THE DIFFUSION OF MICROFINANCE

MATHEMATICAL ECONOMICS

Reporter: 董博 李浩川 李旭峰 田允晴 王浩然

FUDAN UNIV 2018

REPORT

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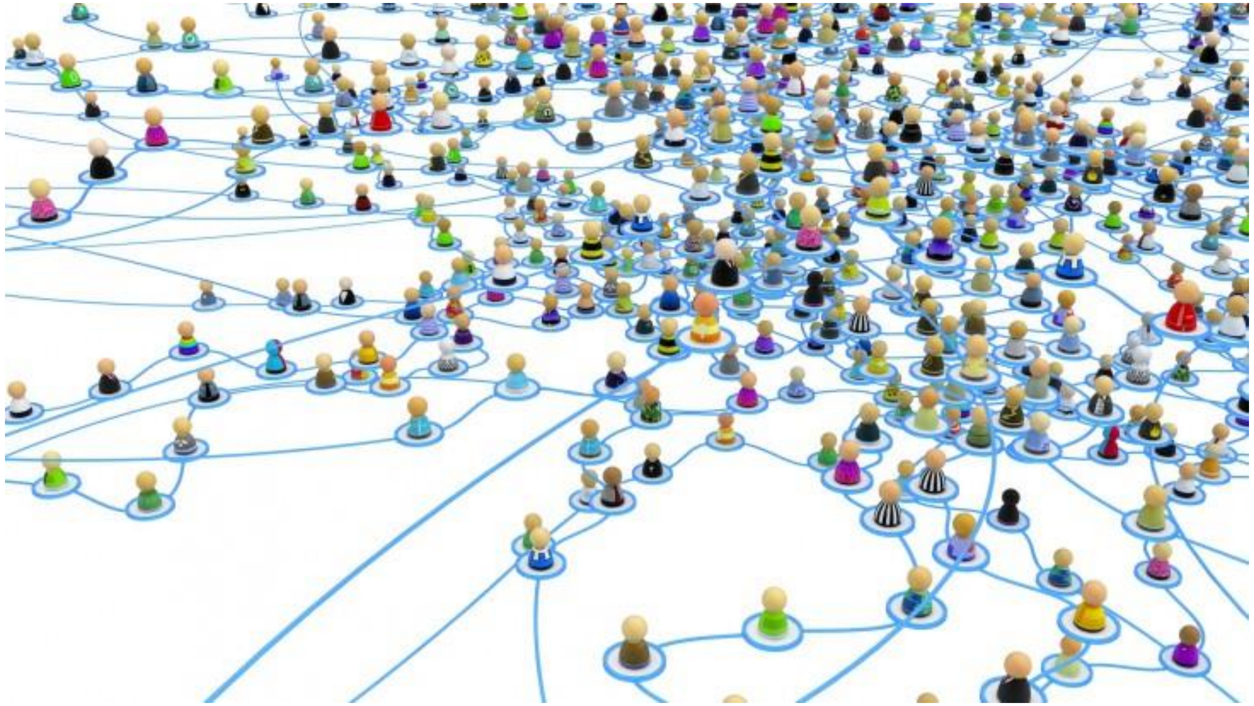
Introduction



Abhijit Banerjee

Papers

Growing Cleavages in India? Evidence from the Changing Structure of Electorates, 1962–2014
Abhijit Banerjee, Amory Gethin, Thomas Piketty
March 2019

Using Gossips to Spread Information: Theory and Evidence from Two Randomized Controlled Trials
Abhijit Banerjee, Arun G. Chandrasekhar, Esther Duflo and Matthew O. Jackson
The Review of Economic Studies, February 2019

Universal basic income in a developing world
Abhijit Banerjee, Paul Niehaus, and Tavneet Suri
February 2019

Private Outsourcing and Competition: Subsidized Food Distribution in India
Abhijit Banerjee, Jordan Kyle Cohen, Rema Hanna, Benjamin Olken and Sudarno Sumarto
Journal of Political Economy, forthcoming

How Much Do Existing Borrowers Value Microfinance? Evidence from an Experiment on Bundling Microcredit and Insurance
Abhijit Banerjee, Esther Duflo and Richard Hornbeck
Economica, October 2018

Changes in Social Network Structure In Response to Exposure to Formal Credit Markets
Working paper, September 2018
Abhijit Banerjee, Arun G. Chandrasekhar, Esther Duflo and Matthew O. Jackson

Can Iron Fortified Salt Control Anemia? Evidence from Two Experiments in Rural Bihar
Abhijit Banerjee, Esther Duflo, and Sharon Barnhardt
Journal of Development Economics, Volume 133, July 2018.

Tangible Information and Citizen Empowerment- Identification Cards and Food Subsidy Programs in Indonesia
Abhijit Banerjee, Rema Hanna, Jordan Kyle, Benjamin Olken, and Sudarno Sumarto
Journal of Political Economy, Vol. 126, Number 2, April 2018

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Abhijit Vinayak Banerjee was educated at the University of Calcutta, Jawaharlal Nehru University and Harvard University, where he received his Ph.D in 1988. He is currently the Ford Foundation International Professor of Economics at the Massachusetts Institute of Technology. In 2003 he founded the **Abdul Latif Jameel Poverty Action Lab** (J-PAL), along with Esther Duflo and Sendhil Mullainathan and remains one of the directors of the lab. In 2009 J-PAL won the BBVA Foundation "Frontier of Knowledge" award in the development cooperation category. Banerjee is a past president of the **Bureau for the Research in the Economic Analysis of Development**, a Research Associate of the NBER, a CEPR research fellow, International Research Fellow of the Kiel Institute, a fellow of the American Academy of Arts and Sciences and the Econometric Society and has been a Guggenheim Fellow and an Alfred P. Sloan Fellow. He received the Infosys Prize 2009 in Social Sciences and Economics. In 2011, he was named one of Foreign Policy magazine's top 100 global thinkers. His areas of research are development economics and economic theory. He is the author of a large number of articles and three books, including Poor Economics (**www.pooreconomics.com**) which won the Goldman Sachs Business Book of the Year. He is the editor of a fourth book, and finished his first documentary film, "The Name of the Disease" in 2006. Most recently, Banerjee served on the U.N. Secretary-General's High-level Panel of Eminent Persons on the Post-2015 Development Agenda.

Esther Duflo

Published Papers and Book Chapters

The following is a list of recent papers. For a complete list and earlier papers, please see the cv.

