Social Networks and Agricultural Performance: A Multiplex Analysis of Interactions among Indian Rice Farmers

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March 2019

1 Introduction

This paper aims to investigate the flow of information and resources among farmer networks and its effect on rice productivity in the Orissa state of India. To investigate the social network effect, we have got a full village level census of multiple social networks from three villages. Furthermore, the availability of rice production data for two periods and directed network information for three different kinds of social interactions allow us to focus on informational gains, exchange of resources and to quantify its causal impact on individual farmers productivity. The availability of information on multiple networks allows not only to study the individual effect of these networks but also to investigate the interconnections across networks.

In this study, we consider three important social networks that exist among the farmers of Orissa. They are information network, credit network and friendship network. Each of these networks carries different endowments that are crucial for enhancing productivity. Information network serves as an informal source of knowledge about agricultural technologies, inputs, improved practices that are generated through the information flow and can improve productivity directly. Credit network is a channel for obtaining informal credit from the network members and therefore acts as a provider of resources. Friendship network enhances social cohesion, develops trust and facilitates the exchange of information and resources among network members. While the role of informational gains have been well established in the literature, the role of other networks is usually neglected. Credit availability is an important factor in agricultural production as it provides the basis for better input access (Narayanan, 2016). For instance, the study by Das, Senapati and John (2009) has shown several gaps in the institutional credit delivery system in India such as inadequate credit availability for marginal and small farmers. In such cases, the informal lending becomes an alternative for the farmers since not only access but timely availability of credit is very important. Friendship is a crucial source for the development of social capital and there are many experimental studies that have shown higher levels of trust among friends (Vollan, 2011; Binzel & Fehr, 2013). Trust is an important factor in any informal transactions which commonly occurs in social networks.

The importance of social networks have been empirically investigated largely in terms of technology adoption (Conley & Christopher, 2001; Munshi, 2004; Bandiera & Rasul, 2006; Maertens & Barrett, 2012). Only a few studies have attempted to quantify the productive externalities of such networks (Foster & Rosenzweig, 1995; Van den Broeck & Dercon, 2011). All these studies have considered the gains from adoption and the process of adoption as facilitated by the diffusion of information through social interactions. However, individuals usually have affiliations with many different network groups and therefore it is inappropriate to assume information and/or resources flow from a singular network. Therefore, considering these networks along with information network provide a holistic understanding of the importance of social interactions in increasing agricultural productivity. Most studies overlook the link between informational gains from social interactions and agricultural production because data at this level is limited.

Van den Broeck and Dercon (2011) have recently quantified the social network effect on Banana production in Tanzania by considering three different networks. But they have considered the networks independently and only as a source of information. On the other hand, it is econometrically challenging to consider the interactions across different networks among same members due to problems of multicollinearity and inference making. (Cai, Wang, Cui & Stanley, 2018) has introduced a network structure framework to incorporate multiple relationships that can be used to develop a single composite multiplex network but did not estimate its causal effect. In this paper, we address these two gaps by considering unique data that provide information on multiple networks (carrying different endowments) and incorporating interaction among these networks using a multiplex framework. With this, our paper showcase the use of both networks and econometric methods to estimate the causal effect of social networks on rice productivity.

2 Data and Methods

2.1 Data description

We answer our research question using cross-section data from three Indian villages. The data were collected in 2016 from the villages Taraboisassan, Kanijpur and Kunarpur in Orissa state as part of the Small Farmers Large Field (SFLF) project's baseline survey by International Rice Research Institute (IRRI), India. The information on social networks, agricultural production activities and socio-economic characteristics were collected from the entire population of three villages and therefore our sample is in a form of full census of households. The information on social networks were gathered at household level and it consists of three different types of interactions. They are the agriculture information network which denote each household's informal agricultural information sources, friendship network depicting their friend zones and credit network representing the informal credit sources. All these are the self-reported intra-village social networks and all the networks involve same members. Agriculture production information was collected for the current season and retrospectively for the previous season.

