also report specifications in which we separately include 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 a vector representing the centrality of those leaders who became microfinance members.

We also explore whether the correlation pattern changes over time by exploiting data provided by BSS about participation levels at regular points in time after the introduction of the program (from 2/2007 to 12/2010 across the 43 villages BSS entered). As discussed above, we expect that the degree of leaders matters more initially (because degree correlates with how many people these individuals regularly interact with) while their importance (eigenvector centrality) matters more later, after information about the program has diffused (because the people that the leaders contacted are themselves more influential). To test this hypothesis, we run regressions of the following form:

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

where y_{rt} is the share of microfinance take up in village r in period t, ξ_r^L is the average degree and/or the average eigenvector centrality for the set of leaders, W_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.

[28]Additional regressions examining other network characteristics, such as betweenness centrality, which do not significantly predict take up, are available upon request.

This regression includes village fixed effects, and so is not biased by omitted village-level characteristics that are time-invariant. The coefficient β_1 will indicate whether degree and/or eigenvector centrality become more or less correlated with take up over time.

4.1.2. *Results.* The cross-sectional results are presented in Table 3. The average degree of leaders is not correlated with subsequent microfinance take up. However, average eigenvector centrality does predict take up. 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 percent) larger. The results are robust to introducing degree and eigenvector centrality at the same time. They are also robust to the introduction of a variety of control variables. Interestingly, we do not find that, conditional on the average centrality of the leaders in a village, the centrality of the leaders who become participants themselves is more strongly correlated with eventual take up. This result suggests that leaders can be conduits of information regardless of their personal participation.

Table 4 presents evidence on how the impact of degree and eigenvector centrality of leaders varies over time. For these specifications, we have taken the interval 2/2007 to 12/2010 and divided it into three periods. In both 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, suggests that, in each subsequent 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 0.7 percentage points greater. The point estimate on the interaction between degree and time is negative in both specifications, although it is not significant.

Overall, these results suggest that social networks play an important role in the diffusion of microfinance and that the villagers chosen by BSS to be the first-informed are indeed important players in the diffusion process. However, these reduced-form results cannot tell us very much about the specific form that diffusion takes in the village since the available theoretical models only provide partial guidance regarding what reduced-form pattern should be expected. To distinguish between models, we exploit individual-level data and our knowledge of the initial injection points (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 and a set of variables that capture village-level 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.[29] We include the variables both one by one and jointly.[30]

Table 5 presents the results of running regressions of the form:

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

where y_r is the fraction of households joining BSS, W_r is a vector of village-level network characteristic 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 the characteristics are included separately (some of the correlations are counter-intuitive; for example, average degree appears negatively correlated with take up), no variable is significant when we include all of the characteristics together. However, as pointed out above, it may be that the cross-village variation in measures such as average degree captures more than just differences in the ease of passing information. To further complicate matters, there is a strong degree of correlation between some of the network variables (see Appendix E Tables A-1 and A-2), which means that they cannot be examined independently. On the other hand, given the small number of villages, it may be impossible to detect patterns even if they exist when the characteristics are all included together.

In addition, much of the theory predicting that characteristics like average degree matter in diffusion processes suggests that there are particular thresholds at which there are sharp "phase transitions" (i.e., jumps in diffusion), and then large flat spaces where there is less of an effect. *It may well be that at the high level of connectedness that we observe in our data (average household degree is near fifteen), degree (nor its variance) is no longer a primary driver of diffusion.*

As we show next, a more structured approach sheds additional light on the transmission mechanisms that characterize 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: $\left(q^N, q^P, p_i^E(\alpha,\beta,\lambda)\right)$.

[29]The first eigenvalue of the adjacency matrix is a measure of the "reach" of a network, or a weighted measure of the number of paths going from nodes to other nodes. The second eigenvalue of the stochasticized adjacency matrix is a measure of how segregated a network is.

[30]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).

The formulation of these models is as described in equations (1) and (2), and the full algorithm dictating how we fit these models is described in Appendix C. Here, we begin with a non-technical discussion of our estimation method. We use the method of simulated moments (MSM). 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 that take up microfinance (to identify β).
(2) Share of households with no neighbors taking up that take up.
(3) Share of households in the neighborhood of a taking leader that take up.
(4) Share of households in the neighborhood of a non-taking leader that take up.
(5) Covariance of the fraction of households taking up with the share of their neighbors that 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 decisions among the set of leaders (who are known to be informed of the program). 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 trimesters that a given village was exposed to microfinance (typically 5 to 8). For each simulation, the moments are calculated. Next, we 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 let $m_{emp,r}$ denote the vector of empirical moments for village r. Then we choose the set of parameters that minimizes 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. 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 $\widehat{\theta}^b = \operatorname{argmin}_{\theta \in \Theta} D_b(\theta)' D_b(\theta)$. This method allows us to estimate standard errors in a computationally simple manner for a GMM model that requires numerous runs of a complicated of a diffusion process.[31]

5.2. **Discussion of identification.** The first set of moments combined with the known injection points allow us to identify the parameters of the model. 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 $q^N = 0.095$ and $q^P = 0.45$ (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 up 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 (typical of the data), the probability that the first person is informed is 97%.[32] The probability that the second person is informed is 45%. The probability that the third person is informed is essentially 1 and the probability that the fourth person is informed is 91%. Though the difference in the fraction of informing friends who take up, which is the source of the endorsement effect, is exactly the same for 1 versus 2 as it is for 3 versus 4 (it is 1 in both cases), the difference in take up between persons 1 and 2 (22%) is much larger than the difference in take up between persons 3 and 4 (12%). This difference captures the pure information effect. To see the pure endorsement effect, let one of the 4 leaders who are friends with person 4 take up. The probability that person 3 and 4 are informed is now more or less the same (about 100%) and therefore in a pure information effect world they would behave identically. However, if there is an endorsement effect, these two will behave quite differently. Assume for the moment that $\lambda = 0.5$ and an individual with no participating friends who is informed joins with probability 0.23. Then person 3, who has a higher fraction of informing friends who take up, is more likely to take up (33% vs 25% for person 4).