Using Gossips to Spread Information: Theory and Evidence from Two Randomized Controlled Trials
The Review of Economic Studies, February 2019
with Abhijit Banerjee, Arun G. Chandrasekhar and Matthew O. Jackson

The Value of Regulatory Discretion: Estimates from Environmental Inspections in India
Econometrica, November 2018
with Michael Greenstone, Rohini Pande and Nicholas Ryan

How Much Do Existing Borrowers Value Microfinance? Evidence from an Experiment on Bundling Microcredit and Insurance
Economica, Volume 85, Issue 340, October 2018
with Abhijit Banerjee and Richard Hornbeck

[DATA]

Can Iron Fortified Salt Control Anemia? Evidence from Two Experiments in Rural Bihar
Journal of Development Economics, Volume 133, July 2018.
with Abhijit Banerjee and Sharon Barnhardt

Double/Debiased Machine Learning for Treatment and Structural Parameters
The Econometrics Journal, Vol. 21, Issue 1, February 2018
with Victor Chernozhukov, Denis Chetverikov, Mert Demirer, Christian Hansen, Whitney Newey and James Robins

NAITRE study on the impact of conditional cash transfer on poor pregnancy outcomes in underprivileged women: protocol for a nationwide pragmatic cluster-randomised superiority clinical trial in France
BMJ Open, 2017.
with Marc Bardou, Bruno Crépon, Anne-Claire Bertaux, Aurélie Godard-Marceaux, Astrid Eckman-Lacroix, Elise Thellier, Frédérique Falchier, Philippe Deruelle, Muriel Doret, Xavier Carcopino-Tusol, Thomas Schmitz, Thiphaine Barjat, Mathieu

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Esther Duflo
CV (PDF Download)
Poor Economics
Short Bio
Courses

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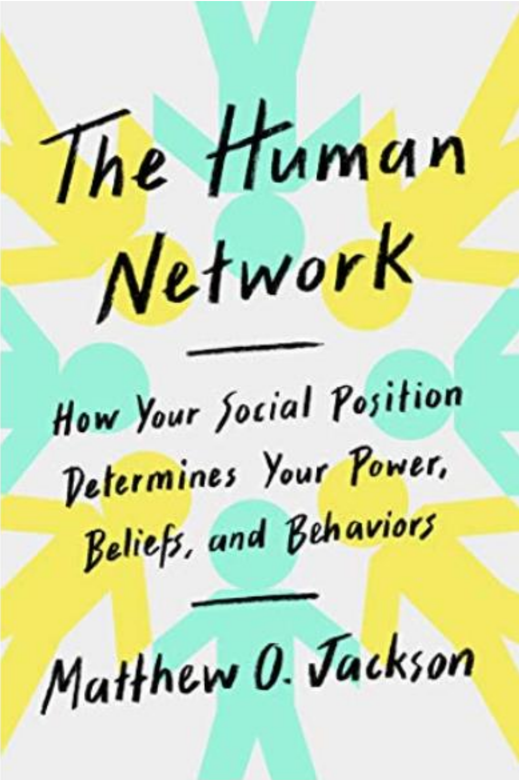
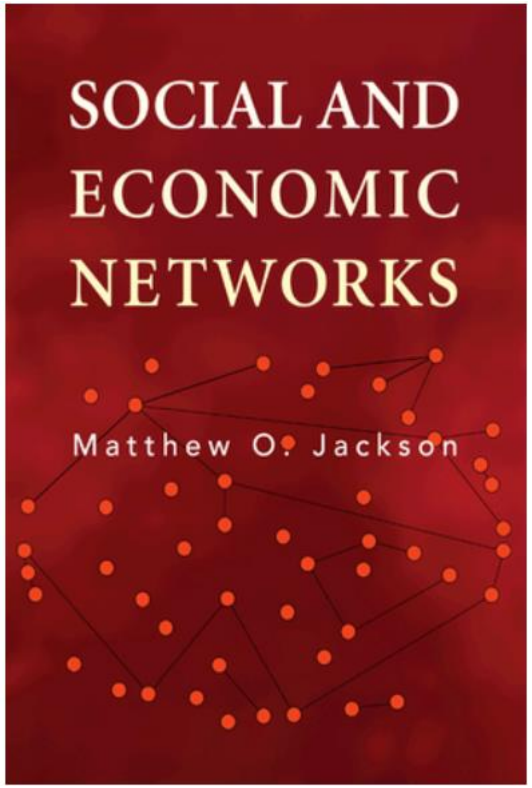
Matthew O. Jackson

Matthew O. Jackson

William D. Eberle Professor of Economics





introduction

1.participant and **non-participant** information passing role

2.find no (statistical) evidence of an **endorsement effect**

3.higher **eigenvector centrality**, higher take up rate

/02

Background and Data

2.1 Background

rural southern Karnataka

Bharatha Swamukti Samsthe(BSS)---
which operates a conventional microcredit program

the diffusion of participation
in a microfinance program

2.1 Background

When BSS starts working in a village

01

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.

02

The leaders present information about microfinance to the village.

03

The villagers contact BSS。

2.1 Background

- 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.
  - These villages are, by and large, linguistically homogeneous but heterogeneous in terms of caste.
  - The majority of the population in these villages is Hindu(印度教徒).
  - The most common primary occupations are agricultural work (growing finger millet, coconuts, cabbage, mulberries and rice), sericultural work (silkworm rearing), and dairy production.

2.2. Data

village questionnaire

- village leadership
- the presence of savings self-help groups
- various geographical features of the area (such as rivers, mountains, and roads)

In 2006, six months prior to BSS's entry into any village, the author conducted a survey in all 75 villages.

individual survey
（随机抽样-分层抽样、46%）

age

caste

education

language

occupation

household census

- demographic information
- GPS coordinates

2.2. Data

names of friends or relatives who visit the respondent's home

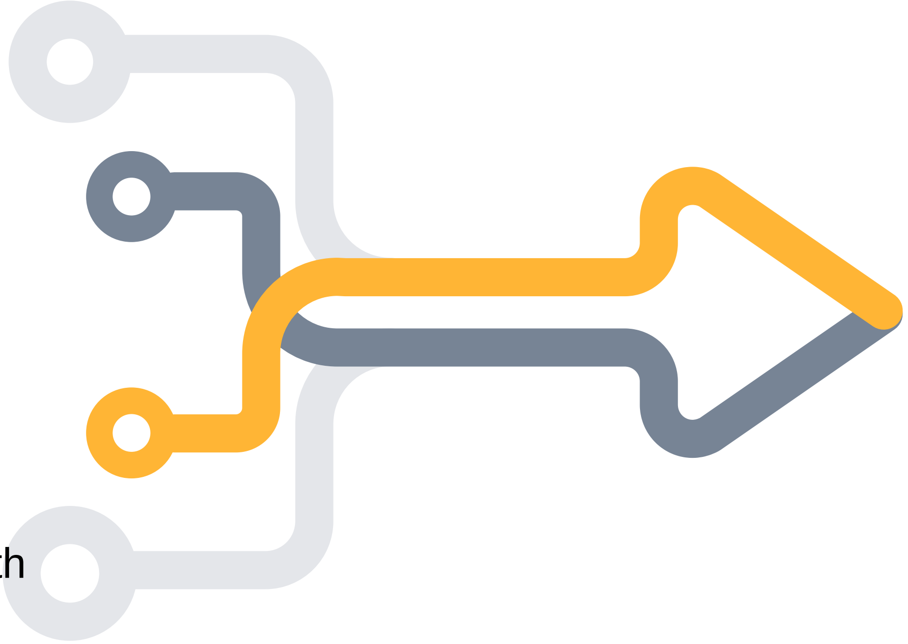
names of those friends or relatives the respondent visits

from whom the respondent would borrow money

to whom the respondent would lend money

who the respondent goes to pray with

……



Social network data along thirteen dimensions

In the 43 villages where they started their operations, BSS provided the author with regular administrative data on who joined the program.