Table (1) provides the summary statistics of our sample farmers. Our network members mostly include male households with an average age of 50.5 years and 7.6 years of education. There is a fair amount of social heterogeneity with majority (67.1 %) of them belonging to Other Backward Castes followed by General castes (21.7 %) and SC&ST (11.2 %). The average productivity is 1738 kg per acre with most of the farmers (96.5 %) using high yielding rice varieties with very few farmers using both hybrids (less than 1 %) and traditional varieties (2.7 %). This indicates a homogeneity of the type of seeds used for the production. The average land holding is about one acre indicating the prominence of small farmers. The average degree for both information and friendship networks are about 1.45 indicating there are less than two friends and informants for every farmer. On the other hand, the average degree of credit network is 0.72 which shows less than one potential credit provider for every farmer. These low number are due to the inclusion of members with zero degree in each of those networks. The average degree of weighted and unweighted multiplex networks are 1.26 and 9.60 respectively. The details about the network methodology follows in the next section. The average similarity index is 0.075 indicating a smaller presence of a common individual in someone's

Table 1: Summary Statistics.

	n	Mean	Std. Dev	Min	Max
Dependent					
Productivity (Kg/acre)	258	1738.35	353.79	875	2812.50
Independent					
Degree centrality					
Information network	258	1.46	4.75	0	70
Friendship network	258	1.43	1.28	0	8
Credit network	258	0.72	0.91	0	6
UMN	258	9.60	5.39	6	82
WMN	258	1.26	4.11	0	60.62
UMN and WMN are the unweighted and weighted multiplex networks respectively.					
Similarity index	256	0.075	0.13	0	1
Individual characteristics					
Age (years)	258	50.53	12.06	20	82
Gender (Female=1; Male=2)	258	1.96	0.20	1	2
Education (years)	258	7.67	3.28	1	16
Caste	258	1.90	0.59	1	4
Caste Categories: General (21.70%) = 1, OBC (67.05%) = 2, SC (10.46%) = 3, ST (0.77%) = 4					
Inputs					
Seed type	258	1.06	0.33	1	3
Seed Categories: HYV (96.51%) = 1, Hybrid (0.77%) = 2 , Traditional (2.71%) = 3					
Seed (Kgs/acre)	258	22.76	6.18	0	80
Labour (hrs/acre)	258	254.25	134.25	0	1090
Fertilizer (Kg/acre)	258	119.92	50.97	0	525
Compost (Loads/acre)	258	0.85	4.99	0	62.5
Land area (acre)	258	1.04	0.66	0.16	3.5

multiple networks.

2.2 Network Framework

We define networks with a set of household heads (vertices) $v \in V_m$ and a set of pairs of vertices that represent connections (edges) E_m, such that $G_m(V_m, E_m) : m \in \{\alpha, \beta, \gamma\}$ for the friendship, information and credit networks respectively. Following Cai et al. (2018) notation, for a set of networks $N = \{G_\alpha, G_\beta, G_\gamma\}$ we define the multiplex networks as pairs $\zeta(N, \Lambda)$, where Λ is a set of interconnections between networks $\Lambda = \{E_{ij} \subseteq V_i \times V_j;\ \forall (i \neq j) \in m\}$. Each network in N has a corresponding adjacency matrix A_m whose entries are defined as $a^m_{ij} = \{1\ if\ (v^m_i, v^m_j) : (i \neq j) \in E_m,\ 0\ otherwise\}$. The weighted multiplex network is a block matrix (for the unweighted case we exclude the vectors of weights w) whose off diagonal elements are identity matrices I_n and diagonal elements are adjacency A_m matrices for each network in N and our sample size is $n = |\bigcup_{i \in m} V_i|$.

$$A^{Multiplex} = \begin{pmatrix} w^{11}A_\alpha & w^{12}I_n & w^{13}I_n \\ w^{21}I_n & w^{22}A_\beta & w^{23}I_n \\ w^{31}I_n & w^{32}I_n & w^{33}A_\gamma \end{pmatrix}$$

