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Supplementary Materials for

The Diffusion of Microfinance

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Material and Methods

Data construction

BSS provided us with a list of 75 villages in which they were planning to start operations. The villages were spread across 5 districts in Karnataka. Prior to BSS's entry, these villages had almost no exposure to microfinance institutions, and limited access to any type of formal credit.

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.

The village questionnaire was used to collect 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 (e.g., roofing material, type of latrine, quality of access to electric power) for every household in each village.

The individual questionnaire was administered to a subsample of households in the village. A household in the village was considered eligible for administering the individual survey if the household had a woman aged 18-50 years living there. All the eligible households were sorted by the religion of the household head. For non-Hindu (Muslim and Christian) households, all households were selected wherever the group only formed a small fraction of the village. The individual survey was then administered to the head of the household, his or her spouse, other adult women between the age 18 and 50 years, and spouses of these women if available. Hindu households, on the other hand, were grouped based on geography obtained from our GPS data and then from each of these groups, 50% of were randomly selected for administering the individual survey. The survey was again given to the same types of individuals – household head, spouse of household head, other women aged between 18 and 50 years and their spouses if available. Individual surveys administered in the above fashion yielded a sample of about 46% of all households per village, and we correct some of our measures for missing data. The individual questionnaire asked for information including age, caste, education, language, native home, etc.

The most important module of the individual questionnaire was the social network data. We collected twelve dimensions of network data including names of (1) those who visit the respondent's home, (2) those whose homes the respondent visits, (3) kin in the village, (4) non-relatives with whom the respondent socializes, (5) those from whom the respondent receives medical advice, (6) those from whom the respondent would borrow money, (7) those to whom the respondent would lend money, (8) those from whom the respondent would borrow material goods (kerosene, rice, etc.), (9) those to whom the respondent would lend material goods, (10) those from whom the respondent gets advice, (11) those to whom the respondent gives advice, and (12) those whom the respondent goes to pray with (at a temple, church, or mosque).

This paper makes use of undirected, unweighted networks constructed at the household level. The network data was constructed as follows. For every village we constructed 12 individual-level adjacency matrices, where a node is a person. We then took the union of this, indicating that a node is linked to another node if it has any single one of these relationships with another. Next, we collapsed the data to the household level, constructing a graph between households in the village where we say one household is linked to another if any of its members are linked. Finally, as is standard in the literature, we removed self-loops (links between household members) for the household level networks. The resulting objects are undirected, unweighted graphs constructed at the household network for every village in our sample.

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 study in early 2011, BSS had entered 43 of the villages. We define a household as having a leader if a member belonged to one of the following pre-specified categories: self-help group leaders, teachers, shop owners (three categories alone which comprise 74% of the leaders), as well as doctors, pujaris/elders, or political/community/organization leaders. We do not have the data to know which specific households were or were not successfully contacted and convinced by BSS in each village. BSS provided us with administrative data over time as to who joined the program, which we matched with our demographic and social network data. We use the the cross-sectional variation in the final take-up data to identify our structural model (Tables 1, S4-S6). Additionally, we construct village-level take-up rates of non-leader households as the outcome variable in the reduced form regressions (Tables 3, S3). For our time-series validation exercise, we collapse the data to the trimester-level, as described in the text (Table 2).

Data description

Table S1 provides descriptive statistics. Villages that BSS entered have an average of 223 households. The average microfinance participation rate for BSS is 18.5%, with a cross-village standard deviation of 8.4%.[1] On average, 12% of households have a member designated as a leader.

One quarter of leaders participate in microfinance, with a standard deviation of 12.5% across villages. About 21% of households (the standard deviation is 8% across households) include someone who is a member of some SHG. These SHGs typically conduct female empowerment programs, including encouragement for savings, skill development (e.g., tailoring), study visits to nearby villages or towns to witness small and medium enterprise development, etc. The average education is 4.92 standards (i.e. the level of schooling attended up to the end of fifth grade), with a standard deviation of 0.99. The fraction of respondents who belong to the "general" (GM) castes and "other backward castes" (OBC) is 63%, with substantial cross-village heterogeneity.[2] About 39% of households have access to some savings instrument (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, t test), though their houses tend to have more rooms (2.69

[1] Participation is measured as a percentage of non-leader households.

