Credit and Social Networks in Rural India

VERY PRELIMINARY DRAFT

Pramila Krishnan
University of Cambridge

Manasa Patnam
University of Cambridge

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ABSTRACT

In this paper we build a measure of social trust by exploiting the overlap between different networks and by extracting link specific structural measures that depend on the link's relationship across different networks. Using detailed loan level credit data together with social networks information, we show that households rely on network connections in various ways. Firstly, we find evidence that they use established social network connections (relatives, neighbors) to forge endogenous network connections of a specific type (credit, risk sharing). We build on recent advances in the statistics of random networks to estimate a latent network formation model to predict link formation in endogenous networks using the structure of exogenous networks. Secondly, we establish the value of credit connections on financial transactions in the informal sector.

KEYWORDS: Networks, Credit, India

JEL Classification: O16, L14

1 Introduction

A vast amount of literature has examined the impact that social networks have on information transmission, risk sharing, exchange and various other household level transactions. Much of the literature has also focused on the value of social networks in acting as an informal mechanism of trust (Bohnet et al. 2010, Granovetter 1983, Greif 1993). Trust also plays an important role in the transmission of credit, particularly in developing countries. McMillan and Woodruff (1999) find that in Vietnam banks, customers identified through business networks receive more credit and that networks are used to sanction defaulting customers. Thus, social networks are sought to mitigate the enforcement problem in being able to allocate transfers between agents. Karlan et al. (2009) show that network connections act as social collateral in order to secure informal credit transactions. Building on well established results in graph theory, the authors define their measure of social trust as the maximum network flow between any two individuals. This is equal to the highest amount that can flow between a lender and a borrower through various paths in the network connecting them. The authors test the implications of this model empirically, using data from Peru, and find a strong positive correlation between social collateral and borrowing that is primarily driven by strong ties – agents are more likely to borrow from friends with whom they have spent more time (stronger trust flow). However the authors' measure of social trust only incorporates measures from one given network and omits the endogeneity of link formation.

In similar vein Jackson et al. (2010) use the concept of overlapping networks to measure and characterize support across networks. They define as social support, the extent to which whether relationships of one type are supported through relationships of another type. For instance using data from rural India the authors find that there is a high degree of overlap or support between networks of social relationships and networks of physical favours.

In this paper we move a step further. We build a measure of social trust by not just exploiting the overlap between different networks but also by extracting link specific structural measures that depend on the link's relationship across different networks. We show that households rely on network connections in various ways. Firstly, we find evidence that they use established social network connections (relatives, neighbors) to forge endogenous network connections of a specific type (credit, risk sharing). Secondly, we establish the value of credit connections on financial transactions in the informal sector.

Our first result is about social trust/collateral. This is a measure of how many people a credit network link has in common in other given networks like relatives, neighbours. This is different from usual homophily related measures that capture link similarity based on individual attributes (are you in the same neighborhood, are you a relative etc). The social collateral variable is a 'link' attribute in that it exploits the structure in the other networks – either through counting the number of people common between two households 'i' and 'j' in a credit connection in another exogenous network or the path distance between 'i' and 'j' in the exogenous network. We try and capture not just the importance on one to one links but the importance of connections. This means that while it is interesting to know that a household can borrow from another households is they are relatives it is more important to know is whether they are to borrow from friends of friends i.e how well they can exploit their social networks to gain credit connections/links.

Our second result is aimed at exploiting the structure of this endogenous credit network to see whether these impacts financial outcomes or credit flow in any way. Conditional on having established credit connections, we find that network connections matter in being able to raise the volume of informal credit being borrowed.

Finally, we contribute to the empirics of social networks, by using recent advances in the statistics of random networks to estimate a latent network formation model to predict link formation in endogenous networks using the structure of exogenous networks.

2 Empirical Strategy

Our main interest is in estimating network formation (credit and rely-on) in each village and subsequently the impact of network properties on each household's credit flow. We follow a two stage strategy. In the first stage we use recent advances in the statistical estimation of social networks and employ a latent cluster model to estimate link and cluster formation. Using the information provided by the parameters of the model, we then predict the probability of each household to link with every other household in the network. Since we believe that social networks exhibit a significant degree of clustering, we also estimate the intra group variance of linkages conditional on having placed each household into a distinct cluster within a network. In the second stage we summarize various network measures based on the given network and measure its impact on household credit flow, distinguishing between formal and informal sources of credit. In order to circumvent the endogeneity of these network statistics we use predicted probability and intra group cluster variance as estimated from the first stage of network formation, as instruments. The key source of identifying exogenous variation comes from the use of link specific social collateral in predicting link formation. Thus we are able to exploit the feature of overlapping networks to both model endogenous network formation as well as to understand network implications on credit flow.

2.1 Network Formation

2.1.1 Specification

We follow the specification proposed by Hoff, Raftery, and Handcock (2002) (henceforth HRT). Each individual i has an unobserved position, Z_i, in a 2-dimensional Euclidean space. We assume that ties between individuals are stochastically independent conditional on the distances between their position. The probability of a tie between any two individuals is then given by,

$$logit(Pr(Y_{ij} = 1|Z, x, \beta)) = \sum_{k=1}^{p} \beta_k x_{k,i,j} - \|Z_i - Z_j\| \tag{1}$$

$$logit(p) = log(\frac{p}{1-p}) \tag{2}$$

where $x_{k,i,j}$ includes a vector of individual specific attributes (between the pair of individuals) such as absolute difference in land, absolute difference in household size, whether the two individuals are of the same caste, as well as one link specific attribute, social collateral. The value of social collateral between two individuals i and j is calculated as the inverse of the path distance between them in the relatives and neighbours network.

More importantly, we incorporate clustering of individuals (see Handcock, Raftery, and Tantrum (2007)) within the network by specifying Z_i as a multivariate normal mixture,

$$Z_i \sim^{iid} \sum_{g=1}^{G} \lambda_g MVN_d(\mu_g, \sigma_g^2 I_d) \qquad i = 1, ..., n \tag{3}$$

where λ_g is the probability that an actor belongs to the g^{th} group so that $\lambda_g > 0$ and $\sum_{g=1}^{G} \lambda_g = 1$, and I_d is the $d \times d$ identity matrix. This allows the position of each individual to be drawn from G different groups, each centered around a different mean dispersed with a different variance.

2.1.2 Estimation

The latent position cluster model can be estimated in two different ways – either implementing a two-stage maximum likelihood estimator or through a fully Bayesian approach that uses a Markov Chain Monte Carlo (MCMC) algorithm. The Bayesian approach tends to be more efficient since it allows for the simultaneous estimation of the latent positions and the clustering model. This means that the positions of the individuals are drawn from a mixture of Gaussians. Each component of the mixture represents a difference group (caste, land, household size etc.) and the positions form a relative cluster of individuals within the space.