This discussion clarifies a difficulty that we face in identifying endorsement effects that is typical of peer effects analyses: we compare the behavior of different households located at different positions in the network who both end up informed, and estimate the endorsement effect as a function of their neighbors' decisions to take up microfinance. However, it is possible that, for example, households with neighbors who take up are themselves more likely to need microfinance (in ways that we have not already conditioned on given our demographic information). For example, neighbors may share a common activity, or have some other common access to finance. Then, even after carefully conditioning on all available information, we might end up attributing this correlated take up to endorsement effects in our estimation. Thus, the traditional pitfalls related to the identification

[31] 1000 runs of a simulated annealing search, for example, would be prohibitively slow.

[32] This is simply $(1 - 0.45^6)$.

of peer effects given potential unobservables apply here as well. However, if anything, such identification issues would tend to inflate the estimates of endorsement effects, and yet we do not find evidence of such effects.

Nonetheless, we implement several robustness checks to address this concern, as described in detail in Section 5.4.

An advantage of the structural approach we employ is that the structure imposes more specific patterns on the moments than would be generated based on the simple intuition that people who are closer to people who take up microfinance should be more likely to take up themselves. To account for the effect that people who are close to each other may simply behave similarly, we compare our structural estimates to those generated by a modified "nested distance model."

$$\mathrm{P}(\text{participation}|X_i, F_i, d_i) = \Lambda(\alpha + X_i'\beta + \lambda F_i + d(i, L^P)\rho). \tag{7}$$

Here $d(i, L^P)$ is the length of the shortest path between i and the nearest leader who participates in microfinance.

We include this model to study how our findings about q^N and q^P hold up when we account for the fact that people closer to participating leaders themselves may be participating due to otherwise omitted characteristics (those close to participating leaders may have similar preferences, for example). To the extent that none of our conclusions of interest are substantively different, there is some assurance that the results of the base structural equation are indeed capturing the true parameters of the structural model.

Moreover and importantly, we use an entirely different set of moments to re-estimate the model. This set of moments is chosen based on the reduced-form regression we presented in Section 4: the moments only exploit proximity to the set of injection points. This second set of moments is:

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

Although, as we discuss below, this alternative set of moments may have some shortcomings; because they are entirely distinct from the first set of moments (with the exception of the first moment), they are immune to some of the potential homophily problems that result from the first strategy. Further, to the extent that the results are similar across the two estimation approaches, this provides reassurance that our results are not spurious.

Finally, we investigate the capacity of the model to replicate time-series patterns in the data (Table 4). Since the estimation of the structural model only exploits whether individuals have ever taken up, the capacity of the model to replicate the time series patterns in the data (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. Panel A.1 presents the parameters of the information model estimated using the first set of moments. q^N is 0.095, and q^P is 0.45, and both of these are significantly different from 0. This suggests that in every round, informed villagers who are themselves participating in the program will inform a given neighbor about the program with probability .45, while those who are not participating inform a given neighbor with probability .095. We are able to reject equality of the two parameters: those who take up microfinance themselves are more likely to inform their neighbors about the program than those who do not.

Panel A.2 presents estimates of the endorsement model, where the agents give weights to the participation decisions of their informed neighbors. In the modeling framework adopted here there does not appear to be evidence for 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 whether the agent's neighbors chose to participate themselves. The information model in which the probability that someone passes information to a neighbor is affected by whether they are participating or not, but where there are no additional endorsement effects, is thus the structural model that fits the data the best.

Finally, we check to see how important a role non-participants play in passing information to their neighbors. 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 one-third of overall informedness and participation. We calculate this figure by comparing the model as fit above to the results based on a model that allows only participants to 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 setting q^N equal to 0 would lead to a decline of roughly one-third in overall participation, from more than 20.7 percent to 13.8 percent, and a similar decline in the fraction of informed agents, from over 86 percent to 59 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 substantially influence both the spread of information and eventual take up.

5.4. **Robustness Checks and Alternative Specifications.** As discussed, one potential concern with these results is that the structural estimation approach inherits the correlated effects and endogeneity problems that plague any effort to estimate peer effects from observational data. Given that 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," it is encouraging that the structural model fits the data better than a mechanical model based on distance to the leaders who take up microfinance. Nonetheless, there remains a concern that the patterns we identify may be spurious. To address this, we perform several robustness and specification checks on the pure information model (which is found to fit the data best).

5.4.1. *A different set of moments.* Our first strategy for testing our model 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 identities a specific set of leaders known to be informed about the program. In particular, these moments focus on participation decisions of individuals local to BSS leaders (who are known to have been informed) and, moreover, do not depend on the leaders' participation decisions themselves. To review, the alternative moments are:

(1) Share of leaders that 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.