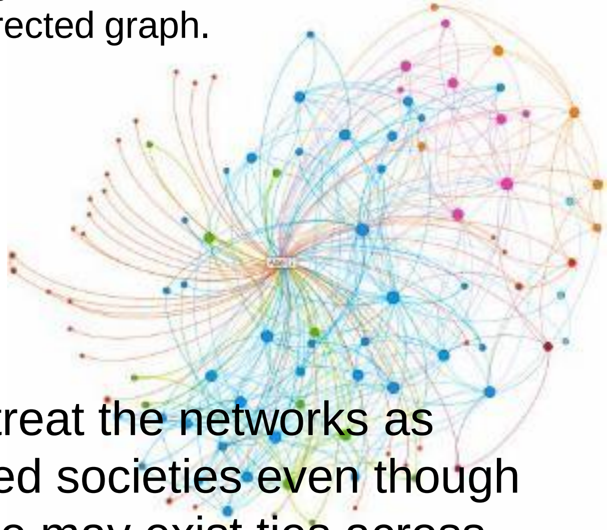
2.3 Network Measurement Concerns and Choices

Whether we should consider the individual or the household as the unit of analysis?

borrowing decisions are often made at the household level.

Directed or undirected?

While the networks derived from these data could be, in principle, directed, in this paper we symmetrize the data and consider an undirected graph.



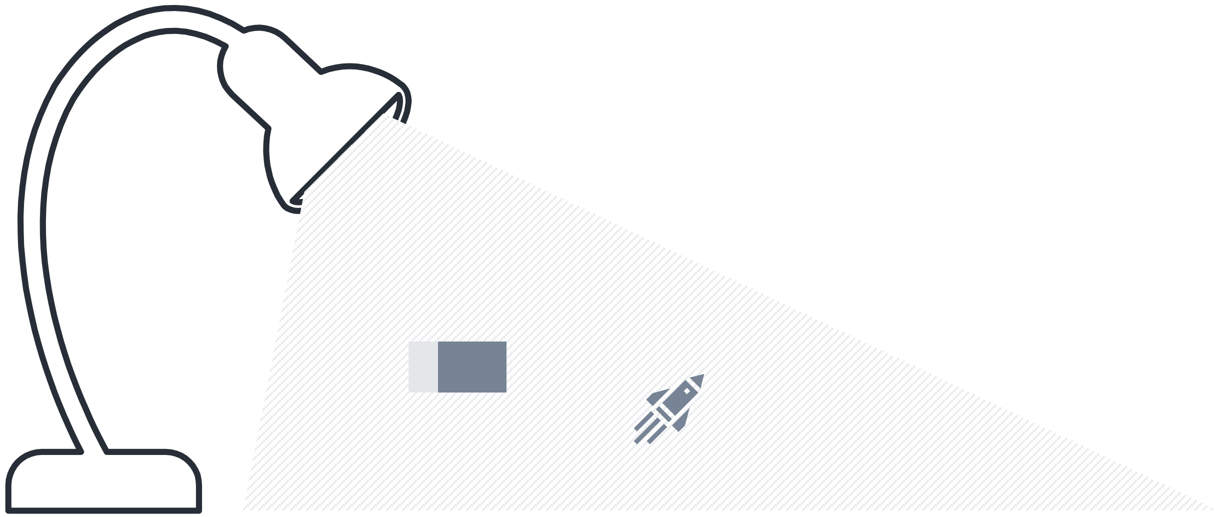
The network data enable us to construct a rich multi-graph with many dimensions of connections between individuals.

We treat the networks as closed societies even though there may exist ties across villages.

Cross-marriages are rare.

The villages are mostly geographically well-separated.

2.4 Descriptive Statistics



average take-up rate for BSS	average take-up rate of leader	average education
18.5%	25%	4.92
8.4%	12.5%	0.99

2.4 Descriptive Statistics

Leaders tend to be no older or younger than the rest of the population (the p-value on the difference is 0.415).

The average degree (the average number of connections that each household has) is almost 15.

The average clustering rate is 26%. 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.

The average eigenvector centrality（a key concept of the importance of injection points， is proportional to the sum of its neighbors' centralities） of leaders is 0.07 (with a standard deviationof 0.017), as opposed to 0.05 (standard deviation of 0.009) for the village as a whole.

/03

The Model and the Result

Introduction to social network analysis

Social networks represent relationships involving social entities such as friendship, neighborhood

In this paper, there exists 13 dimensions where people are able to build relationship, like friends, relatives, go to pray with, borrow money from and so on

We think that two households can be lined in a undirected graph only if one of above dimensions are correlated. As a result, from our survey data, we can build a social network graph under any village

Network characteristics

Degree: the number of links that a household has. And due to my graph is undirected, in-degree equals to out-degree of a node.

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

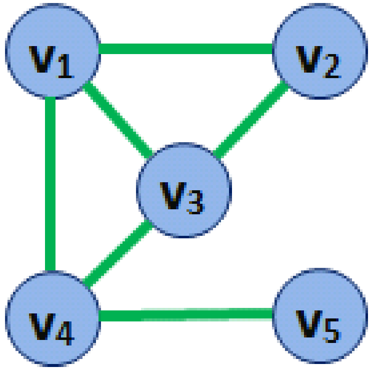
Eigenvector centrality: The measure of how important a node is in the sense of iterative paths through a network, which is the most important evaluation in our model.

Average path length: the mean length of the shortest path between any two house-
holds in the village, which is used as a distance measure.

Adjacency matrix: the adjacency matrix of a finite graph G on n vertices is the n × n matrix where the non-diagonal entry $a_{ij}$is 1 if vertex *i* is linked to vertex *j*, 0 otherwise, and the diagonal entry is null.

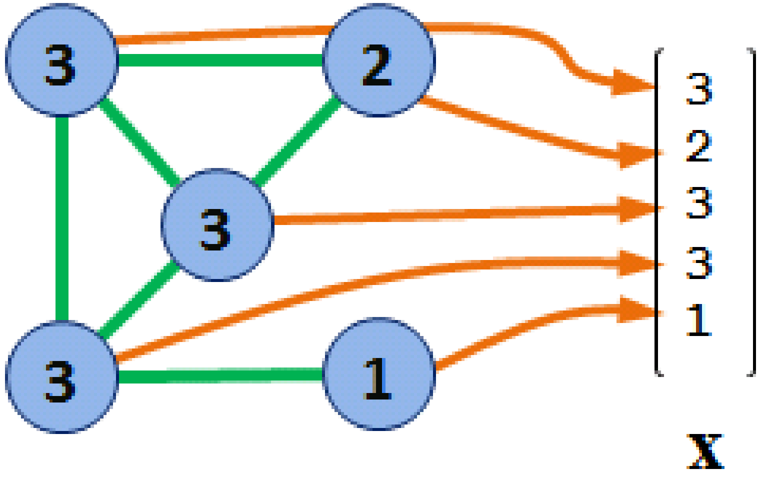
Intuitional concept for Eigenvector centrality

Consider the graph below and its 5×5 adjacency matrix A:



$$\mathbf{A} = \begin{bmatrix} - & 1 & 1 & 1 & 0 \\ & - & 1 & 0 & 0 \\ & & - & 1 & 0 \\ & & & - & 1 \\ & & & & - \end{bmatrix}$$

And then consider , x, a 5x1 vector of values, one for each vertex in the graph. In this case, we've used the degree centrality of each vertex.