Under the Bayesian approach, we estimate a mixture model, introducing a new variable K_i whch equals g if the ith individual belongs to the g^{th} group. The prior distribution is specified as follows:

$$\beta_k \sim^{iid} N(\xi_k, \psi_k^2) \qquad k = 1, ..., p, \tag{4}$$

$$\mu_g \sim^{iid} MVN_d(0, \omega^2 I_d) \qquad g = 1, ..., G, \tag{5}$$

$$\sigma_g^2 \sim^{iid} \sigma_0^2 Inv\chi_\alpha^2 \qquad g = 1, ..., G, \tag{6}$$

$$(\lambda_1, ..., \lambda_G) \sim Dirichlet(\upsilon_1, ..., \upsilon_G) \tag{7}$$

2.1.3 Number of Clusters

The choice of the optimal number of clusters is akin to the problem of model selection. Under the Bayesian approach, model selection is based on computing the probability of each of the competing models. In this case it would imply choosing the number of clusters as given by the model that gives us the best fit relative to models with different number of clusters. The Bayesian method performs well (and better than the two-step maximum likelihood version) when the choice of the number of cluster is unknown. This is because it allows for the uncertainty in cluster assignment and uncertainty in individual's latent position simultaneously and in a sense is able to use the clustering information when estimating latent positions.

2.2 Credit Flow

In the second stage we estimate the effect of social networks on the amount of credit flow in the formal and informal sectors. For the purpose of estimating social network effects we calculate the following network statistics: We represent a network by a graph (N, g), which consists of a set of nodes $N = 1, ..., n$ and an $n \times n$ matrix $g = [g_{ij}]_{i,j \in N}$ (referred to as an adjacency matrix), where $g_{ij} \in \{0, 1\}$ represents the availability of an edge from node i to node j. The graph is a directed graph (or digraph) if $g_{ij} \neq g_{ji}$ for all $i, j \in N$.

- **Total Degree:** Represents the total number of direct connections each household has. Total degree in any graph G is defined as the sum of each node's incoming connections (defined as *indegree*, $\sum_j g_{ji}$) and outgoing connections (defined as *outdegree*, $\sum_j g_{ij}$).

- **Average Path distance:** The shortest path distance from node i to node j is measured as the minimum number of edges between these nodes. Average shortest path distance of any node i to all other nodes in the network is the mean value of shortest path distance over all other nodes j, $j \neq i \in N$.

- **Maximum strongly connected component:** A directed graph is called 'strongly connected' if each node is reachable from each other node via a path. A 'strongly connected component' is a subgraph (i.e. a component of the entire graph) that is strongly connected. A strongly connected component component which has the most number of members (relative to the other strongly connected component components) is termed as a maximum strongly connected component. Such a component therefore has the property that within itself all nodes are reachable to each other node via a path and it contains the maximum number of components in the network. Intuitively, this is the most dense and strongly connected component of any network.

- **Minimum path distance to powerful node:** This is measured as the shortest path distance of any node i to any powerful node j, $j \neq i \in N$ in the network. A node is defined as powerful if that household has been mentioned in the list of households that hold influential positions (eg. caste leader, landlord etc.) in the village from the community questionnaire.

We then estimate the effect of social network properties using the following specification:

$$ln\_credit_{hv} = \alpha + \beta N_{hv} + \gamma X_{hv} + \epsilon_{hv} \tag{8}$$

where N_{hv} denotes the network statistic of interest and X denotes a vector of household specific demographics. For the IV regressions we instrument N_{hv} with each household's average predicted probability of link formation and variance of the cluster they belong to.

3 Data

This paper uses household survey data networks data from the Village Level Studies (VLS) survey of the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) in six village. The ICRISAT-villages are a set of villages, studied since 1975 by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), near Hyderabad. The core data set used in this paper is based on 240 households from three districts and six villages: Aurepalle and Dokur in Mahbubnagar District in A.P., and Shirapur and Kalman in Sholapur District and Kanzara and Kinkheda in Akola District in Maharashtra. Since 2001, new data collection has started covering the same households interviewed in 1975 alongwith some new households. The total sample consisted of 530 households. The ICRISAT VLS data provide detailed loan level information on borrowing and lending of each household since 200 for a period of four years. Credit information is also distinguished by types (agricultural loan, marriage loan etc.) and sources (moneylender, employer, national bank etc.) of loans. The survey also collected basic information on household demographics, assets, landholding, caste, livestock etc.

3.1 Networks Survey

The 2005 survey also contained a module on social networks. Information was collected about households that can be asked for credit, support in terms of need or with whom land tenure relationships exist. The respondent could have virtually state the same people in the credit and rely-on list. However, emphasis was placed on the fact that the rely-on list includes non financial help, such as in kind or in the form of specific services or labour. The full network datasets was constructed by creating incoming ties and outgoing ties for not only sample households but all other households who have been named as links but are not in the sample. Since the survey asked about the basic attributes of each link we are able to created a quasi-census dataset giving a good approximation of linkages in the villages. We matched every person who was named as a link by any households to other households who that have named the same link. Hence we were able to append many incoming ties to a link which is not a sample household. However we have no information on out-ties for those individuals that are not in the sample.

4 Results

The following credit networks have a directed edge (tie) between two individuals if they borrow from each other. The directedness indicates the form of the credit relationship in that it can be unilateral (only one of the two individuals borrows from the other) or bilateral (both individuals borrow from each other). The measurement process for this data imposed a constraint on the out-ties of each individual. In particular, for the sample households the survey asked each individual to name five other individuals who she had borrowed from. Moreover we have no information on out-ties for those individuals that are not in the sample. On the other hand, the in-ties are not constrained, so each individual's incoming ties can be interpreted as her popularity, to the extent that many others borrow from her.

4.1 Structure of Credit Network in Villages

As an example of credit network estimation we reproduce results, in terms of figures for one village – Dokur. Figure (2(a)) plots the sociogram of the credit relationships in Dokur. The figure shows that credit connections in Dokur are densely knit with most people in the village have some interconnections amongst each other. We fit a two-dimensional, three cluster, latent space model to this network. The choice of the number of clusters is motivated by the Bayesian Information Criterion for different competing models based on the same attributes but different number of clusters. Figure (2(c)) plots the BIC values for each of the different cluster models. This indicates a clear choice of three clusters, since this provides the best fit relative to the rest. After identifying the number of clusters, a MCMC algorithm was run, with 10,000 burn-in iterations, that were discarded and a further 4000 iterations, of which we kept every 10th value. These fits are summarized in Figure (2(b)). The figure shows the minimum Kullback-Leibler estimates of the social positions of the individuals. We can see that the individuals are separated into three different clusters. The posterior means of the variances are 6.117, 5.26 and 5.25 respectively. This implies that Cluster 3 is more tightly clustered. The density plots of the clusters are shown in Figure (2(d)). The parameter estimates are reported in Table (10).

4.2 Credit Transactions and Credit Networks

We now report results on the determinants of the volume of credit flow. We distinguished credit borrowed between thee types of sources: amount borrowed from the formal sector, amount borrowed from moneylenders and landlords and amount borrowed from friends and relatives. We are interested in examining how the amount of credit flow is influenced by social vs. physical collateral. We proxy social collateral by using various credit network related statistics.

Table (**??**) reports estimates of the determinants of the amount of credit borrowed, both informally and formally. After identification of clusters we define a dense cluster as that cluster which has the minimum intra-cluster variance. Therefore for Dokur, it is Cluster 3 whereas for Shirapur it is Cluster 1. We are then interested in seeing whether belonging to a dense group increase the flow of credit. Significant and positive for log of informal credit.