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

as compared to 2.28–the difference has a P-value of 0.00, t test).

Turning to network characteristics, the average degree, or number of connections each household has, is almost 15 while the average degree of leaders is 18. Because our data is constructed from star subgraph sampling, the average degree estimates are computed only using surveyed households. These are small worlds, with an average network path length of 2.8 between households, and a graph clustering rate of 26%. This means that the ratio of the number of closed triples to the number of two-stars is just over a quarter.[3]

Model and Estimation

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:

1. Node i's information status: $s_{it} \in \{0, 1\}$, indicating uninformed/informed respectively.[4]

2. 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 t.[5] Define I^t be the historical stock.

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 $L := \{i \in N : \; i \text{ is a leader}\}$.

[3]Here we report the graph clustering, also known as the transitivity ratio. Similar results are true with the average clustering coefficient. Again we account for the star subgraph sampling in our computation. The clustering rate 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 (22) and the references in (21).

[4]Note that therefore $s_{i,t+1} \geq s_{it}$ for all t.

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

(b) Next, those newly informed agents decide whether or not to participate based on their characteristics and the participation decisions of their neighbors: m_{i0} are distributed as Bernoulli with $p_i(\beta, \lambda)$, where λ may be set to 0 in the information model without any endorsement effects, for each $i \in I_0$. In the case of endorsement effects, for the initial period $F_{i0} = 0$.

(c) Next, each $i \in I^0$ transmits to $j \in N_i$ with probability $m_{i1}q^{\mathrm{P}} + (1 - m_{i1})\, q^{\mathrm{N}}$. 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) Newly informed agents are now I_t.

   (b) Newly informed agents decide whether or not to participate based on their characteristics and the decisions of their neighbors: m_{it} are distributed as Bernoulli with $p_i(\beta, \lambda)$ for each $i \in I_t$. In the case of the model with endorsement $F_{it} = |\{j | j \in I(i,t), m_{jt} = 1\}| / |I(i,t)|$ 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 $m_{it}q^{\mathrm{P}} + (1 - m_{it})\, q^{\mathrm{N}}$. 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.

3. The process repeats for T periods.[6]

Structural estimation and bootstrap

Let Θ be the parameter space and Ξ a grid on Θ, described below. 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 micro-

[6] We mainly use T as the number of trimesters exposed to BSS with a 0 period for the leaders. We also run alternative time scales such as quarters and months (see Table S5).

finance participation 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.

   (c) Find $\xi^{\star b} = \operatorname{argmin} Q^{\star b}(\xi)$, with $Q^{\star b}(\xi) = D(b,\xi)'\widehat{W}D(b,\xi)$. [7]

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 $B = 1000$, $S = 75$. We selected the grid according to the following algorithm. Let τ denote the time scale (trimesters, quarters, months) by which the model can be estimated.

[7] Estimate $\widehat{W} = \left(R^{-1}\sum_r d(r,\widetilde{\theta})d(r,\widetilde{\theta})'\right)^{-1}$ for a first-stage estimate $\widetilde{\theta}$ via the same algorithm with identity matrix weighting.

1. Select the grid for $q_r^N(\tau)$ and $q^P(\tau)$ for the information model.

   (a) For each village r, estimate an information model, setting $q_r^N(\tau) = q_r^P(\tau) = q_r(\tau)$.

   (b) Begin with $q_r(\tau) = 0$ and compute the fraction of informed in the village.

   (c) If the informed rate is less than 0.67, increase $q_r(\tau)$ by 0.000005 and repeat.

   (d) Once the informed rate reaches 0.67, stop increasing the step-size and call this $q_r^*(\tau)$.

   (e) Average $q_r^*(\tau)$ over all R villages, $q^*(\tau) := \sum q_r^*(\tau)/R$.

   (f) Round $q^*(\tau)$ to the nearest hundredths place and divide by 10 to determine the size of increments on the grid from 0 to $q^*(\tau)$.