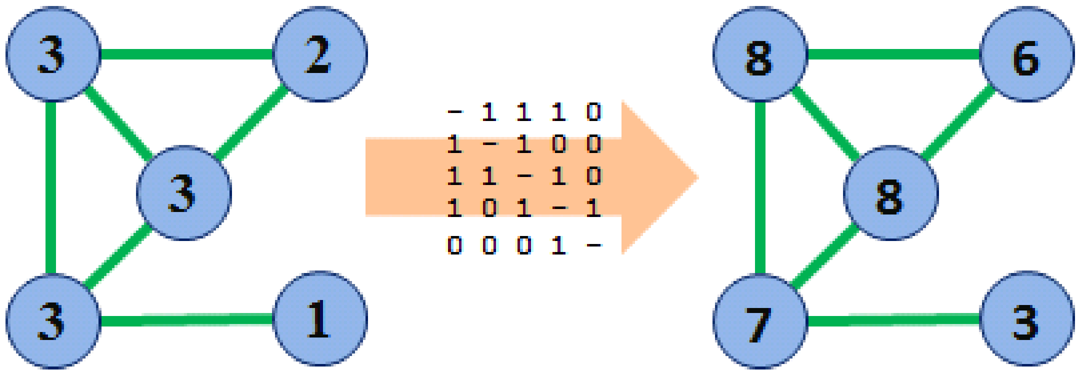


Intuitional concept for Eigenvector centrality

Now let‘s look at what happens when we multiply the vector x by the matrix A. The result, of course, is another 5×1 vector.

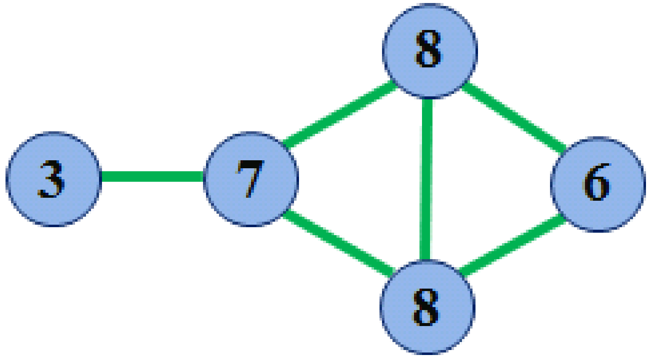
$$
\mathbf{A} \times \mathbf{x} = \begin{pmatrix} - & 1 & 1 & 1 & 0 \\ 1 & - & 1 & 0 & 0 \\ 1 & 1 & - & 1 & 0 \\ 1 & 0 & 1 & - & 1 \\ 0 & 0 & 0 & 1 & - \end{pmatrix} \begin{bmatrix} 3 \\ 2 \\ 3 \\ 3 \\ 1 \end{bmatrix} = \begin{pmatrix} 0\text{x}3 + 1\text{x}2 + 1\text{x}3 + 1\text{x}3 + 0\text{x}1 \\ 1\text{x}3 + 0\text{x}2 + 1\text{x}3 + 0\text{x}3 + 0\text{x}1 \\ 1\text{x}3 + 1\text{x}2 + 0\text{x}3 + 1\text{x}3 + 0\text{x}1 \\ 1\text{x}3 + 0\text{x}2 + 1\text{x}3 + 0\text{x}3 + 1\text{x}1 \\ 0\text{x}3 + 0\text{x}2 + 0\text{x}3 + 1\text{x}3 + 0\text{x}1 \end{pmatrix} = \begin{bmatrix} 8 \\ 6 \\ 8 \\ 7 \\ 3 \end{bmatrix}
$$

What multiplication by the adjacency matrix does, is reassign each vertex the sum of the values of its neighbor vertices.



Intuitional concept for Eigenvector centrality

This has, in effect, "spread out" the degree centrality. That this is moving in the direction of a reasonable metric for centrality can be seen better if we rearrange the graph a little bit:



This vector is called an Eigenvector of the matrix **A**.
The elements of this vector are the Eigenvector centralities of the vertices of the graph.
In summary, multiple adjacency matrix with the weighs vector and then you would get the centrality measure of each nodes.

$$\begin{pmatrix} 8 \\ 6 \\ 8 \\ 7 \\ 3 \end{pmatrix}$$

Conceptual Framework

The conceptual framework is used to simulate the diffusion of microfinance in every iteration

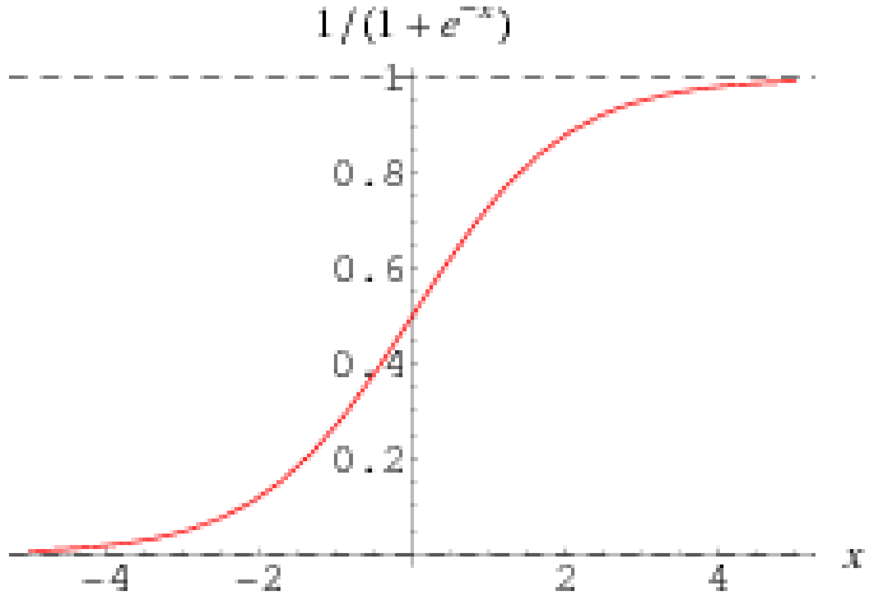
Before delving into our model, let's first introduce the state propensities of a node:

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

Additionally, we should exploit logistic function (or sigmoid function) to estimate probability.

Compared to sign function with bad properties of non-derivation and non-continuity at zero point, logistic function is continuous and differentiable on real field.

The threshold of 0 or 1 is usually set as 0.5 , that's to say,
When f(x) > 0.5, probability = 1;
When f(x) < 0.5, probability = 0;



Decision-making

Someone may tell you that your future is your own and do not base your decisions on the advice of those who don't have to deal with the results.