Here, we are exploiting differences in behavior between those who are more or less directly connected to the leaders (and hence more or less likely to be informed about the program). The interpretation of the second moment (covariance of take up and minimum distance to a 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 acquisition. The last two moments allow us to separately identify q^N and q^P: if these moments are equal, the variance in take up should increase less between distance 1 and distance 2 villagers than if they are different.

The identification assumption this approach relies on is that friends of leaders are similar to other people in the network in terms of their propensity to take up microfinance. In Appendix E Table A-3, we investigate whether friends of leaders are different from others in the network. We show that people who are farther 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 underlying demand for a microcredit product.

To further address the concern about endogeneity of network position, we control for individual characteristics. We also recognize that there could still be potential biases. However, because the source of variation is completely different than that which motivated the first set of moments, and the source of potential biases is also different (here we worry more about the differences between those who are and are not close to leaders, but less about correlated effects), it will nevertheless be encouraging if the estimated effects are the same. This comparison will function as an over-identification test of sorts, since the differing 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 $q^N = 0.08$ and $q^P = 0.65$, and the difference between the two remains significant.

5.4.2. *Controlling for social distance to leaders who took up microfinance.* Our second check is to control for a possible bias in our main estimate, which is that people's need for microfinance could be related to their network position, and in particular correlated with their distance from the leaders. To account for this we add a control for a household's distance to leaders who chose to take up microfinance to our main MSM simulation, as shown in (7). This nested specification ensures that our estimation relies on the specific functional form implied by the model, rather than being driven by correlated behaviors which just happen to correlate with network position in a way that would be proxied for by information transmission from leaders.

The results after controlling for shortest distance to a leader who took up microfinance in the information model are presented in Panel C of Table 6. Both estimates are comparable to those from the original information model. Here, $(q^N, q^P) = (0.1, 0.45)$. The difference between the two parameters remains significant.

5.5. **How well does the model predict the aggregate patterns?** Finally, to provide an additional 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 endorsement effects, and set $q^N = 0.095$ and $q^P = 0.45$. To test the model, we simulate the information model in each of our networks, construct the basic statistics from the simulated data that we had calculated previously using the real data, and run exactly the same regressions. The basic cross-sectional patterns are not interesting to replicate, since village-level take up of microfinance is one of the moments 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 to match the pattern observed in the real data over time provides a useful cross-validation of our structural model.

Table 7 presents results regarding whether the model is able to replicate the time series patterns found in the real 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. Moreover, the parameter estimates are rather similar. Thus, despite not having used this source of variation (within-village variation over time in microfinance take up), we are able to replicate the fact that microfinance take up depends increasingly over time on the centrality of the leaders (conditional on factors such as village and time fixed effects). [33]

6. Conclusion

Our analysis has made three main contributions to the understanding of network structure and diffusion.

First, taking advantage of arguably exogenous variation across villages in the set of initially informed individuals (induced by BSS's 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 social network characteristics are relatively insignificant determinants of diffusion.

Second, using microdata to estimate a structural network-based model of the diffusion of information, we distinguish basic information transmission effects from other endorsement effects. The estimation suggests that information passing is important in determining/limiting participation, but that once informed, an individual's decision is not significantly affected by the participation of her acquaintances. This suggests that endorsement effects do not significantly impact diffusion.

Third, our structural model is novel in that it includes and differentiates information transmission by non-participants, in contrast with more standard diffusion models in which transmission functions as a contagion (and so non-participants cannot affect diffusion). Our findings suggest that participants pass information with higher likelihood than non-participants, but that both forms of information passing are nonetheless important. Indeed, non-participants account for roughly one-third of information spread and subsequent participation.

The results hold up based on several robustness checks. The information model is unaffected by a modification in which adoption is also a function of distance to a participating leader and does a good job of replicating the aggregate dynamic pattern in the data (including the fact that eigenvector centrality of leaders matters more over time). Moreover, our conclusions are unaffected when we re-estimate the model using an entirely different set of moments.

Our findings not only shed light on microfinance, but also suggest that further research is needed. 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 analyses of diffusion. Second, we find differences in the role of pure information versus endorsement effects in this setting. This suggests that it will be useful to develop richer models of peer effects and diffusion that further disentangle

[33] 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 various roles that interactions can play in promoting diffusion, and to investigate this dichotomy across a wider range of applications. Finally, we highlight the role of non-participants in diffusion and this mechanism deserves further attention in future work.

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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)
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: Sample includes 43 BSS villages. 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. Standard errors are heteroskedasticity robust. In this and all subsequent tables, * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Village Leader Characteristics and Take Up

	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)
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. We report heteroskedasticity-robust standard errors. Taking Leaders are those leaders that take up microfinance.

Table 4: Importance of Leader Characteristics Over Time

	Take-Up Rate	Take-Up Rate
	(1)	(2)
Eigenvector Centrality of Leaders	0.406**	0.461*
	(0.202)	(0.233)
Degree of Leaders	-0.00176	-0.00179
	(0.00145)	(0.00137)
Number of Households	3.30e-05	2.57e-05
	(5.97e-05)	(6.04e-05)
Savings		-0.0176
		(0.0308)
Fraction GM		0.00671
		(0.00641)
Observations	117	117
R-squared	0.974	0.975

Note: The dependent variable is the microfinance take-up rate in a village in a period. Every covariate is interacted with survey period. Regressions include village fixed effects and period 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)
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. Network characteristics are village-level averages. Standard errors are heteroskedasticity-robust.