   (g) Construct the grid for $q^N(\tau)$ by selecting points in $q^*(\tau)/10$ increments from 0 to $q^*(\tau)$ and 0.05 increments from $q^*(\tau)$ to 1. In the trimesters case, this gives the following grid for $q^N(\tau)$: [(0 : 0.004 : 0.04), (0.05 : 0.05 : 1)].

   (h) Construct the grid for for $q^P(\tau)$ by allowing it to be fine for a wider portion of the grid than $q^N(\tau)$. Select points in 0.005 increments from 0 to 0.1 (0.1 is higher than $q^*(\tau)$ for all τ) and let the remainder of the grid consist of points in 0.05 increments up to 1: [(0 : 0.005 : 0.1), (0.15 : 0.05 : 1)].

2. Select the grid for $q_r^N(\tau)$, $q^P(\tau)$ and λ in the information model with endorsement.

   (a) Because using the above algorithm to construct the grid for the information model with endorsement would result in a very large number of points, the estimation of which would be prohibitively slow, we cap the total number of grid combinations that need to be estimated to 7,000.

   (b) The grids for $q_r^N(\tau)$ and $q^P(\tau)$ are constructed in 0.05 increments from 0 to 0.5 and 0.1 increments from 0.6 to 1: [(0 : 0.05 : 0.5), (0.6 : 0.1: 1)].

(c) The grid for λ is constructed to allow for estimation of effect sizes of ± 10 percentage points from the average probability of participating in microfinance, allowing the fraction of participating friends to change from 0 to one-half in equation (1). These effect sizes correspond to λ values of -1 and 1. Points are selected in 0.1 increments from -1 to -0.3 and from 0.4 and 1 and the grid is finer around 0, where points are selected in 0.05 increments from -0.25 to 0.3: [(-1 : .1 : -0.3), (-0.25 : .05 : 0.3), (0.4 : .1 : 1)].

Supplementary Text

Centrality

We construct several measures of average leader centrality, in addition to communication, diffusion, and degree. We also include eigenvector centrality,[8] betweenness centrality, Katz-Bonacich centrality, decay centrality, and closeness centrality.[9]

Table S2 presents several regressions where the outcome variable is the average centrality of the leaders (across various centrality types) and the explanatory variables are demographic covariates: number of households, self-help group participation rate in the village, savings participation rate in the village, caste composition, and fraction of village households that are designated as leaders. These are precisely the demographic controls used in Table 3 of the paper. Every column presents a different regression and the columns present coefficients and standard errors on explanatory variables. We find little relationship between the various measures of centrality and the demographic covariates. The only exception, as expected, is with the number of households; larger networks are associated with lower average centrality of leaders (P-values 0.041, 0.097, 0.246, 0.000, 0.001, 0.089, 0.004, 0.000, t-test).

[8] We use an ℓ_2 normalization.

[9] We use parameter $0.8 \cdot 1/\lambda_1$ for Bonacich centrality and 0.18 for decay centrality.

Table S3 presents an expansion of Table 3. Every column presents a regression of the microfinance take-up rate in a village on various measures of centrality (separately, and then together). We find that in addition to communication and diffusion centrality being significantly associated with greater microfinance participation, the average eigenvector centrality of leaders and the average betweenness centrality of leaders are also significantly associated with participation, even conditional on demographic controls (Table S3, Panel C, columns 4-5, P-values 0.08 and 0.001, t-test). However, as presented in Table 3, the once all the measures are included together, the either communication centrality or diffusion centrality remains significant while the remainder no longer do so.

Alternative weights

Table S4 presents estimation results from alternative weightings of an individual's neighbors participation decisions in (1). We allow an individual i to place weight ω_{ij} on individual j by $\omega_{ij} = d_j/(\sum A_{ik}d_k)$, where d_j is the degree of node j, or $\omega_{ij} = \xi_j/(\sum A_{ik}\xi_k)$, where ξ_j is the eigenvector centrality of node j.