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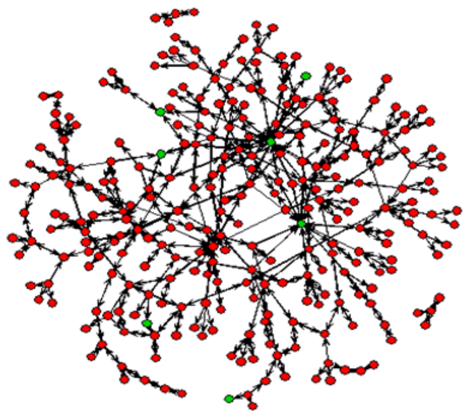
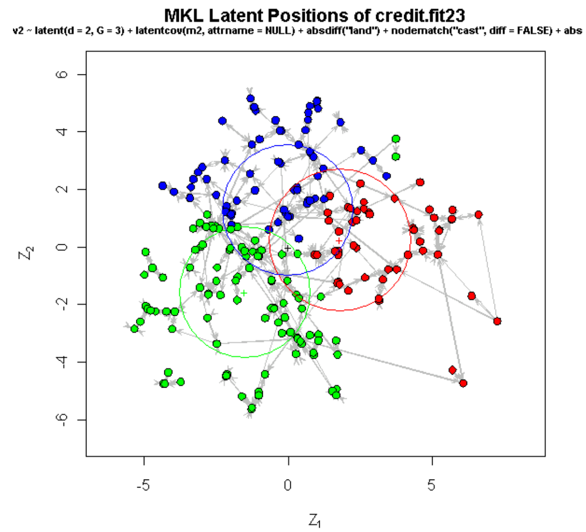
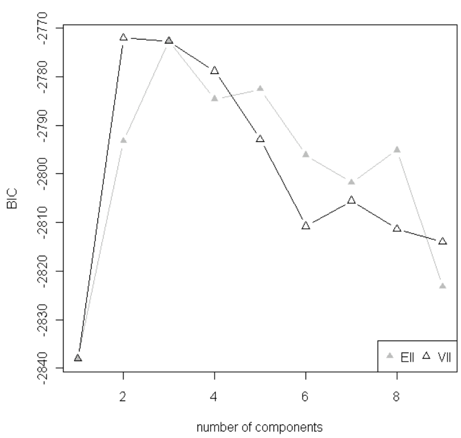
Figure 1: Example Network and Latent Space Modelling- Dokur