Table 6: Structural Estimates

	(1)	(2)	(3)	(4)
Panel A: Standard Moments				
Panel A.1: Information Model	q^N	q^P		$q^N - q^P$
	0.095	0.450		-0.36
	[0.0118]	[0.2043]		[0.2054]
Panel A.2: Information Model with Endorsement	q^N	q^P	λ	$q^N - q^P$
Eigenvector Weighted	0.050	0.550	-0.20	-0.50
	[0.0066]	[0.1313]	[0.1614]	[0.1340]
Degree Weighted	0.050	0.450	-0.15	-0.40
	[0.0146]	[0.1831]	[0.1704]	[0.1909]
Uniform Weighted	0.050	0.400	-0.15	-0.35
	[0.0108]	[0.1459]	[0.1489]	[0.1510]
Panel A.3: Distance from Taking Leader Model	ρ			
	-0.253			
	[0.0404]			
Panel B: Alternative Moments	q^N	q^P		$q^N - q^P$
	0.075	0.650		-0.58
	[0.0382]	[0.1765]		[0.1975]
Panel C: Nested Distance Model	q^N	q^P	ρ	$q^N - q^P$
	0.100	0.450	-0.10	-0.35
	[0.0269]	[0.1893]	[0.0456]	[0.1921]

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 minimum 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 includes the minimum 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: Importance of Leader Characteristics Over Time (Simulated)

	Take-Up Rate	Take-Up Rate
	(1)	(2)
Eigenvector Centrality of Leaders	0.484**	0.429
	(0.242)	(0.256)
Degree of Leaders	-0.00101	-0.000994
	(0.00119)	(0.00108)
Number of Households	2.52e-05	3.39e-05
	(5.18e-05)	(5.22e-05)
Savings		0.0270
		(0.0217)
Fraction GM		-0.00625
		(0.00440)
Observations	117	117
R-squared	0.974	0.976

Note: The dependent variable is the microfinance take-up rate in a village in a period, averaged over 1000 simulations. Every covariate is interacted with survey period. Regressions include village fixed effects and period fixed effects. Standard errors are clustered at the village level.

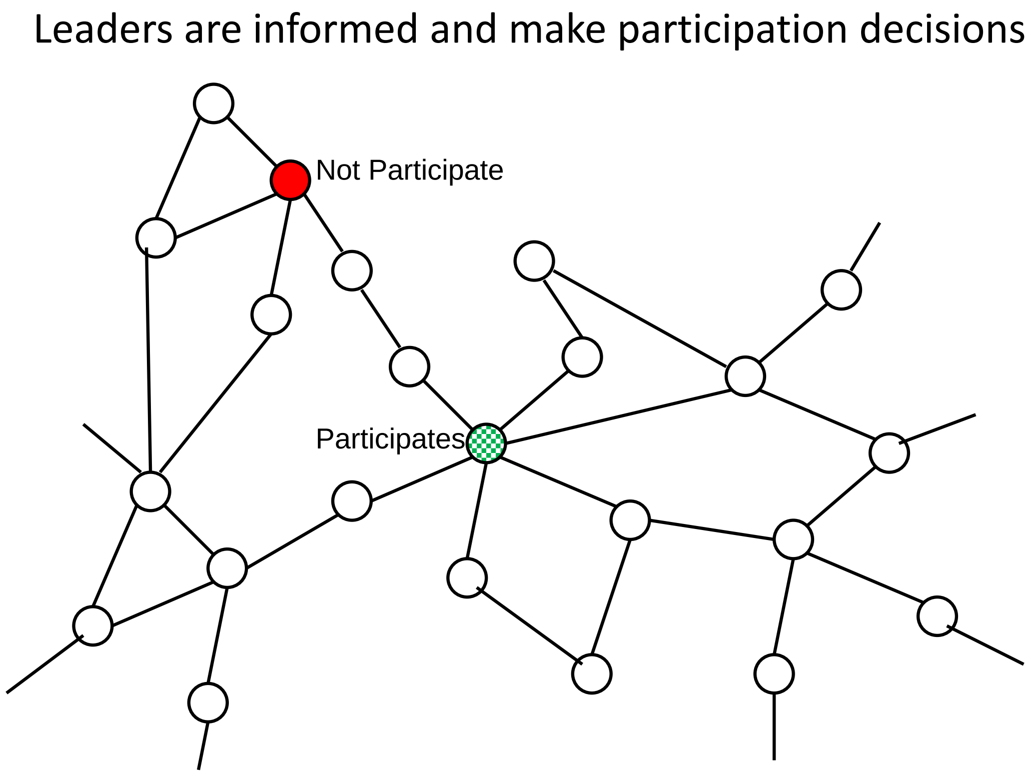

FIGURE 1. Leaders are initially informed and decide whether or not to participate. Participation is indicated by a green-checkered pattern and non-participation by a red-solid pattern.