Similar to Cai et al. (2018), the vectors of weights are defined from equation (1) where r^θ are the r-squared values of a univariate regression analysis taking the out-degree of each network N as explanatory variable for agricultural productivity.

$$w^{ij} = \frac{r^i r^j}{\sum\limits_{(i,j,\theta) \in m} r^\theta} \tag{1}$$

From $A^{Multiplex}$, the degree of each household heads is aggregated with Cai et al., 2018 equation.

$$k_i = \sum_{\lambda=0}^{|m|-1} k_{i+\lambda N} \tag{2}$$

We expect that the overlap of social relationships enhances the bond between pairs (v_i, v_j) of farmers. That is, the social bond between them is stronger if they are not only friends but also providers of information and/or credit. To capture this type of social strength in the multiplex framework we develop a Jacquard based of Similarity Index. We define the open neighbourhood of a vertex as $\nu_{G_m}(v_i) = \{v_i \in V_m \mid (v_i, v_j) \in E_m\}$ from which the similarity index for the multiplex is

$$S(v) = |m|^{-1} \sum_{i \neq j \in m} \frac{|\nu_{G_i}(v) \cap \nu_{G_j}(v)|}{|\nu_{G_i}(v) \cup \nu_{G_j}(v)|} \tag{3}$$

2.3 Econometric Framework

After we obtain our measures of degree centrality, our next focus is to identify the causal effects of these social networks on agricultural productivity. We test whether multiple social networks improve productivity through an exchange of information/knowledge and resources among rice farmers of Orissa. Most importantly to analyse if all the three networks increase productivity when considered independently, and together using multiplex.

To answer this, we model farmer's output (production per acre) as a function of social networks using Cobb-Douglas production function as follows.

$$log(y_t) = \alpha + \beta D_k + \Gamma X + ZK + \eta F + \epsilon \tag{4}$$

Where, X is a vector of inputs with $\Gamma = [\gamma_1, \ldots, \gamma_l]$ coefficients, K is a vector of individual characteristics with $Z = [\zeta_1, \ldots, \zeta_j]$ coefficients and F is vector of neighbourhood characteristics including the average productivity of neighbourhood in the previous period with $\eta = [\eta_1, \ldots, \eta_j]$ coefficients. From equation (4), the variables of interest is the out-degree $D = \{D_1, D_2, \ldots, D_k\}$ of the Information, Credit, Friendship and weighted and unweighted Multiplex networks which are estimated separately.

If there exist a social network effect, then we expect the coefficient of social network (β) to be positive and significant. Our equation (4) allows for considering effect of different types networks – information, friendship, credit and multiplex on rice productivity.

Identifying social network effects is not straightforward as it involves several challenges. We address three econometric issues which arise when trying to identify the network effects. Firstly, the simultaneity problem. That is, there exists a simultaneity in the relationship between an individual's productivity and the degree of his network. For example, a farmer's productivity may increase with the number of connections he has because it provides him a source of information. On the other hand, a farmer will be contacted by other farmers only if he is more productive than the others. Manski (1993, 2000) also talks about similar problem of simultaneity which is called as a reflection problem. It arises because the behaviour of farmers in the network affects the behaviour of an individual farmer in that network and vice versa. He offers to make use of lagged behaviour of the network members as a solution for this identification problem therefore making the model dynamic. However, this will suffice only if the process of social effect is observed out of equilibrium along with the information and timing of lagged observations. An out of equilibrium situation could be one in which only few farmers adopt productivity enhancing techniques and the others do not see a need to do so or have not followed it yet (Van den Broeck & Dercon, 2011). In our data we have information on productivity for two seasons of rice production. At the same time, we have an out of equilibrium situation where only few farmers have been following productivity enhancing techniques for example use of hybrid seeds for production. Our network data offers several options to tackle this issue of endogeneity. Since we have got information on the directed network, we make use of out-degree information as the network measure. It means we consider an edge only for the case in which a farmer obtains information from other farmers but not vice versa. This solves the problem of bidirectionally of flow of information and resources. At the same time, we also account for the lagged productivity of network members and in this case, it denotes the quality of the network.