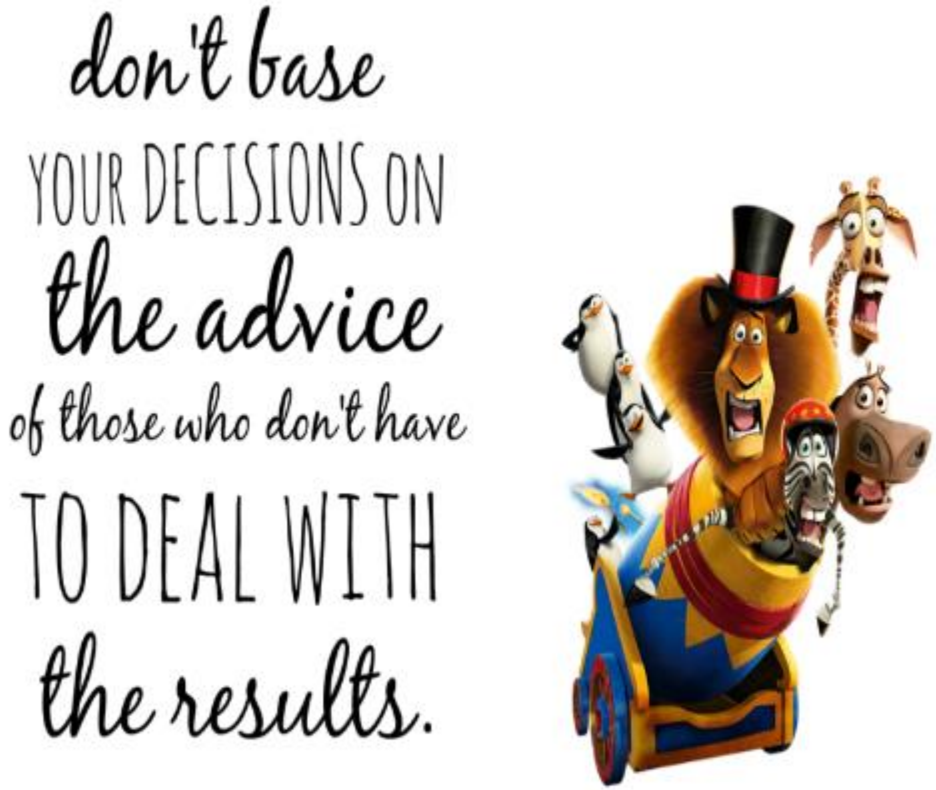
If we only take personal(to be exactly, household) features into consideration

Information

$$p_i = P(participation|X_i) = \Lambda(\alpha + X_i'\beta)$$

$$where\ \ \Lambda\ means\ sigmoid\ function$$

$where\ we\ only\ allow\ the\ person's\ covariate(X_i)$ to influence take up



Decision-making

However, your own decisions are also affected by your acquaintances.

So we should add the impact of your acquaintances into our model

the information model with endorsement effects
(or sometimes the endorsement model, for short)

$$p_i^E = P(participation|X_i, F_i) = \Lambda(\alpha + X_i'\beta + \lambda F_i)$$

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*

Conceptual Framework

Initialize t = 0 Based on our social network graph:

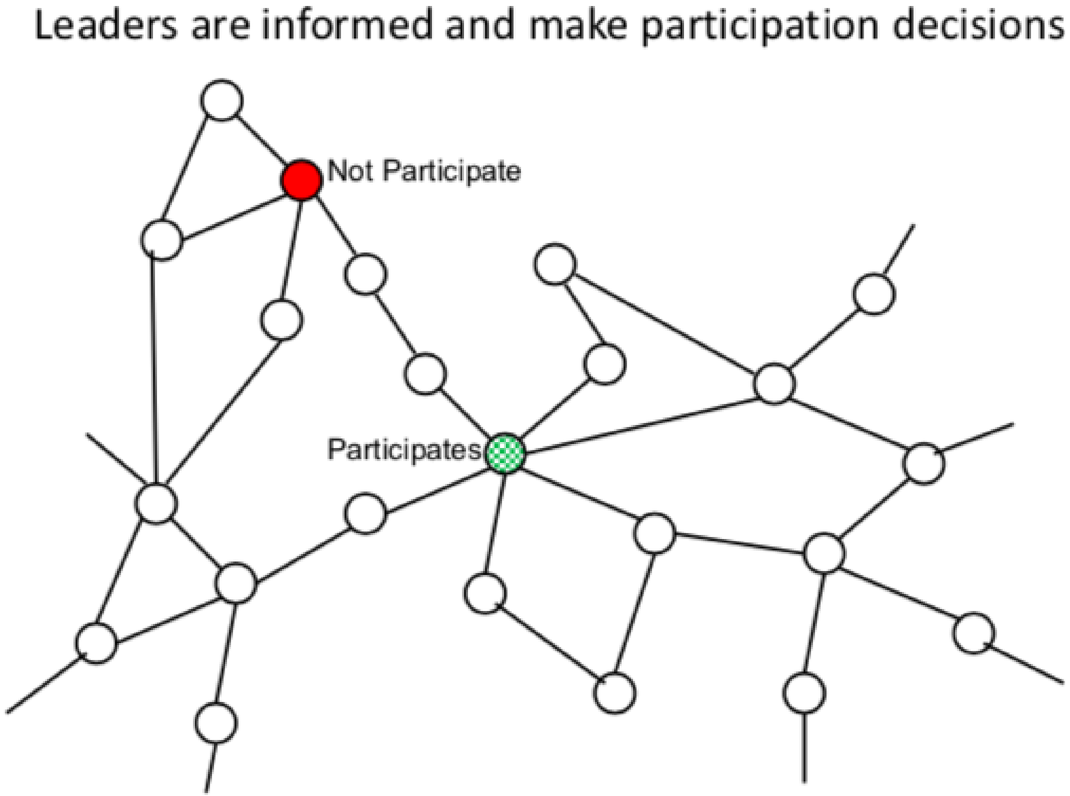
a) The set of initial leaders are informed about the operating plans and their information statuses are updated

$$s_{i0} = 1 \; \forall \, i \; \in \; L \; and \; s_{i0} = 0 \; \forall \, i \; \notin \; L$$

b) Those newly informed agents decide whether or not to participate:

$$p_i(\alpha, \beta) \; or \; p_i^E(\alpha, \beta, \lambda)$$

α, β, λ are initialized with the Bernoulli distribution



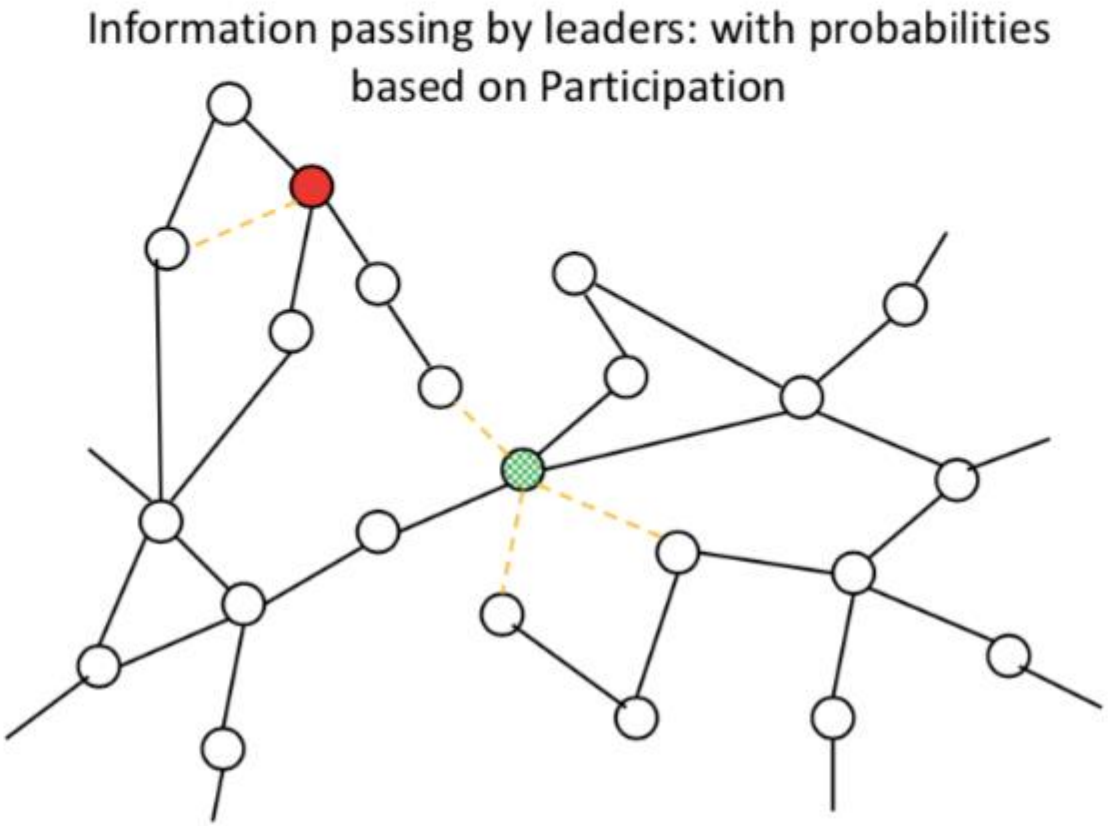
Conceptual Framework

Initialize t = 0 Based on our social network graph:

c) Each $i \in I^0$ transmits to j $\in N$ with probability

$$m_{i1}q^P + (1 - m_{i1})q^N$$

Let I_1 be the set of $j's$ informed via this process who were not member of I^0, and let $I(j)$ be the set of $i's$ who informed j



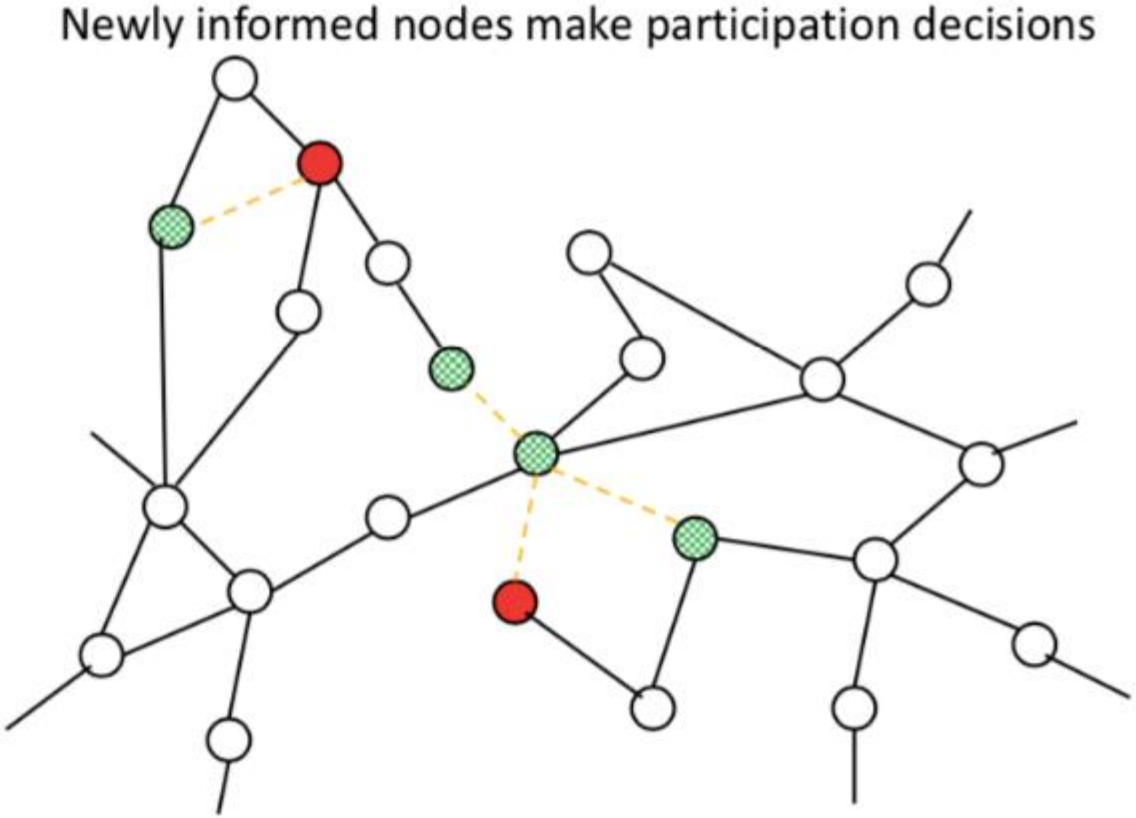
Conceptual Framework

Iteration at time t:

a) The newly informed agents are now I_t

b) Those newly informed agents decide whether or not to participate with $p_i(\alpha, \beta)$ or $p_i^E(\alpha, \beta, \lambda)$