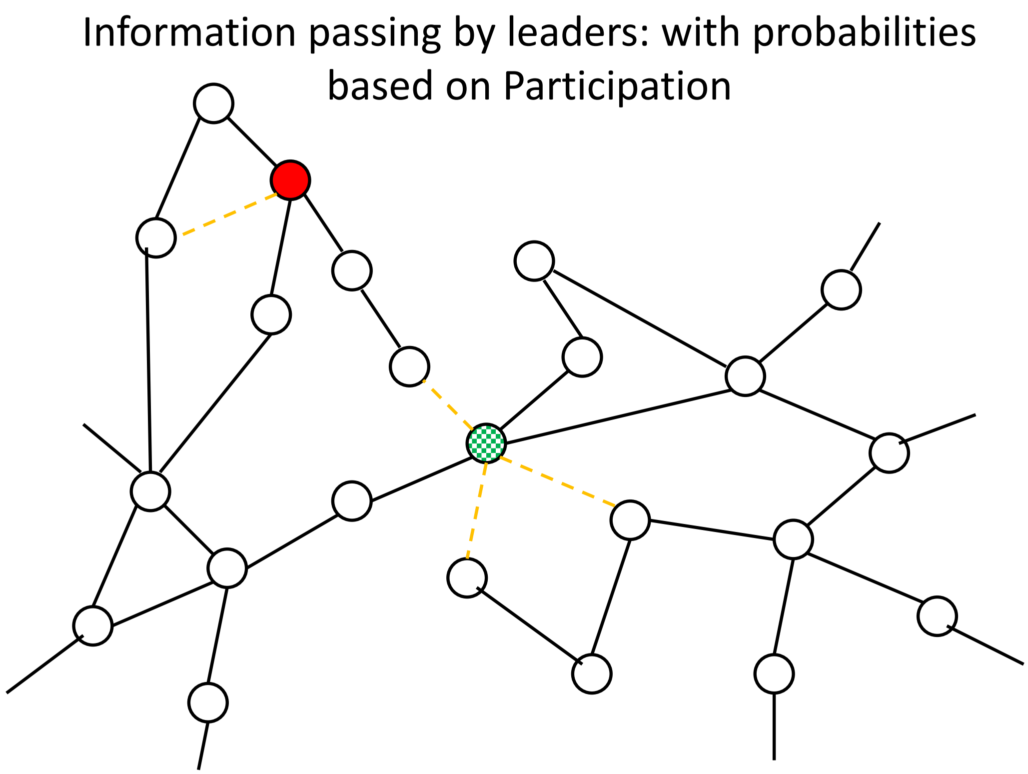

FIGURE 2. Nodes that participate have a higher probability of passing on information. Lighter-dashed line shading reflects information passing.

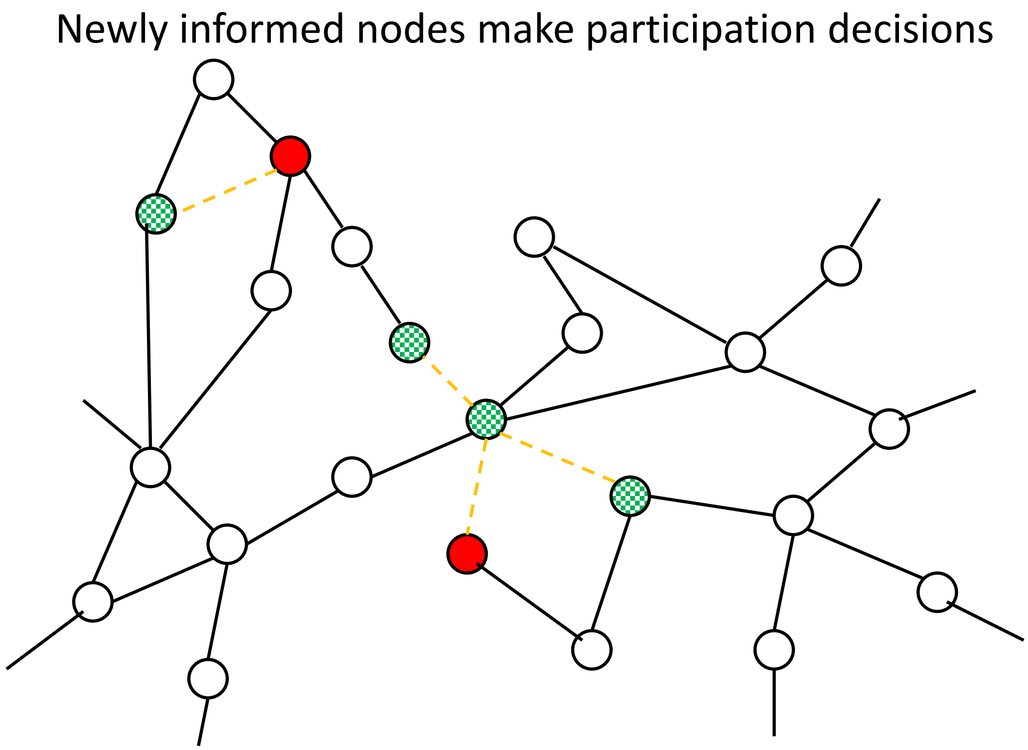

Figure 3. Newly informed nodes decide whether or not to take up microfinance.