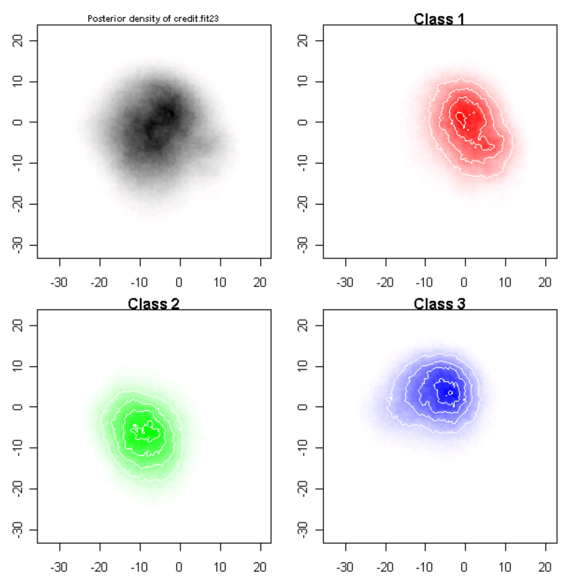
(a) Credit Network - Dokur



(b) Cluster and Latent Positions



(c) BIC plot for Latent Position Clustering



(d) Cluster Densities

Figure 2: Distribution of Loan Amount by Source of Credit and Farm Size

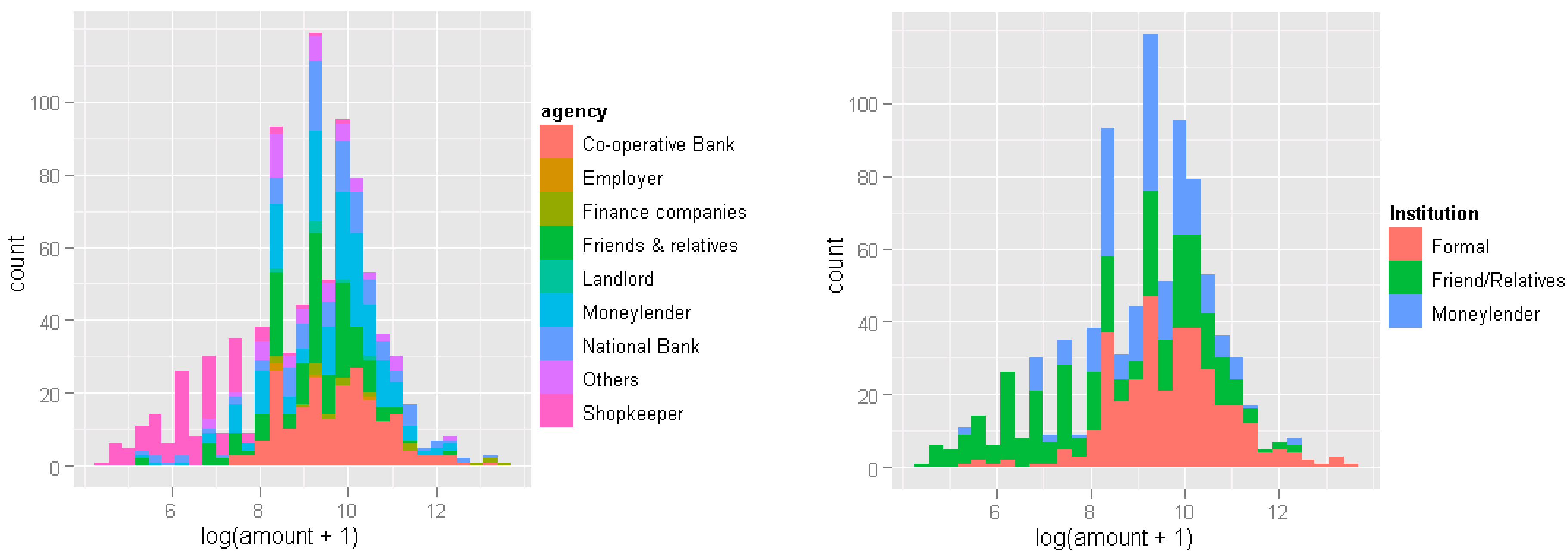


Figure 3: Distribution of Loan Amount by Institutional Type and Agency

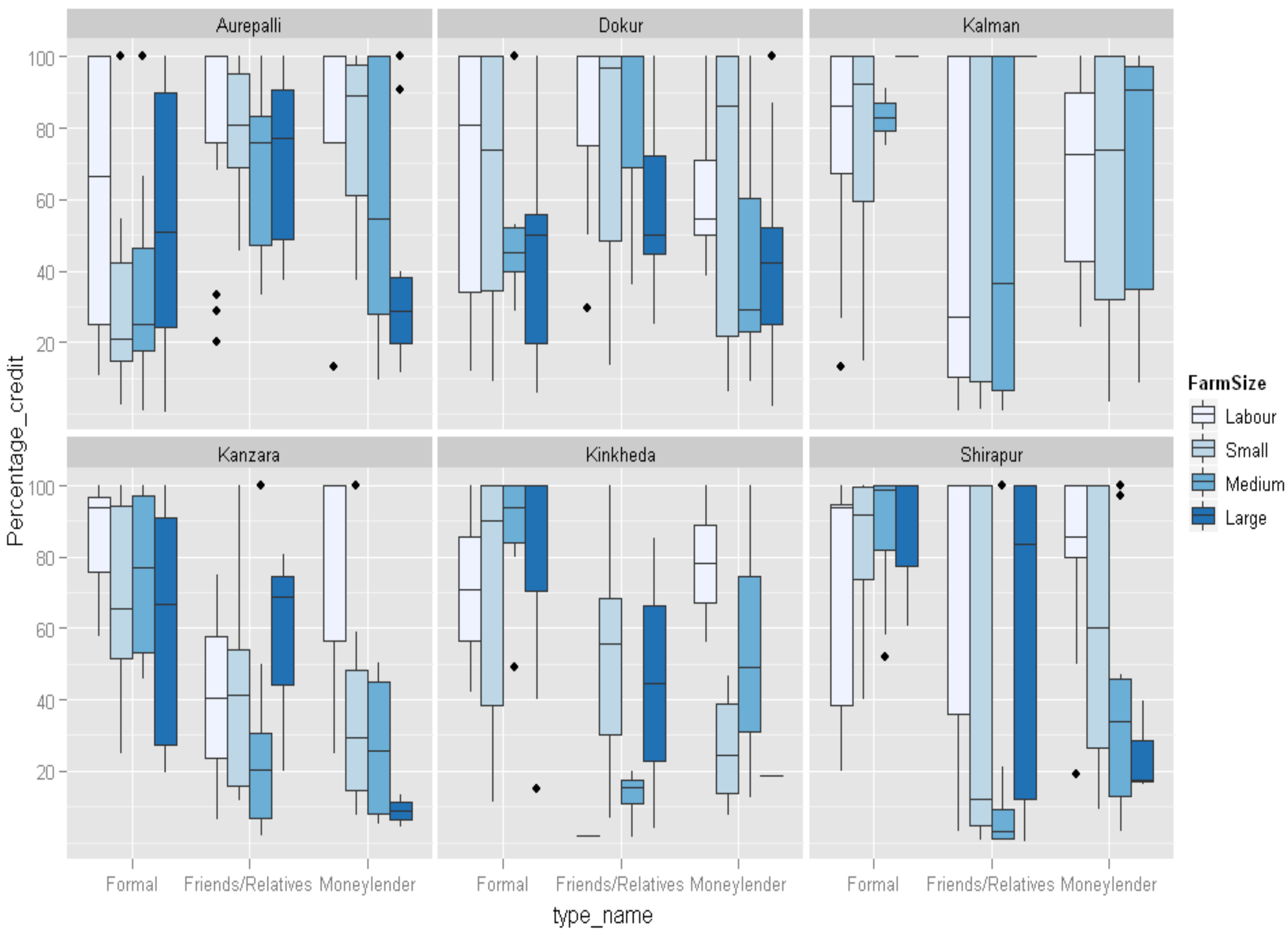


Table 1: Overlap Between Networks

Overlap of	Obs	Mean	Std. Dev.	Min	Max
Credit and Relative Network	546	0.061966	0.184411	0	1
Credit and Relyon Network	546	0.338736	0.410984	0	1
Relyon and Relative Network	579	0.163903	0.291808	0	1

Table 2: Types of Loan: Share in Total Amount Borrowed

Share in Total	Obs	Mean	Std. Dev.	Min	Max
Agricultural Loan	552	0.408095	0.385604	0	1
Land Loan	552	0.017019	0.083496	0	1
Health Loan	552	0.04575	0.157583	0	1
Housing Loan	552	0.084253	0.214469	0	1
Marriage loan	552	0.090639	0.210696	0	1
Other/Consumption Loan	552	0.354244	0.356377	0	1

Table 3: Sources of Lending

	# HH	Percentage of total HH
All Sources	109	0.204
Formal Only	57	0.107
Moneylender/Landlord Only	48	0.090
Friends/Relatives Only	64	0.120
Formal+Moneylender/Landlord	74	0.138
Formal+Friends/Relatives	91	0.170
Friends/Relatives+Moneylender/Landlord	45	0.084
No Source	47	0.088

Table 4: Types of Loan: Amount Borrowed from Formal Sector

Share in Total	%age HH with Loan	Mean	Std. Dev.	Min	Max
Agricultural Loan	49.91	25576.67	43123.80	200	510000
Land Loan	1.68	11916.67	8697.16	2500	25000
Health Loan	1.50	9487.50	7181.08	2333.33	23333.33
Housing Loan	3.74	27104.17	54717.42	750	192000
Marriage loan	2.80	17011.11	16332.18	3166.67	60000
Other/Consumption Loan	24.30	27275.13	68592.48	100	590000

Table 5: Types of Loan: Amount Borrowed from Monelylender

Share in Total	%age HH with Loan	Mean	Std. Dev.	Min	Max
Agricultural Loan	21.87	10076.85	10585.18	333.33	50000
Land Loan	2.24	14065.97	10390.53	375	30000
Health Loan	7.48	6024.38	10231.31	100	60000
Housing Loan	10.28	14917.42	16357.72	666.67	70000
Marriage loan	12.90	17068.84	16744.40	333.33	85000
Other/Consumption Loan	32.90	10326.56	17828.57	250	180000

Table 6: Types of Loan: Amount Borrowed from Friends & Relatives

Share in Total	%age HH with Loan	Mean	Std. Dev.	Min	Max
Agricultural Loan	16.64	15678.93	22384.74	200	125000
Land Loan	1.87	17150.00	18229.45	833.33	50000
Health Loan	5.42	6695.69	6487.69	250	20000
Housing Loan	9.35	13531.43	18449.07	71.67	100000
Marriage loan	8.41	18177.04	18279.69	1500	100000
Other/Consumption Loan	37.01	7376.18	17226.21	63	200000

Table 7: Detailed Sources of Credit

Agency	Village					
	Aurepalli	Dokur	Shirapur	Kalman	Kanzara	Kinkheda
Co-operative Bank						
Beneficiaries (%age)	0.374	0.298	0.462	0.200	0.406	0.444
Share in total credit of Village (%age)	16.0	13.4	56.2	25.4	16.2	51.8
Share in total credit of Household (%age) - Mean	39.424	41.045	81.511	59.436	59.226	77.643
Share in total credit of Household (%age) - Standard Dev	31.014	34.104	22.534	32.788	29.624	26.946
Share in total credit of Household (%age) - Median	26.852	27.521	92.308	58.856	57.250	84.770
Average Interest Rate	12.174	11.786	11.761	10.955	13.923	9.875
Average Amount	14534.783	17267.857	57373.134	47204.545	12234.615	20625.000
Employer						
Beneficiaries (%age)	0.016	0.021	0	0	0	0
Share in total credit of Village (%age)	0.2	1.4	0	0	0	0
Share in total credit of Household (%age) - Mean	62.121	75	0	0	0	0
Share in total credit of Household (%age) - Standard Dev	53.569	35.355	0	0	0	0
Share in total credit of Household (%age) - Median	62.121	75	0	0	0	0
Average Interest Rate	24	27	0	0	0	0
Average Amount	4000	25000	0	0	0	0
Finance companies						
Beneficiaries (%age)	0.033	0.032	0.034	0.027	0	0
Share in total credit of Village (%age)	4.9	0.8	25	1.4	0	0
Share in total credit of Household (%age) - Mean	58.569	31.044	66.975	48.531	0	0
Share in total credit of Household (%age) - Standard Dev	35.650	27.472	34.181	36.544	0	0
Share in total credit of Household (%age) - Median	60.662	18.868	72.106	57.143	0	0
Average Interest Rate	19	44	8.250	16	0	0
Average Amount	51250	9333.333	341400	18666.667	0	0
Friends & relatives						
Beneficiaries (%age)	0.179	0.404	0.276	0.300	0.297	0.204
Share in total credit of Village (%age)	11.3	23.2	9.2	8.1	13.7	5.9
Share in total credit of Household (%age) - Mean	68.282	53.302	56.042	65.912	39.597	27.543
Share in total credit of Household (%age) - Standard Dev	32.458	30.806	35.844	33.222	35.785	25.579
Share in total credit of Household (%age) - Median	81.006	48.585	44.418	78.431	25.714	18.692
Average Interest Rate	34.364	34.263	7.500	1.030	3.737	0
Average Amount	21454.545	22052.632	15737.500	10112.576	14194.737	5118.182