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



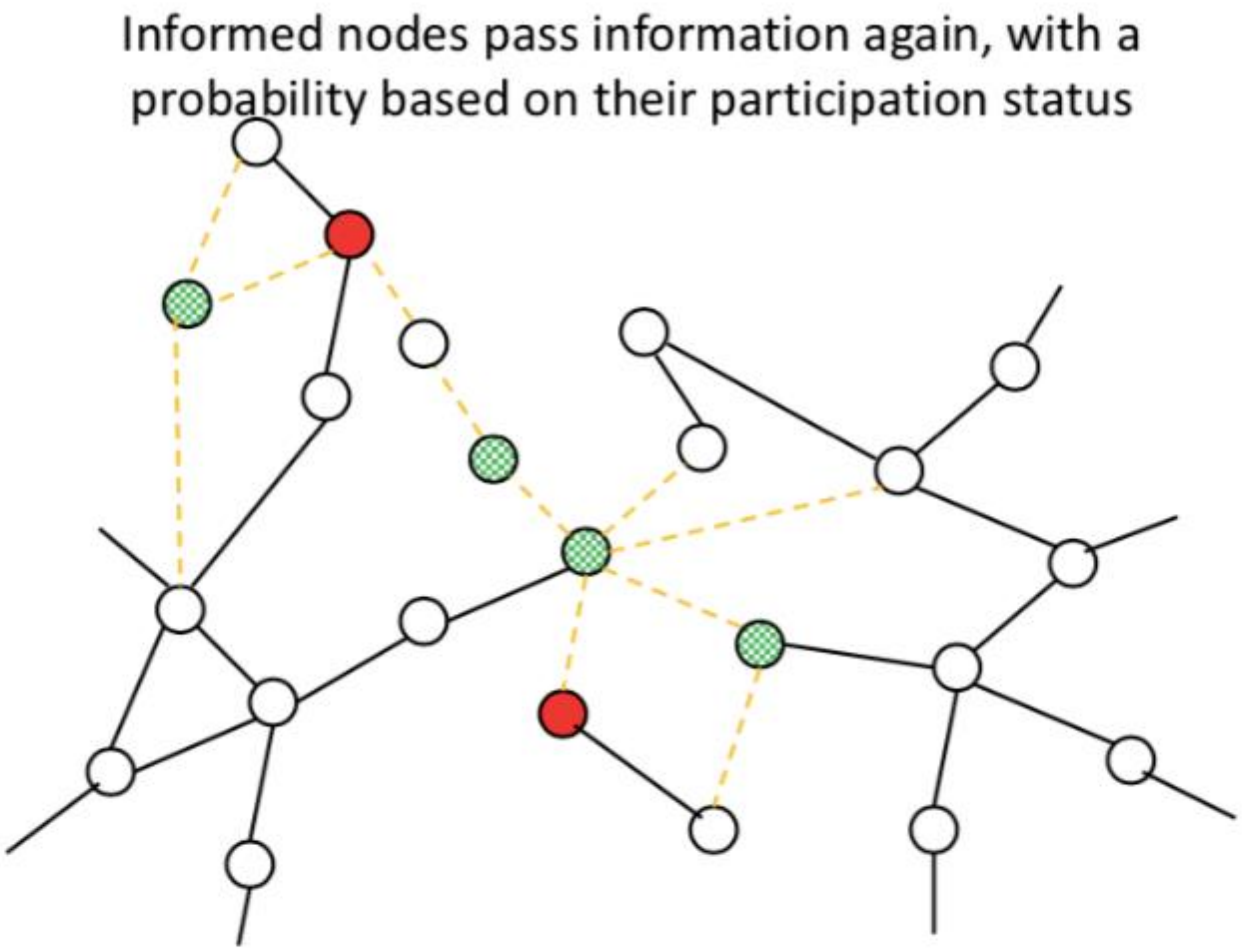
Conceptual Framework

Iteration at time t:

c) For all nodes $i \in I^t$, each i transmits to j $\in N_i$ with probability

$$m_{i1}q^P + (1 - m_{i1})q^N$$

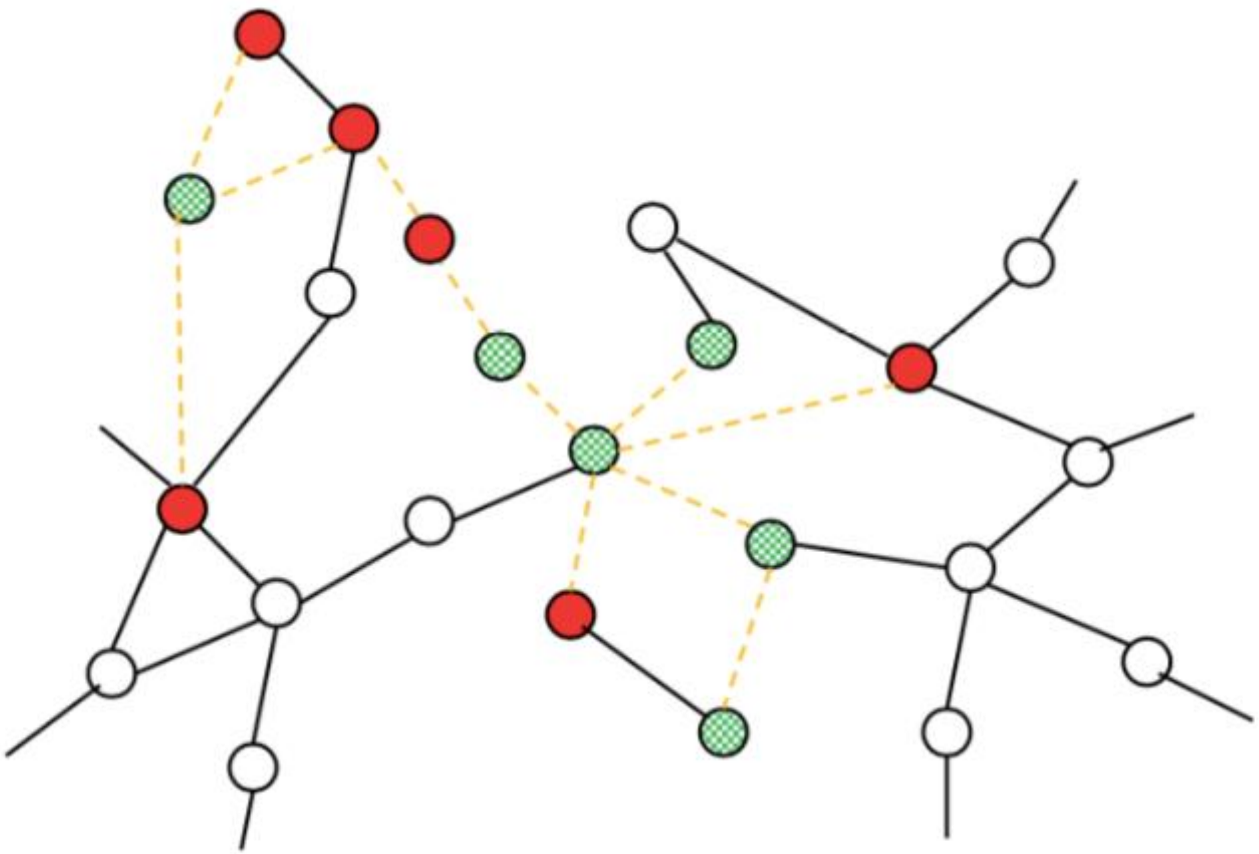
Let I_{t+1} be the set of $j's$ informed via this process who were not in I^t, let $I(j, t+1)$ be the set of $i's$ who informed *j, and the process repeats*



Conceptual Framework

Iteration at time t:

Newly informed nodes decide whether to participate



Structural Estimation —— Parameter Updating

Method of simulated moments(MSM)
We are seeking to estimate the following models:
(1) Information Model: (q^N, q^P, $p_i(\alpha, \beta)$)
(2) Information Model with Endorsement Effects: (q^N, q^P, $p_i^E(\alpha, \beta, \lambda)$)

We would exploit a series of moments which could be calculated from survey data
(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.

Structural Estimation —— Intuition

Those moments would be compared to the same ones derived from our iteration simulation and then calculate cost function. Every parameter should be responsible for its cost and be updated.

a) We initialize parameter from its parameter space Θ, which is discretized

b) Implement 75 iterations and get the final simulated values of parameters

c) Minimize cost function, which is defined as

$$\hat{\theta} = arg\min_{\theta \in \Theta}\left(\frac{1}{R}\sum_{r=1}^{R} m_{sim,r}(\theta) - m_{emp,r}\right)^{T} \left(\frac{1}{R}\sum_{r=1}^{R} m_{sim,r}(\theta) - m_{emp,r}\right)$$

$$where\ m_{sim,r}\ denotes\ simulated\ moments\ for\ village\ r, m_{emp,r}\ denotes\ the\ empirical\ ones$$

Main conclusion review

- Microfinance participation is higher when the injection points have higher eigenvector centrality
- Participants are more likely to pass information than informed non-participants
- The endorsement effect is not significant in a person’s participation decision making

Reduced-form analysis: Do injection points matter?