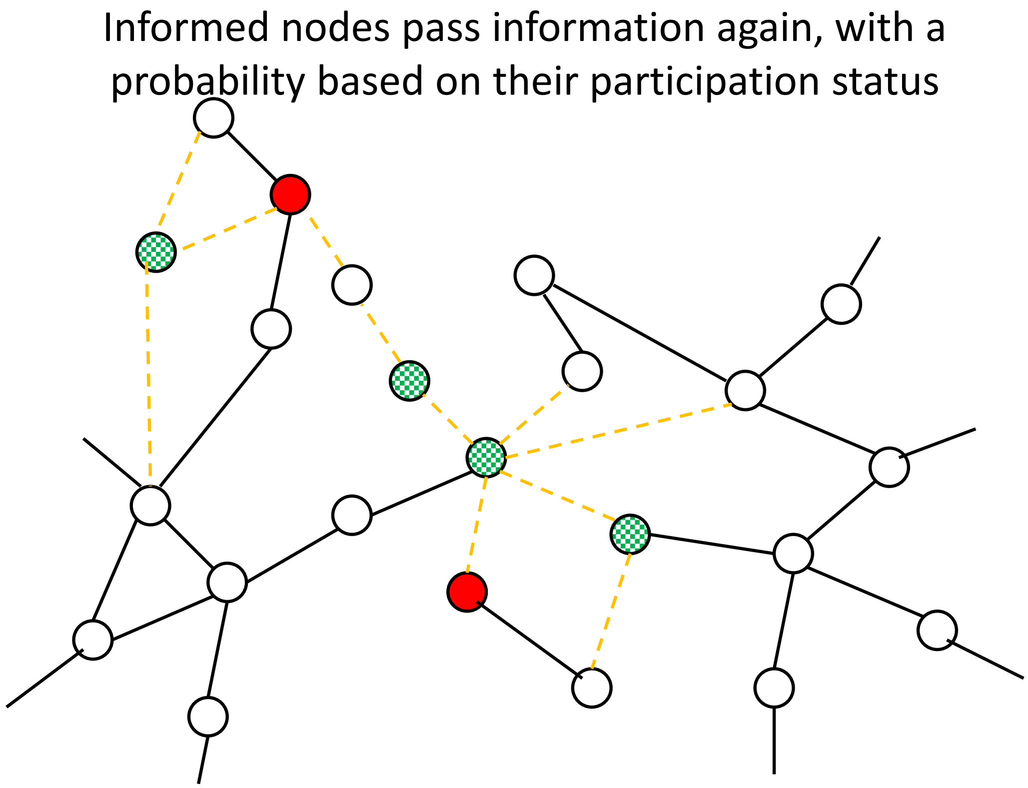

FIGURE 4. Informed nodes pass on information to neighbors with a probability that depends on whether they participate.

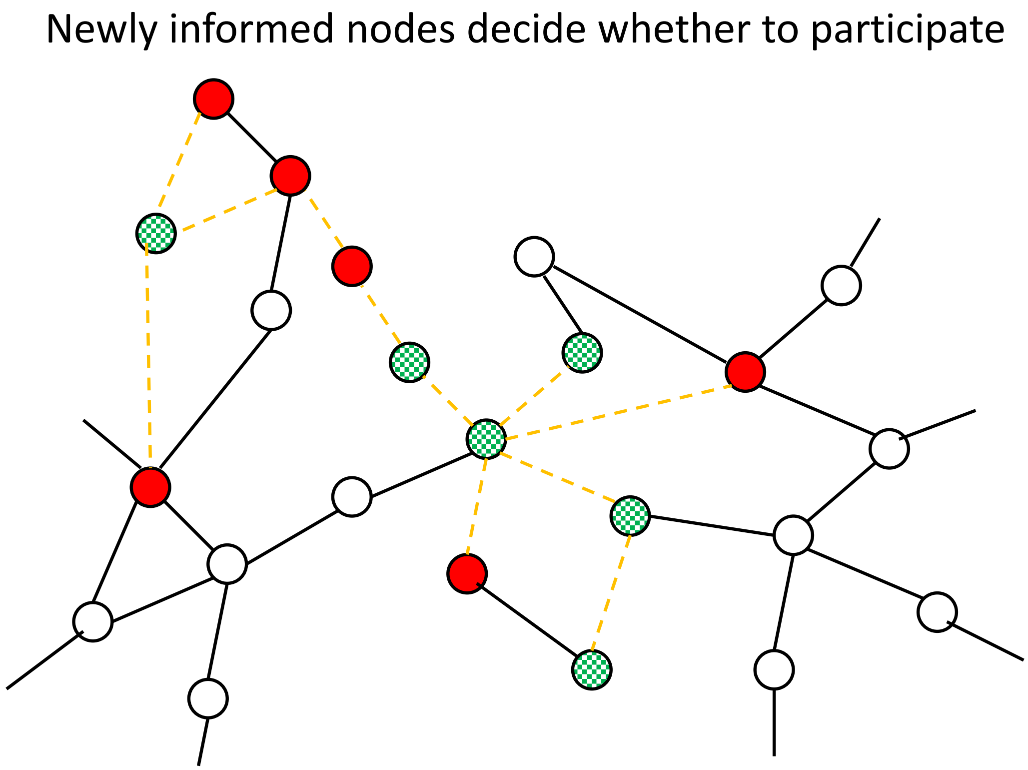

FIGURE 5. Participation decisions are made by newly informed nodes. This process of information passing and participation decision-making then repeats.

Appendix A. Glossary of network terminology

In this section, we provide background information on some terms and variables, and describe how they are measured in our data.[34]

- *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 with 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 iterative paths through a network.
- *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 randomly-selected household i to household j in a village.
- *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 the expansion of a network from initial points is more rapid in that more more nodes are reached in a given number of steps.
- *Fraction of nodes in the giant component:* the share of nodes in the graph that are in the largest connected component.
  - Many social networks (especially those with connectivity as high as is observed in our data) have a giant component that connects almost all nodes. In this case, the measure approaches 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. Given this, the measure reflects 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

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

is the second largest eigenvalue (in magnitude) of this matrix. The largest is mechanically equal to one.