The results are comparable to those in the Table 1, supporting the hypotheses that $q^{\mathrm{N}} > 0$ and $q^{\mathrm{P}} > q^{\mathrm{N}}$ at the 5% significance level from the bootstrapped distribution. We find small negative endorsement effects which are not significantly different from zero at the 5% level for eigenvector weighting but are marginally significant at the 5% level for degree weighting.

Alternative timing structures

In principle, the model can be estimated using different time scales, as we do not truly observe the rounds of communication. To check for robustness, we estimated the model on several scales: trimesters, quarters and months. Table S5 presents the results for quarters and months.

Irrespective of the timing, we find support for the hypotheses that $q^{\mathrm{N}} > 0$ and $q^{\mathrm{P}} > q^{\mathrm{N}}$ (see the 2.5 and 97.5 percentiles of the bootstrapped distribution of the parameter and parameter difference estimates). The only substantive difference across the various timings is that a finer time scale tends to skew the bootstrapped distribution of q^{P}, leading to the occasional large estimate of q^{P} required to match the moments. This leads to larger standard errors for both q^{P} and $q^{\mathrm{N}} - q^{\mathrm{P}}$ and an asymmetric distribution, though $q^{\mathrm{N}} - q^{\mathrm{P}} < 0$ is robust even at the 5% significance level (as seen from the quantiles of the bootstrap).

Tables

Table S1. Descriptive Statistics. Sample includes 43 BSS villages and 32 non-BSS villages. Fraction GM or OBC refers to share of households that are not SC/ST.

	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	14.827	2.558	13.355	2.443
Graph Clustering	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	2.770	0.208	2.714	0.228
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
Degree of Leader	18.101	3.784	16.120	3.190
Eigenvector Centrality of Leader	0.074	0.017	0.088	0.020
Betweenness Centrality of Leader	0.030	0.009	0.018	0.006
Bonacich Centrality of Leader	4.341	0.419	4.404	0.545
Decay Centrality of Leader	5.413	1.085	4.432	0.946
Closeness Centrality of Leader	0.431	0.034	0.420	0.046
Diffusion Centrality of Leader	5.485	1.745	--	--
Communication Centrality of Leader	0.065	0.045	--	--
	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			
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
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

Table S2. Explaining the Average Centrality of Leaders. This table presents separate regressions (columns) where the dependent variable is the average centrality of the leaders in a village and the explanatory variables are demographic covariates.

	Communication	Diffusion	Degree	Eigenvector	Betweenness	Bonacich	Decay	Closeness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of Households	-0.0002	-0.008	0.012	-0.00021	-0.00009	-0.002	0.008	-0.0004
	(0.0001)	(0.004)	(0.011)	(0.00004)	(0.00003)	(0.001)	(0.003)	(0.00006)
Savings	0.119	4.742	0.581	0.006	0.020	0.300	-0.557	-0.036
	(0.072)	(3.272)	(6.102)	(0.017)	(0.010)	(0.647)	(1.781)	(0.050)
SHG Participation	0.010	4.361	-3.609	0.017	0.014	1.366	-1.243	-0.056
	(0.085)	(4.281)	(10.548)	(0.032)	(0.015)	(1.134)	(2.751)	(0.078)
Fraction GM/OBC	-0.009	0.112	1.034	-0.005	0.002	-0.181	-0.136	-0.004
	(0.010)	(0.479)	(1.372)	(0.004)	(0.003)	(0.149)	(0.376)	(0.011)
Fraction Leaders	-0.163	-16.886	-7.757	-0.055	-0.065	-2.505	-1.002	-0.012
	(0.231)	(10.173)	(21.777)	(0.101)	(0.069)	(2.898)	(6.705)	(0.198)
R-squared	0.183	0.177	0.079	0.521	0.368	0.180	0.207	0.425