Table 8: Detailed Sources of Credit (contd.)

Agency	Village					
	Aurepalli	Dokur	Shirapur	Kalman	Kanzara	Kinkheda
Landlord						
Beneficiaries (%age)	0.008	0.032	0	0	0.016	0.019
Share in total credit of Village (%age)	0.2	1.9	0	0	0.3	1.0
Share in total credit of Household (%age) - Mean	62.500	41.667	0	0	100	63.694
Share in total credit of Household (%age) - Standard Dev	0.000	14.434	0	0	0	0
Share in total credit of Household (%age) - Median	62.500	50	0	0	100	63.694
Average Interest Rate	24	30	0	0	36	0
Average Amount	10000	23333.333	0	0	5000	10000
Moneylender						
Beneficiaries (%age)	0.577	0.553	0.117	0.127	0.297	0.259
Share in total credit of Village (%age)	49.8	47.9	3.4	3.2	24.8	16.6
Share in total credit of Household (%age) - Mean	76.489	74.291	49.062	56.214	35.334	44.302
Share in total credit of Household (%age) - Standard Dev	23.249	26.799	38.976	43.662	21.749	33.422
Share in total credit of Household (%age) - Median	81.081	76.716	38.462	57.115	33.333	30.615
Average Interest Rate	35.451	36	91.765	53.143	54.632	62.429
Average Amount	29383.099	33326.923	13558.824	9250	25700	11321.429
National Bank						
Beneficiaries (%age)	0.276	0.170	0.028	0.255	0.328	0.241
Share in total credit of Village (%age)	11.9	8.6	2.5	47.8	41.0	21.6
Share in total credit of Household (%age) - Mean	32.508	56.055	67.434	65.350	72.301	73.200
Share in total credit of Household (%age) - Standard Dev	31.010	29.160	35.704	30.833	25.792	36.282
Share in total credit of Household (%age) - Median	22.650	50	70.833	68.627	79.365	100
Average Interest Rate	13.559	12	12.250	11	11	10.539
Average Amount	14644.118	19343.750	43500	69942.857	38428.571	15923.077
Others						
Beneficiaries (%age)	0.130	0.128	0.055	0.136	0.047	0.093
Share in total credit of Village (%age)	5.6	2.3	2.5	13.7	2.8	2.9
Share in total credit of Household (%age) - Mean	32.436	28.928	54.115	45.326	61.337	38.158
Share in total credit of Household (%age) - Standard Dev	22.007	28.413	38.739	38.740	33.785	35.731
Share in total credit of Household (%age) - Median	23.650	23.370	49.737	42.254	46.512	22.727
Average Interest Rate	27	31.500	9.250	16.267	19.667	10.800
Average Amount	14665.625	6875	21125	37366.667	18333.333	5600
Shopkeeper						
Beneficiaries (%age)	0.016	0.011	0.441	0.345	0.172	0.056
Share in total credit of Village (%age)	0.2	0.6	1.3	0.5	1.3	0.2
Share in total credit of Household (%age) - Mean	54.141	50.000	39.461	51.975	39.463	2.427
Share in total credit of Household (%age) - Standard Dev	64.855	0.000	45.963	47.151	43.847	1.172
Share in total credit of Household (%age) - Median	54.141	50	8.001	40.157	12.500	1.869
Average Interest Rate	18	36	0	0	3.273	0
Average Amount	4000	20000	1368.984	514.632	2409.091	566.667

Table 9: Access to Credit by Farm Size Groups

	Access to Credit	Share of Grp. In Total Credit	Avg. Credit	Formal		Informal	
				Access	%age in Credit	Access	%age in Credit
Aurepalli							
Labour	82.05	21.04	27546.88	38.46	31.42	69.23	68.58
Small	91.30	11.32	22580.95	65.22	21.13	82.61	78.87
Medium	87.10	26.08	40477.78	61.29	27.39	83.87	72.61
Large	96.67	41.57	60060.34	76.67	40.36	76.67	59.64
Total	88.61	100	38443.58	58.53	32.92	77.23	67.08
Dokur							
Labour	73.91	13.11	27882.35	26.09	14.77	60.87	85.23
Small	100	15.24	23956.52	34.78	25.59	86.96	74.41
Medium	100	19.31	36736.84	31.58	16.62	94.74	83.38
Large	96.55	52.33	67553.57	79.31	28.76	82.76	71.24
Total	92.55	100	41545.98	45.74	24.09	80.85	75.90
Shirapur							
Labour	67.57	2.92	8000.60	13.51	45.00	64.86	55.00
Small	88.41	45.89	51471.31	55.07	79.62	73.91	20.38
Medium	89.66	42.91	112919.23	75.86	90.30	62.07	9.70
Large	90	8.27	62883.33	60	85.52	60	14.48
Total	83.44	100	56542.27	48.96	83.67	68.27	16.32
Kalman							
Labour	85.71	8.67	14798.00	42.86	62.90	71.43	37.10
Small	81.97	77.05	63125.90	40.98	77.70	70.49	22.30
Medium	64.71	9.94	36997.00	11.76	49.64	64.71	50.36
Large	100	4.34	44439.25	50	98.45	50	1.55
Total	80.90	100	46024.39	37.27	74.53	69.09	25.47
Kanzara							
Labour	61.54	15.84	35000	23.08	40.36	53.85	59.64
Small	95	15.59	14505.26	80	68.03	75	31.97
Medium	100	21.60	25453.33	93.33	67.47	80	32.53
Large	83.33	46.96	166000	83.33	48.80	66.67	51.20
Total	73.43	100	37604.26	59.37	54.49	59.37	45.50
Kinkheda							
Labour	30	3.57	11233.33	20	51.93	20	48.07
Small	83.33	24.25	15253.33	77.78	56.16	44.44	43.84
Medium	84.62	28.46	24409.09	76.92	88.08	46.15	11.92
Large	90	43.72	45833.33	90	75.52	40	24.48
Total	70.37	100	24828.95	64.81	73.55	37.03	26.44