- This measure captures segregation patterns in a network, and also provides bounds on the rate of convergence of beliefs in some models (see Golub and Jackson, 2009). A lower second eigenvalue means a network is more integrated and that iterative updating procedures run on such a network converge faster.

Appendix B. Model Structure

We formally describe our structural model in this section. The model is simulated in discrete time periods. 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,[35]
- 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 to be the set of newly informed nodes at time t.[36] 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 $i \in I_0$. 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, $F_i = |\{j | j \in I(i,t), m_{jt} = 1\}| / |I(i,t)|$ where $I(i,t)$ is the set of i's who informed j.
  (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 and j. 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.

[35]So, note that $s_{i,t+1} \geq s_{it}$ for all t.
[36]That is $I_t := \{i : s_{it} = 1, s_{it-1} = 0\}$.

Appendix C. Structural Estimation and Bootstrap Algorithm

Let Θ be the parameter space and Ξ a grid on Θ. Put $\psi(\cdot)$ as the moment function and let $z_r = (y_r, x_r)$ denote the empirical data for village r with a vector of microfinance take-up decisions, y_r, and covariates, x_r, that include leadership status and other covariates included in the model. 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. This nests the case with $B = 1$ in which we just find the minimizer of the objective function.

(1) Pick lattice $\Xi \subset \Theta$. For $\xi \in \Xi$ on the grid:
   (a) For each village $r \in [R]$, compute
$$d(r,\xi) := \frac{1}{S}\sum_{s\in[S]} m_{sim,r}(s,\theta) - m_{emp,r}.$$
   (b) For each $b \in [B]$, compute
$$D(b,\xi) := \frac{1}{R}\sum_{r\in[R]} \omega_r^b \cdot d(r,\xi)$$
   where $\omega_r^b = e_{br}/\bar{e}_r$, with e_{br} iid exp(1) random variables and $\bar{e}_r = \frac{1}{R}\sum e_{br}$ if we are conducting bootstrap, and $\omega_r^b = 1$ if we are just finding the minimizer.[37]
   (c) Find $\xi^{\star b} = \operatorname{argmin} Q^{\star b}(\xi)$, with $Q^{\star b}(\xi) = D(b,\xi)' D(b,\xi)$.
(2) Obtain $\{\xi^{\star b}\}_{b\in B}$.
(3) For conservative inference on $\widehat{\theta}_j$, the j^{th} component, consider the $1-\alpha/2$ and $\alpha/2$ quantiles of the $\xi_j^{\star b}$ marginal empirical distribution.

In all simulations we use $B = 1000$, $S = 75$. The grids we employ are as follows:

- Information model: $q^N,\ q^P \in [0.01 : 0.01 : 0.99]$.[38]
- Endorsement Model:
  $q^N \in [0.025, 0.05, 0.1, 0.15, (0.2 : 0.1 : 0.8)]$
  $q^P \in [0.1, 0.2, 0.3, 0.4, 0.45, 0.5, 0.55, 0.6, 0.65, 0.7, 0.8, 0.9]$
  $\lambda \in [(-1 : 0.1 : -0.2), (-0.15 : 0.05 : 0.3), 0.4, 0.5, 0.7, 1]$.
- Nested Distance Model:
  $\rho \in [-0.3 : 0.05 : 0.3],\ q^N \in [0.01, 0.02, 0.025, 0.05, 0.1, 0.15, (0.2 : 0.1 : 0.8), 0.9]$
  $q^P \in [0.025, 0.05, 0.1, 0.2, 0.3, 0.4, 0.45, 0.5, 0.55, 0.6, 0.65, 0.7, 0.8, 0.9, 0.95]$.

[37]If desired, use a refinement lattice Ξ' with $\Xi \subset \Xi' \subset \Theta$, estimate $D(b,\xi')$ for $\xi \in \Xi' - \Xi$ from an interpolation of $D(b,\Xi)$.

[38]Interpolating Grid: $q^N, q^P \in [0.01 : 0.001 : 0.99]$.

Appendix D. A Placebo Test: Does the model predict tile roof adoption?

Another robustness check we may conduct is a "placebo" test. If we are really missing some unobservable correlated effects that are biasing our estimates, then they could also bias estimates related to a decision that is similar to the choice of whether to participate in microfinance, but is not at all dependent on information passing from the initial injection points in our microfinance study. If the results for such a placebo test look similar to those from our estimation of microfinance take up, then we have to worry that our model is biased and information passing is proxying for some other unobserved correlates. Thus, we redo our analysis using whether a household has a tiled roof as a placebo outcome. The share of households that have such a roof is 32 percent (roughly similar to the microfinance participation rate). Further, having a tiled roof could be related to wealth and possibly to neighbors' behaviors (just as microfinance participation is), and so potentially correlated among people who are neighbors in the network. Consequently, potential biases ought to be present. However, there should be no role for information passing when we fit our model, especially information passing from the initial injection points. Thus, if our technique is flawed, then it may appear as if information passing impacts roofing decisions when in reality it does not.

The model is estimated with the same set of injection points and moments as the main model. The only change is that microfinance participation is replaced with roof tiling.