Table S3. Microfinance Take-Up versus Centralities of Leaders. This table presents coefficients and standard errors from ordinary least squares regressions (standard errors, which are heteroskedasticity-robust, are denoted in brackets). The dependent variable is the microfinance take-up rate of non-leader households. The covariates are various measures of centrality and, when noted, control variables. Within a panel, each column represents a different regression. Panel A includes no controls. Panel B controls for number of households. Panel C controls for number of households, savings, self-help group participation, fraction of general caste members, and fraction of households that are BSS leaders.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Panel A: No Controls					
Communication Centrality	0.882								0.621	
	(0.314)								(0.400)	
Diffusion Centrality		0.023								0.015
		(0.008)								(0.009)
Degree			-0.003						-0.005	-0.004
			(0.003)						(0.005)	(0.005)
Eigenvector				2.579					3.728	3.939
				(0.616)					(2.229)	(2.204)
Betweenness					4.661				1.049	0.981
					(0.751)				(1.600)	(1.560)
Bonacich						0.053			-0.075	-0.103
						(0.032)			(0.067)	(0.060)
Decay							-0.024		0.013	0.014
							(0.010)		(0.026)	(0.026)
Closeness								0.633	-0.302	-0.087
								(0.283)	(0.515)	(0.517)
R-squared	0.226	0.236	0.025	0.270	0.270	0.069	0.093	0.066	0.468	0.449
					Panel B: Only Number of Households					
Communication Centrality	0.682								0.617	
	(0.317)								(0.407)	
Diffusion Centrality		0.019								0.015
		(0.007)								(0.009)
Degree			-0.001						-0.006	-0.005
			(0.002)						(0.005)	(0.005)
Eigenvector				1.774					3.813	4.086
				(0.950)					(2.343)	(2.282)
Betweenness					3.283				1.009	0.904
					(1.116)				(1.630)	(1.612)
Bonacich						0.025			-0.076	-0.105
						(0.027)			(0.068)	(0.060)
Decay							-0.009		0.020	0.026
							(0.009)		(0.044)	(0.042)
Closeness								-0.220	-0.559	-0.554
								(0.360)	(1.495)	(1.451)
R-squared	0.356	0.378	0.235	0.296	0.327	0.246	0.242	0.237	0.469	0.450
					Panel C: All Controls					
Communication Centrality	0.766								0.713	
	(0.335)								(0.428)	
Diffusion Centrality		0.022								0.018
		(0.007)								(0.009)
Degree			-0.001						-0.005	-0.003
			(0.002)						(0.006)	(0.006)
Eigenvector				1.721					3.572	3.692
				(0.954)					(2.330)	(2.265)
Betweenness					3.824				1.709	1.710
					(1.086)				(1.776)	(1.687)
Bonacich						0.024			-0.072	-0.106
						(0.029)			(0.070)	(0.063)
Decay							-0.010		0.032	0.034
							(0.009)		(0.047)	(0.045)
Closeness								-0.303	-1.077	-0.891
								(0.333)	(1.551)	(1.496)
R-squared	0.406	0.442	0.269	0.324	0.382	0.278	0.281	0.276	0.530	0.515

Table S4. Alternative Weights. See caption to Table 1 for explanation of estimation procedure.

	q^N	q^P	λ	q^N - q^P
	(1)	(2)	(3)	(4)
Information Model with Endorsement				
Degree Weighted	0.050	0.800	-0.300	-0.750
Standard Error	[0.0073]	[0.2430]	[0.1547]	[0.2452]
2.5, 97.5 percentiles of bootstrap distr.	[0.05, 0.05]	[0.2, 1]	[-0.4, 0]	[-0.95, -0.15]
Eigenvector Weighted	0.050	0.500	-0.250	-0.450
Standard Error	[0.0061]	[0.2327]	[0.1299]	[0.2360]
2.5, 97.5 percentiles of bootstrap distr.	[0.05, 0.05]	[0.2, 1]	[-0.4, 0.05]	[-0.95, -0.15]

Table S5. Alternative Timing Estimates. See caption to Table 1 for explanation of estimation procedure. The grid for q^N is [(0:0.003:0.03), (0.05:0.05:1)] in the quarters model and [(0:0.001:0.01), (0.05:0.05:1)] in the months model. The grid for q^P is [(0:0.005:0.1), (0.15:0.05:1)] in both models.