Table 10: Network Formation: Credit Networks

	(1) Aurepalli	(2) Dokur	(3) Shirapur	(4) Kalman	(5) Kanzara	(6) Kinkheda
Social Collateral	3.924**	5.406**	11.025**	10.11**	7.779**	7.715**
	(0.223)	(0.283)	(0.655)	(0.655)	(0.645)	(0.845)
Diff. Land	0.075**	0.034**	0.026+	-0.014	-0.001	0.028*
	(0.007)	(0.011)	(0.018)	(0.010)	(0.012)	(0.017)
Diff. HH Size	0.404**	0.373**	0.394**	0.536**	0.382**	0.197*
	(0.038)	(0.036)	(0.053)	(0.065)	(0.070)	(0.116)
Same Caste	0.057	1.047**	1.389**	1.303**	1.973**	0.427
	(0.121)	(0.159)	(0.192)	(0.233)	(0.301)	(0.416)
Intercept	-3.445**	-2.521**	-0.696*	-0.236	-2.142**	-0.0104
	(0.157)	(0.184)	(0.272)	(0.273)	(0.388)	(0.0280)
N	88209	77284	106276	85264	14641	6724
Overall BIC	11089.54	9032.109	9838.841	8565.216	3085.961	1638.698
Likelihood BIC	8635.281	6373.716	6001.82	5038.23	1993.000	1274.972
Clustering BIC	2454.262	2658.393	3837.020	3526.987	1092.962	363.7258

i) Standard errors in parentheses

Table 11: Network Formation: Rely-On Networks

	(1) Aurepalli	(2) Dokur	(3) Shirapur	(4) Kalman	(5) Kanzara	(6) Kinkheda
Social Collateral	6.235**	7.966**	10.581**	12.462**	7.006**	6.984**
	(0.213)	(0.275)	(0.573)	(0.739)	(0.430)	(0.621)
Diff. Land	0.047**	0.023+	0.003	-0.022*	0.026	0.049*
	(0.010)	(0.016)	(0.015)	(0.013)	(0.020)	(0.024)
Diff. HH Size	0.319**	0.545**	0.466**	0.403**	0.464**	0.300**
	(0.030)	(0.041)	(0.049)	(0.046)	(0.065)	(0.116)
Same Caste	0.964**	1.598**	1.875**	1.995**	1.559**	2.694**
	(0.115)	(0.146)	(0.164)	(0.233)	(0.246)	(0.368)
Intercept	-3.007**	-3.646**	-1.782**	-1.198**	-3.861**	-2.615**
	(0.134)	(0.184)	(0.174)	(0.271)	(0.359)	(0.484)
N	91809	90000	128881	97969	21316	9604
Overall BIC	11046.64	10063.18	10726.57	9184.794	3625.297	2280.847
Likelihood BIC	7981.493	7062	6859.675	5784.607	2574.315	1491.886
Clustering BIC	3065.145	3001.181	3866.891	3400.187	1050.982	788.9606

i) Standard errors in parentheses

Table 12: Amount of Credit Borrowed: Total Degree in Credit Network

OLS Estimates

	(1) log_amount1	(2) log_amount2	(3) log_amount3
totaldegree	0.1223*	0.0784+	0.0631
	(0.0547)	(0.0464)	(0.0570)
hhsize	0.1285+	0.2081**	0.0771
	(0.0674)	(0.0569)	(0.0628)
education_upto	0.1675**	-0.0631	0.0921*
	(0.0445)	(0.0393)	(0.0414)
land	0.1226**	-0.0270	0.0064
	(0.0372)	(0.0262)	(0.0307)
casterank	-0.1411*	-0.1645**	-0.1894**
	(0.0694)	(0.0618)	(0.0654)
power	1.0828**	-0.7483*	-0.1706
	(0.3917)	(0.3405)	(0.3825)
Village FE	yes	yes	yes
N	470	470	470
r2	0.2106	0.4147	0.1302
F	14.8578	41.9140	7.6952

i) Robust Standard errors in parentheses

IV Estimates

	(1) First Stage	(2) log_amount1	(3) log_amount2	(4) log_amount3
pred_prob	255.9497**			
	(22.2346)			
var	0.2063			
	(0.2305)			
totaldegree		0.0830	0.0053	0.1318
		(0.1057)	(0.0878)	(0.1081)
hhsize	0.0720	0.1311*	0.2130**	0.0726
	(0.0527)	(0.0664)	(0.0560)	(0.0641)
education_upto	0.0551	0.1699**	-0.0585	0.0878*
	(0.0344)	(0.0439)	(0.0392)	(0.0411)
land	0.0100	0.1237**	-0.0248	0.0044
	(0.0238)	(0.0366)	(0.0258)	(0.0310)
casterank	-0.0847+	-0.1437*	-0.1693**	-0.1848**
	(0.0467)	(0.0688)	(0.0614)	(0.0652)
power	0.8381**	1.1192**	-0.6805*	-0.2343
	(0.3025)	(0.3928)	(0.3389)	(0.3850)
Village FE	yes	yes	yes	yes
N	470	470	470	470
r2	0.3690	0.2101	0.4114	0.1285
F	20.3830	14.2225	40.6304	7.6344

i) Robust Standard errors in parentheses

Table 13: Amount of Credit Borrowed: Average Path in Credit Network

OLS Estimates

	(1) log_amount1	(2) log_amount2	(3) log_amount3
avgpath	2.9863	2.5457	6.5292^{+}
	(3.5131)	(2.9928)	(3.5623)
hhsize	0.1398*	0.2160**	0.0883
	(0.0669)	(0.0570)	(0.0613)
education_upto	0.1741**	-0.0590	0.0940*
	(0.0439)	(0.0391)	(0.0410)
land	0.1239**	-0.0266	0.0032
	(0.0371)	(0.0261)	(0.0303)
casterank	-0.1517*	-0.1718**	-0.1990**
	(0.0692)	(0.0618)	(0.0645)
power	1.1632**	-0.7037*	-0.1843
	(0.3905)	(0.3394)	(0.3793)
Village FE	yes	yes	yes
N	470	470	470
r2	0.2023	0.4123	0.1340
F	14.4178	41.0004	7.9126

i) Robust Standard errors in parentheses

IV Estimates

	(1) First Stage	(2) log_amount1	(3) log_amount2	(4) log_amount3
pred_prob	3.6867**			
	(0.3153)			
var	0.0275**			
	(0.0031)			
avgpath		5.7758	0.7797	18.0985**
		(5.8055)	(5.0107)	(6.3727)
hhsize	-0.0010	0.1428*	0.2142**	0.1006^{+}
	(0.0007)	(0.0663)	(0.0564)	(0.0608)
education_upto	0.0003	0.1733**	-0.0584	0.0906*
	(0.0004)	(0.0435)	(0.0386)	(0.0409)
land	0.0006^{+}	0.1217**	-0.0253	-0.0058
	(0.0003)	(0.0368)	(0.0258)	(0.0312)
casterank	0.0005	-0.1541*	-0.1703**	-0.2087**
	(0.0007)	(0.0680)	(0.0611)	(0.0645)
power	0.0092*	1.1323**	-0.6842*	-0.3122
	(0.0039)	(0.3880)	(0.3354)	(0.3766)
Village FE	yes	yes	yes	yes
N	470	470	470	470
r2	0.8894	0.1999	0.4117	0.1144
F	519.9111	14.0515	40.6644	8.3885

i) Robust Standard errors in parentheses

Table 14: Amount of Credit Borrowed: Belong to a Maximally Connected Subcomponent in Credit Network