The second issue is the endogenous formation of network groups. Since we have considered self-reported network information, it suffers from a potential self-selection bias. This explains a case wherein productivity and network formation can be affected by common unobserved factors. For instance, individuals can choose peers based on similar characteristics such as age, ethnicity, gender, etc, that could also explain output variable. This is generally addressed using instrumental variable approach. We do not have external instrumental variable that satisfies the exclusion restriction condition in order to serve as an instrument for our network variables. Therefore, we solve this issue by following Lewbel (2012)'s instrumental variable approach in which our model identifies and estimate the endogenous regressor model using heteroscedasticity present in the auxiliary equation (equation for social network). Here the instruments are generated by using the variables that are in the productivity (main) equation.

Third, estimating the joint effect of multiple social networks is challenging econometrically due to two reasons. The first being the correlation between these networks since these networks represent the existence of links between same set of people. Secondly, interacting these network measures introduces the problem of inference as they are all continuous variables. Our paper address this by employing multiplex network methodology (Cai et al., 2018) which helps in constructing one large network using all the three network layers and therefore obtaining one composite network measure.

Finally, for both information and credit networks we use directed network as they suffer from simultaneity. For friendship network we use undirected network as we assume that friendship does not strongly depend on the productivity of the farmer. From these individual networks the multiplex network is obtained as explained in the previous section. For identifying the model using instruments we have considered triangular approach for information and friendship networks whereas, we have used simultaneous linear model identification for credit network. We considered simultaneous model for credit network because we assume that less productive (poor) people tend to mention higher number of potential credit givers than the high productive (rich) farmers as here it refers to small amount of credit. Therefore, even after using directed network we suspect simultaneity issue in the credit network and hence we apply the simultaneous version of Lewbel (2012)'s instrumental variable approach. For the multiplex network we use triangular system approach to not force simultaneity on information and friendship part of the network for adjusting issue with credit part of network. Our paper therefore has provided evidence for combining both network and econometric procedures in order to tackle the identification problem of social network effects.

3 Results

3.1 Network Characteristics

We present in Table (2) a summary of global network measurements. The *geodesic distance* between two vertices is a measurement of the shortest path connecting two farmers. We observe similar average shortest paths for the Information and Credit Networks and a higher value for the friendship network. Shortest paths between farmers is an indicator of the accessibility or higher probability of establishing a new connection for members of these networks. Additionally, we report also *Diameter* which is the longest geodesic distance in the network. The friendship network reports the highest diameter that reflect the presence of a group or cluster of interconnected farmers. The *Components* of a graph is a maximally connected subgraph, which means groups of farmers connected only among themselves. A high number of components reflects a sparse network, meaning that there are subgraphs or groups that do not share connections or members. Finally, we also present the measurement of *Density* which is a ratio of the number of edges to the total potential edges in the graph or an overall measurement of how connected or sparse a network is. From our three networks, the Information and Friendship networks report higher connectivity in comparison to credit, which is expected since Information and Friendship are less formal, require less effort to establish and maintain connections. The structure of all networks are presented in the Appendix (A).

Table 2: Global Network Statistics

Network	**Diameter**	**Density*100**	**Components**	**Size max(clique)**	**Avg. Geodist.**
Information	14	0.52	105	3	3.76
Credit	8	0.26	176	2	3.22
Friendship	17	0.53	94	3	5.28

3.2 Network Correlations

Table 2 describe the dyadic correlation across all the three networks obtained by Quadratic Assignment Procedure (QAP). For village 1, It indicates a significant dyadic correlation of 0.14 between Information and Friendship networks meaning that if two households are connected by information network, they are also likely to be friends. Similarly, there is a significant dyadic correlation of 0.22 between information and credit networks in village 3 indicating some households in the information network also exchange credit. Although there exist significant correlations in two villages, the coefficients indicate that the correlations are weak.