	q^N	q^P	q^N - q^P
	(1)	(2)	(3)
Quarters	0.030	0.200	-0.170
Standard Error	[0.0099]	[0.0985]	[0.0991]
2.5, 97.5 percentiles of bootstrap distr.	[0.027, 0.05]	[0.1, 0.5]	[-0.47, -0.059]
Months	0.010	0.085	-0.075
Standard Error	[0.0005]	[0.1020]	[0.1020]
2.5, 97.5 percentiles of bootstrap distr.	[0.009, 0.01]	[0.05, 0.55]	[-0.54, -0.04]

Table S6. Estimates Dropping Injection Point-Based Moments and Observations. See caption to Table 1 for explanation of estimation procedure. The grid for q^N and q^P is [(0:0.05:0.5), (0.6:0.1:1)] in all cases. Case 1 drops moments 3 and 4 in the estimation procedure. Case 2 is case 1 but additionally excluding all observations corresponding to injection points. Case 3 is case 2 but additionally purging injection points from the neighborhoods of all other nodes when computing the moments.

	q^N	q^P	q^N - q^P
	(1)	(2)	(3)
Case 1	0.050	0.300	-0.250
Standard Error	[0.0098]	[0.1136]	[0.1168]
Case 2	0.050	0.300	-0.250
Standard Error	[0.0169]	[0.1079]	[0.1199]
Case 3	0.050	0.300	-0.250
Standard Error	[0.0098]	[0.1002]	[0.1040]

Table S7. Correlation of DC(q,T). This table presents correlation of the diffusion centrality of leaders evaluated at various values of q and T with those presented in the main text, where q is the inverse of the first eigenvalue of the adjacency matrix and T is the number of trimesters that a village was exposed to BSS. We present DC(q,T) with q taking values from 0.25*1/λ to 2*λ with T taking values from 0.25*T to 2*T.

		Scale for number of periods							
		0.25	0.5	0.75	1	1.25	1.5	1.75	2
Scale for q	0.25	0.9768	0.9812	0.9818	0.9819	0.9819	0.9819	0.9819	0.9819
	0.5	0.9813	0.9897	0.9918	0.9924	0.9926	0.9927	0.9928	0.9928
	0.75	0.9841	0.9946	0.9975	0.9985	0.9990	0.9992	0.9993	0.9993
	1	0.9858	0.9970	0.9996	1	0.9996	0.9991	0.9983	0.9978
	1.25	0.9869	0.9983	0.9999	0.9994	0.9978	0.9962	0.9946	0.9935
	1.5	0.9877	0.9989	0.9997	0.9985	0.9962	0.9944	0.9925	0.9915
	1.75	0.9883	0.9992	0.9993	0.9977	0.9952	0.9934	0.9916	0.9906
	2	0.9888	0.9994	0.9990	0.9972	0.9946	0.9929	0.9911	0.9902

References and Notes

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3. There is an old and large literature that studies information diffusion (*17*–*25*). However, empirical evidence on the role of injection points is still sparse.

4. For experimental approaches to controlling for and analyzing the role of homophily in diffusion, see (*26*, *27*).

5. Individuals were allowed to name as many as five to eight network neighbors, depending on the category. The data exhibit almost no top-coding; fewer than 10% of the respondents named the maximum number of individuals in any single category.

6. The main difference is the number of households: Villages that BSS entered had 223.2 households on average (SD = 56.17); those it did not enter had 165.8 households on average (SD = 48.95).

7. One could imagine that households need some time to think, or to process information from their neighbors, before adoption (*21*, *28*). However, in our setting, one period (4 months) encompasses much of this decision time. It may be that in the long run (over a period of years) they would reconsider their decisions, which our model does not address, and so we do not capture long-run reactions to neighbors' experiences. For instance, it could be that there are coordination problems as people wait for others to participate before participating themselves. This seems unrealistic in our context: It takes about 1 to 2 years to learn how neighbors did with microfinance (whether they managed to repay, whether they benefited, etc.). Our data show that most of the adoption of microfinance takes place within the first year in a village (before the first cycle of loans is complete).

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13. For an example of a method of simulated moments approach used in a spatial setting, see (*29*).

14. For example, 1000 runs of a simulated annealing search would be prohibitively slow.

15. The results are essentially identical without controls.

16. For background on centrality definitions, see (*30*).

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