Initial model:

$$y_r = \beta_0 + \beta_1 \cdot \xi_r^L + W_r'\delta + \varepsilon_r$$

- where y_r is the average village-level microfinance take-up rate;
- ξ_r^L is a vector of network statistics for the leaders (degree and eigenvector centrality);
- W_r is a vector of village level controls

endogenous?

Reduced-form analysis: Do injection points matter?

Model after being modified:

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

- where y_r is the average village-level microfinance take-up rate;
- ξ_r^L is a vector of network statistics for the leaders (degree and eigenvector centrality);
- W_r is a vector of village level controls;
- ξ_r^{LM} is a vector representing the centrality of those leaders who became microfinance members

Result

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.

Structural estimation (MSM)

- **Information Model:** $(q^N,\ q^P,\ p_i(\alpha,\beta))$

- **Information Model with Endorsement Effects:** $(q^N, q^P, p_i^E(\alpha,\beta,\lambda))$

- q^N denote the probability that an informed agent who does not herself participate informs others in a single round

- q^P denote the probability that an informed participating agent informs others in a single round

- λ is the coefficient in the participation decision equation

Result

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]

/04

The Extension of the Model

Do network characteristics matter?

$$y_r = W_r'\beta + X_r'\delta + \varepsilon_r$$

- where W_r is a vector of village-level network characteristic covariates;
- X_r is a vector of village-level demographic covariates;

Result

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.

Reason

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.

Do correlation pattern change over time?

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

- 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;
- α_t are period fixed effects

Result

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.

/05

Robustness Checks

Test the exogenous of eigenvector centrality

- **Intuition:** villages where leaders are less important or less connected are also less likely to take up microfinance for other reasons. (for example)

If eigenvector centrality is not correlated with other village characteristics (exogenous)

Eigenvector centrality can influence the final take-up rate

Result

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.

Re-estimate with an entirely different set of moments

- **Intuition:** those close to participating leaders may have similar preferences, for example

- **The set of moments:**

  (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.

- **Some shortcomings**

Result

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]

Check for network position

- **Intuition:** people's need for microfinance could be related to their network position**,** and in particular correlated with their distance from leaders

People who are close to each other may simply behave similarly

- **Structural Model:**

$$P(participation \mid X_i, F_i, d_i) = \Lambda(\alpha + X_i'\beta + \lambda F_i + d(i, L^P)\rho)$$

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

Result

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]

“Placebo” Test

- **Introduction**
  - The same structural model and same method of MSM
  - The only change is that microfinance participation is replaced with roof tiling

- **Why roof tiling?**
  - The share of household that have such a roof is **similar** to the microfinance take-up rate
  - Having a tiled roof could be related to wealth and possibly to neighbors’ behaviors, similar to microfinance take-up

Result

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.

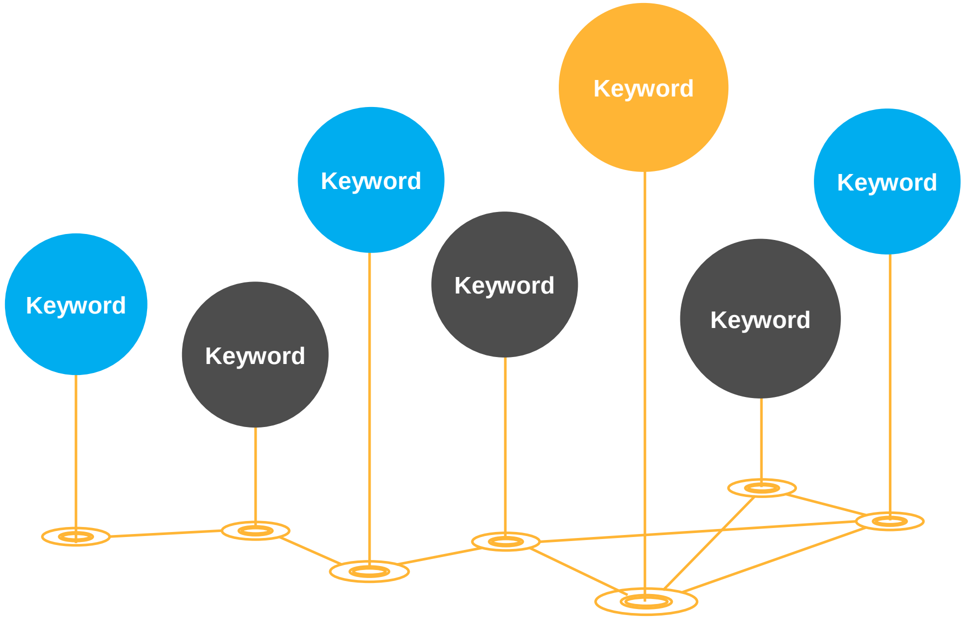
/06

Conclusions

THREE CONCLUSIONS

Like the former analyze, we can draw 3 conclusions:

From our 2 important models



Participants will pass information with higher likelihood

- But the non-participants are also important as well

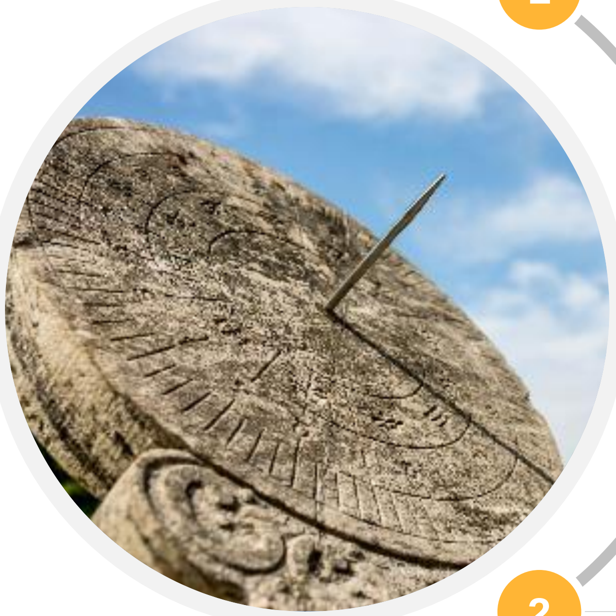
The higher injection point’s participation rate, the higher village participation rate

- Injection point works, with their eigenvector centralities

There exists no endorsement effects, but Information effects does work

- But it has nothing with personal choice of participation

TWO MODELS



1

REDUCED-FORM MODEL

- Can not explicitly show the diffusion method, so introduce individual data and initial injection points

2

STRUCTURAL MODEL

- Use shooting method to estimate parameters
- Tell apart endorsement effect and information effect
- But with endogenous problems of homophily (peer effects)
- ---introduce distance
- Gradually enlarge and complete the model