It is important to note what we should expect to observe when fitting the model if our model and technique are *not* biased. The model is such that an individual can take an action only when informed. *Thus, if information passing does not affect roof tiling, then all households should appear informed and their decisions should not be affected by information passed from the injection points. If the information passing parameters are so low that they significantly constrain some households' possibility of taking up tile roofs, then we would worry that the information passing is proxying for other characteristics that affect network position and behavior, and might worry that the same would then be true of our microfinance estimation.* This means that if our model is working properly, we should expect q^N and q^P to not significantly different from each other and also large enough so that most households end up informed.The results, presented in Table A-4, are consistent with the model working well: we estimate q^N and q^P to be 0.90 and 0.80, respectively (with q^N actually greater than q^P, although the difference is not statistically significant). In addition, q^N and q^P are not significantly different from 1. Thus, the model works with tile roofs exactly as it should, providing very different estimates than it did when we examined microfinance participation.

Appendix E. Miscellaneous Tables

Table A-1: Correlation of Network Characteristics

	No. of HH	Degree	Clustering	Eig. Cent.	Bet. Cent.	Path Length	Fraction	First Eig	Second Eig
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Number of Households	1								
Degree (Corrected)	0.0975	1							
Clustering (Corrected)	-0.116	0.4445	1						
Eigenvector Centrality	-0.8993	0.1262	0.0509	1					
Betweenness Centrality	-0.8706	-0.1967	0.1668	0.8016	1				
Path Length (Corrected)	0.4163	-0.8064	-0.2329	-0.617	-0.2104	1			
Fraction in Giant Comp.	0.0023	0.7274	0.222	0.2098	0.1583	-0.6063	1		
1st Eigenvalue of Adj. Mat	0.2813	0.9123	0.3998	-0.1288	-0.4577	-0.6648	0.4858	1	
2nd Eigenvalue of Stoch. Adj.	0.4656	-0.0081	0.393	-0.5459	-0.2708	0.3971	0.0261	0.0573	1
Spectral Gap	-0.3501	0.4107	-0.2821	0.5258	0.0386	-0.714	0.2543	0.3647	-0.688

Note: Correlations at the village level. Network statistics used are described in Appendix A.

Table A-2: Principal Components

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Eigenvalues										
Component	Eigenvalue	Difference	Proportion	Cumulative						
Comp1	3.974	0.831	0.397	0.397						
Comp2	3.144	1.453	0.314	0.712						
Comp3	1.690	1.017	0.169	0.881						
Comp4	0.673	0.399	0.067	0.948						
Comp5	0.275	0.152	0.028	0.976						
Comp6	0.122	0.050	0.012	0.988						
Comp7	0.073	0.047	0.007	0.995						
Comp8	0.026	0.010	0.003	0.998						
Comp9	0.016	0.009	0.002	0.999						
Comp10	0.007	.	0.001	1.000						
Panel B: Eigenvectors										
	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9	Comp10
Number of Households	-0.310	0.392	-0.205	0.190	-0.184	0.036	0.545	0.506	-0.228	-0.178
Degree (Corrected)	0.329	0.418	0.053	0.010	-0.051	-0.179	0.217	-0.245	0.589	-0.475
Clustering (Corrected)	0.099	0.205	0.610	-0.470	-0.318	0.434	0.163	-0.061	-0.185	0.053
Eigenvector Centrality	0.396	-0.313	0.110	-0.014	0.214	-0.165	0.642	0.158	0.150	0.447
Betweenness Centrality	0.225	-0.399	0.385	0.211	-0.112	-0.014	-0.209	0.582	0.065	-0.445
Path Length (Corrected)	-0.475	-0.143	0.031	0.059	-0.183	0.354	-0.002	0.130	0.714	0.253
Fraction in Giant	0.291	0.253	0.156	0.772	-0.193	0.238	-0.107	-0.142	-0.079	0.316
1st Eigenvalue of Adj. Mat	0.228	0.477	-0.058	-0.263	0.024	-0.221	-0.402	0.510	0.155	0.391
2nd Eig. of Stoch. Adj. Mat	-0.273	0.245	0.438	0.138	0.801	0.086	-0.006	0.046	0.011	-0.053
Spectral Gap	0.376	-0.015	-0.450	-0.105	0.302	0.716	-0.015	0.133	0.026	-0.150

Note: Principal component decomposition of network level characteristics across the 43 villages in the sample.

Table A-3: Minimum Distance to Set of Leaders and Household Characteristics

	Distance	Distance	Distance	Distance	Distance	Distance	Distance	Distance	Distance	Distance	Distance	Distance	Distance
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Degree	-0.0301***												
	(0.00114)												
Clustering		-0.162***											
		(0.0366)											
Betweenness Centrality			-9.473***										
			(0.774)										
Eigenvector Centrality				-3.523***									
				(0.194)									
Number of Rooms					-0.0688***								
					(0.00645)								
Number of Beds						-0.0170***							
						(0.00597)							
Electricity							0.158***						
							(0.0129)						
Latrine								0.0681***					
								(0.00940)					
Education									-0.00895***				
									(0.00217)				
Own House/Rent House										-0.0130			
										(0.00964)			
GM or OBC											-0.0123		
											(0.0206)		
Savings												-0.0605***	
												(0.0202)	
SHG Participation													0.0465
													(0.0454)
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

Note: The dependent variable is the minimum distance to the set of leaders. * , **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A-4: Structural Estimates of Tiled Roofing Model

q^N	q^P	q^N - q^P
0.900	0.800	0.10
[0.2613]	[0.1479]	[0.2219]

Note: We present the results of a placebo test, estimating the diffusion model in which whether a household has tiled roofing is the outcome variable of the diffusion process. q^N represents the probability that a household that is informed about tiled roofing 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. The estimation uses the moments described in Section 5.1. 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.