OLS Estimates

	(1) log_amount1	(2) log_amount2	(3) log_amount3
max_conn	0.6493^{+}	0.1343	0.7251*
	(0.3380)	(0.2851)	(0.3242)
hhsize	0.1336*	0.2127**	0.0779
	(0.0666)	(0.0564)	(0.0617)
education_upto	0.1758**	-0.0581	0.0969*
	(0.0441)	(0.0390)	(0.0408)
land	0.1227**	-0.0254	0.0044
	(0.0365)	(0.0259)	(0.0298)
casterank	-0.1382*	-0.1674**	-0.1812**
	(0.0693)	(0.0623)	(0.0656)
power	1.1644**	-0.6822*	-0.1476
	(0.3919)	(0.3382)	(0.3797)
Village FE	yes	yes	yes
N	470	470	470
r2	0.2070	0.4117	0.1373
F	15.3183	40.6251	7.9889

i) Robust Standard errors in parentheses

IV Estimates

	(1) First Stage	(2) log_amount1	(3) log_amount2	(4) log_amount3
pred_prob	24.8436**			
	(3.1313)			
var	0.2823**			
	(0.0372)			
max_conn		0.7240	0.1132	2.6082**
		(0.7106)	(0.6280)	(0.7686)
hhsize	0.0051	0.1332*	0.2128**	0.0690
	(0.0082)	(0.0659)	(0.0557)	(0.0633)
education_upto	-0.0010	0.1759**	-0.0581	0.0992*
	(0.0055)	(0.0436)	(0.0385)	(0.0414)
land	0.0041	0.1223**	-0.0253	-0.0057
	(0.0036)	(0.0361)	(0.0256)	(0.0305)
casterank	-0.0199*	-0.1369*	-0.1678**	-0.1491*
	(0.0084)	(0.0698)	(0.0627)	(0.0695)
power	0.0344	1.1607**	-0.6811*	-0.2398
	(0.0487)	(0.3870)	(0.3343)	(0.3940)
Village FE	yes	yes	yes	yes
N	470	470	470	470
r2	0.3237	0.2057	0.4116	0.0747
F	27.9052	14.4235	40.6291	8.2649

i) Robust Standard errors in parentheses

Table 15: Amount of Credit Borrowed: Minimum Path Distance to Power in Credit Network

OLS Estimates

	(1) log_amount1	(2) log_amount2	(3) log_amount3
pathdpower_max	0.6501	0.4108	0.8640^{+}
	(0.4797)	(0.4262)	(0.4955)
hhsize	0.1387*	0.2146**	0.0840
	(0.0664)	(0.0565)	(0.0615)
education_upto	0.1712**	-0.0606	0.0909*
	(0.0440)	(0.0392)	(0.0412)
land	0.1215**	-0.0276	0.0021
	(0.0369)	(0.0259)	(0.0299)
casterank	-0.1533*	-0.1722**	-0.1989**
	(0.0691)	(0.0618)	(0.0647)
power	1.1802**	-0.6857*	-0.1334
	(0.3901)	(0.3369)	(0.3788)
Village FE	yes	yes	yes
N	470	470	470
r2	0.2039	0.4126	0.1335
F	14.6484	40.8453	7.7998

i) Robust Standard errors in parentheses

IV Estimates

	(1) First Stage	(2) log_amount1	(3) log_amount2	(4) log_amount3
pred_prob	17.2805**			
	(2.6087)			
var	0.0976**			
	(0.0274)			
pathdpower_max		1.4563	0.1332	3.2807*
		(1.2378)	(1.1046)	(1.3797)
hhsize	-0.0029	0.1362*	0.2114**	0.0783
	(0.0065)	(0.0601)	(0.0546)	(0.0581)
education_upto	0.0057^{+}	0.1476**	-0.0597	0.0697^{+}
	(0.0034)	(0.0401)	(0.0384)	(0.0406)
land	0.0061*	0.0977**	-0.0241	-0.0195
	(0.0029)	(0.0339)	(0.0261)	(0.0294)
casterank	0.0046	-0.1846**	-0.1683**	-0.2098**
	(0.0059)	(0.0610)	(0.0594)	(0.0616)
power	0.0167	1.0214**	-0.6309^{+}	-0.1838
	(0.0340)	(0.3480)	(0.3221)	(0.3570)
Village FE	yes	yes	yes	yes
N	470	470	470	470
r2	0.4599	0.1975	0.4120	0.0742
F	52.4304	13.8015	40.6433	7.7310

i) Robust Standard errors in parentheses

Table 16: Amount of Credit Borrowed: Minimum Path Distance to Power in Credit Network

OLS Estimates

	(1) log_amount1	(2) log_amount2	(3) log_amount3
pathdpower_max	0.5760	0.4190	0.7889^{+}
	(0.4371)	(0.4156)	(0.4548)
hhsize	0.1334*	0.2123**	0.0704
	(0.0602)	(0.0549)	(0.0567)
education_upto	0.1527**	-0.0614	0.0843*
	(0.0397)	(0.0381)	(0.0383)
land	0.1040**	-0.0261	-0.0015
	(0.0332)	(0.0253)	(0.0272)
casterank	-0.1791**	-0.1701**	-0.1944**
	(0.0620)	(0.0600)	(0.0598)
power	1.0430**	-0.6380^{+}	-0.1225
	(0.3509)	(0.3259)	(0.3463)
Village FE	yes	yes	yes
N	470	470	470
r2	0.2039	0.4126	0.1335
F	14.6484	40.8453	7.7998

i) Robust Standard errors in parentheses

IV Estimates

	(1) First Stage	(2) log_amount1	(3) log_amount2	(4) log_amount3
pred_prob	17.2805**			
	(2.6087)			
var	0.0976**			
	(0.0274)			
pathdpower_max		1.3012	0.1581	3.6921*
		(1.3563)	(1.1467)	(1.5074)
hhsize	-0.0029	0.1408*	0.2138**	0.0930
	(0.0065)	(0.0661)	(0.0561)	(0.0631)
education_upto	0.0057^{+}	0.1674**	-0.0591	0.0743^{+}
	(0.0034)	(0.0442)	(0.0395)	(0.0438)
land	0.0061*	0.1168**	-0.0258	-0.0184
	(0.0029)	(0.0376)	(0.0267)	(0.0322)
casterank	0.0046	-0.1573*	-0.1707**	-0.2165**
	(0.0059)	(0.0680)	(0.0612)	(0.0667)
power	0.0167	1.1642**	-0.6795*	-0.2029
	(0.0340)	(0.3862)	(0.3331)	(0.3909)
Village FE	yes	yes	yes	yes
N	470	470	470	470
r2	0.4599	0.1975	0.4120	0.0742
F	52.4304	13.8015	40.6433	7.7310

i) Robust Standard errors in parentheses

Table 17: Raising Money: Total Degree in Relyon Network

Whether HH can raise 1000 Rs.

	(1) borrow_1000	(2) totaldegree	(3) borrow_1000
pred_prob		324.1218**	
		(46.6602)	
var		-0.3761	
		(0.2466)	
totaldegree	0.1283**		0.1010*
	(0.0386)		(0.0503)
hhsize	0.0537	0.0482	0.0553
	(0.0441)	(0.0484)	(0.0440)
education_upto	0.0553*	0.0321	0.0558*
	(0.0230)	(0.0354)	(0.0231)
land	0.0398	0.0209	0.0398
	(0.0322)	(0.0226)	(0.0323)
casterank	-0.0250	-0.0215	-0.0260
	(0.0325)	(0.0477)	(0.0325)
power	0.2831	1.1826**	0.3246
	(0.2575)	(0.3423)	(0.2527)
Village FE	yes	yes	yes
N	495	495	495
r2		0.4461	
F		21.2234	

i) Robust Standard errors in parentheses

Whether HH can raise Year's Income

	(1) borrow_income	(2) totaldegree	(3) borrow_income
pred_prob		324.1218**	
		(46.6602)	
var		-0.3761	
		(0.2466)	
totaldegree	-0.0372+		-0.0439
	(0.0224)		(0.0404)
hhsize	-0.0470	0.0482	-0.0464
	(0.0329)	(0.0484)	(0.0330)
education_upto	0.0781**	0.0321	0.0781**
	(0.0204)	(0.0354)	(0.0204)
land	0.0676**	0.0209	0.0677**
	(0.0163)	(0.0226)	(0.0163)
casterank	-0.0292	-0.0215	-0.0296
	(0.0288)	(0.0477)	(0.0288)
power	0.5100**	1.1826**	0.5174**
	(0.1690)	(0.3423)	(0.1769)
Village FE	yes	yes	yes
N	495	495	495
r2		0.4461	
F		21.2234	

i) Robust Standard errors in parentheses

Table 18: Raising Money: Average Path in Relyon Network

Whether HH can raise 1000 Rs

	(1) borrow_1000	(2) avgpath	(3) borrow_1000
pred_prob		3.5741**	
		(0.3227)	
var		-0.0271**	
		(0.0041)	
avgpath	3.9370*		6.3886^{+}
	(1.7901)		(3.2789)
hhsize	0.0577	0.0002	0.0561
	(0.0442)	(0.0007)	(0.0445)
education_upto	0.0594**	0.0001	0.0590**
	(0.0230)	(0.0004)	(0.0227)
land	0.0342	0.0005	0.0344
	(0.0339)	(0.0003)	(0.0338)
casterank	-0.0329	-0.0004	-0.0317
	(0.0319)	(0.0007)	(0.0319)
power	0.3690	-0.0001	0.3613
	(0.2503)	(0.0038)	(0.2485)
Village FE	yes	yes	yes
N	495	495	495
r2		0.8586	
F		341.4928	

i) Robust Standard errors in parentheses

Whether HH can raise Year's Income

	(1) borrow_income	(2) avgpath	(3) borrow_income
pred_prob		3.5741**	
		(0.3227)	
var		-0.0271**	
		(0.0041)	
avgpath	5.2023**		-4.5601^{+}
	(1.6316)		(2.5477)
hhsize	-0.0553^{+}	0.0002	-0.0392
	(0.0333)	(0.0007)	(0.0312)
education_upto	0.0786**	0.0001	0.0681**
	(0.0207)	(0.0004)	(0.0199)
land	0.0692**	0.0005	0.0653**
	(0.0163)	(0.0003)	(0.0147)
casterank	-0.0230	-0.0004	-0.0274
	(0.0290)	(0.0007)	(0.0281)
power	0.4444**	-0.0001	0.4273**
	(0.1703)	(0.0038)	(0.1630)
Village FE	yes	yes	yes
N	495	495	495
r2		0.8586	
F		341.4928	

i) Robust Standard errors in parentheses

Table 19: Raising Money: Belong to a Maximally Connected Subcomponent in Relyon Network

Whether HH can raise 1000 Rs

	(1) borrow_1000	(2) max_conn	(3) borrow_1000
pred_prob		312.7863**	
		(48.6207)	
var		-0.0891	
		(0.2493)	
max_conn	0.1440	0.8408*	0.8056*
	(0.2204)	(0.3533)	(0.4032)
hhsize	0.0614	0.0409	0.0494
	(0.0444)	(0.0489)	(0.0440)
education_upto	0.0606**	0.0273	0.0554*
	(0.0231)	(0.0347)	(0.0223)
land	0.0355	0.0193	0.0350
	(0.0341)	(0.0221)	(0.0320)
casterank	-0.0354	-0.0108	-0.0275
	(0.0322)	(0.0471)	(0.0325)
power	0.3605	1.1835**	0.3385
	(0.2455)	(0.3414)	(0.2398)
Village FE	yes	yes	yes
N	495	495	495
r2		0.4514	
F		22.4326	

i) Robust Standard errors in parentheses

Whether HH can raise Year's Income

	(1) borrow_income	(2) max_conn	(3) borrow_income
pred_prob		13.4820**	
		(2.9335)	
var		-0.3414**	
		(0.0414)	
max_conn	0.2583		-0.6959*
	(0.1710)		(0.3440)
hhsize	-0.0558^{+}	0.0087	-0.0381
	(0.0332)	(0.0073)	(0.0325)
education_upto	0.0760**	0.0057	0.0725**
	(0.0205)	(0.0039)	(0.0195)
land	0.0693**	0.0019	0.0646**
	(0.0158)	(0.0036)	(0.0158)
casterank	-0.0232	-0.0127^{+}	-0.0359
	(0.0288)	(0.0070)	(0.0287)
power	0.4476**	-0.0011	0.4400**
	(0.1679)	(0.0360)	(0.1653)
Village FE	yes	yes	yes
N	495	495	495
r2		0.5760	
F		118.6666	

i) Robust Standard errors in parentheses

Table 20: Raising Money: Minimum Path to Power in Relyon Network

Whether HH can raise 1000 Rs

	(1) borrow_1000	(2) pathdpower_max	(3) borrow_1000
pred_prob		8.1647**	
		(2.4090)	
var		-0.1853**	
		(0.0260)	
pathdpower_max	-0.0459		1.4059*
	(0.2930)		(0.6412)
hhsize	0.0628	-0.0023	0.0552
	(0.0439)	(0.0061)	(0.0420)
education_upto	0.0618**	0.0090**	0.0448*
	(0.0230)	(0.0031)	(0.0220)
land	0.0347	0.0053*	0.0271
	(0.0345)	(0.0026)	(0.0311)
casterank	-0.0382	-0.0059	-0.0281
	(0.0327)	(0.0055)	(0.0318)
power	0.3604	-0.0277	0.3651
	(0.2436)	(0.0309)	(0.2335)
Village FE	yes	yes	yes
N	495	495	495
r2		0.3758	
F		37.4774	

i) Robust Standard errors in parentheses

Whether HH can raise Year's Income

	(1) borrow_income	(2) pathdpower_max	(3) borrow_income
pred_prob		8.1647**	
		(2.4090)	
var		-0.1853**	
		(0.0260)	
pathdpower_max	0.1309		-1.1695*
	(0.2319)		(0.5913)
hhsize	-0.0508	-0.0023	-0.0447
	(0.0328)	(0.0061)	(0.0315)
education_upto	0.0758**	0.0090**	0.0801**
	(0.0204)	(0.0031)	(0.0197)
land	0.0675**	0.0053*	0.0676**
	(0.0160)	(0.0026)	(0.0158)
casterank	-0.0268	-0.0059	-0.0342
	(0.0287)	(0.0055)	(0.0279)
power	0.4524**	-0.0277	0.4018*
	(0.1680)	(0.0309)	(0.1656)
Village FE	yes	yes	yes
N	495	495	495
r2		0.3758	
F		37.4774	

i) Robust Standard errors in parentheses