Table 3: QAP correlation for individual social networks

Correlation between farmers social networks in village 1			
Networks	Information	Friendship	Credit
Information	1.00***	0.14***	-0.03
Friendship	0.14***	1.00***	0.01
Credit	-0.03	0.01	1.00***
Correlation between farmers social networks in village 2			
Networks	Information	Friendship	Credit
Information	1.00***	-0.01	-0.01
Friendship	-0.01	1.00***	-0.01
Credit	-0.01	-0.01	1.00***
Correlation between farmers social networks in village 3			
Networks	Information	Friendship	Credit
Information	1.00***	0.01	0.22***
Friendship	0.01	1.00***	0.03
Credit	0.22***	0.03	1.00***

***, ** and * indicate significance at 1 percent, 5 percent and 10 percent respectively.

3.3 Regression Output

The estimation of social network effects are performed for all the individual networks and multiplex networks separately. The individual specific characteristics such as age, education, caste, and neighbourhood characteristics such as average age and average education are used. Among inputs we have controlled for the use of fertilisers, compost (organic manure), labour hours, seeds and machines used.

Table (4) presents the estimation of individual social networks effect on rice productivity. First, second and third regression results shows the output for information, friendship and credit networks respectively. Our analysis involves members who have at least one network link (degree=1) in the respective network. Thus, individuals with zero degree are disregarded from the analysis. There are 171 members who have at least one degree in the information network with an average degree (Standard deviation) of 2.1 (5.5) households. Similarly, friendship and credit network have an average degree (standard deviation) of 1.8 (1.17) and 1.4 (0.82) with 193 and 129 households respectively. All three networks have shown positive effects while only information network have a significant effect on productivity. In a Cobb-Douglas production function the coefficients imply elasticities therefore, an increase of information degree by 100 percent over the mean have shown to increase productivity by 3.9 percent. All regressions have accounted for the inputs, individual specific characteristics and village fixed effects. Among other factors the average productivity of network members has a positive and significant effect with the coefficient of 0.23. It indicates that if the average lagged productivity of network members increases by one percent, then the current productivity of a network member increases by 0.23 percent. This represents the quality of information network. Testing for the relevance of generated instruments (F test) shows that all the instruments jointly significantly explain the social network variables. Over-identification test for the instruments showed both information and credit networks have not over-identified whereas friendship network is over-identified at 10 percent level of significance. Similarly test for weak identification showed both information and credit networks are not weakly identified with C-D Wald F statistic of 15.35 and 110.50 respectively above 10 percent Stock-Yogo critical level, meaning the instruments are strong and significant. For friendship network the instruments have been identified weakly with C-D Wald statistic of 2.35. Since our instruments are relevant but weak, we report the weak instrument robustness inference with Anderson-Rubin Wald test. It showed p value of 0.02 and therefore it is significant and robust for the presence of weak instrument.

The joint estimation of three social networks using multiplex measure is presented in Table (5). These results are obtained by following Cobb-Douglas production function. A member who is at least present in one of the three networks is considered for estimating the effect of multiplex networks. The result shows that both weighted and unweighted measures having moderately significant (at 10 percent) and positive effect on productivity with the coefficients 0.045 and 0.07 respectively. For further discussions, we consider the output of weighted measure as weights provide relevant importance for each network in the multiplex based on their capacity to explain the variations in productivity. The coefficient for the multiplex is slightly higher than that of the coefficient for information network when considered alone and it shows a small improvement in the network effect on productivity for considering the multiple networks. It shows that when information, friendship and credit networks are considered together, it enhances productivity and therefore provide a better measure of social network effect. Since each of them carry endowments that complements each other for increasing productivity, multiplex represent a holistic representation of the network. Our estimate for multiplex network is downward biased as the credit network is partly but not completely treated for simultaneity in the multiplex.

Table 4: Effect of individual social networks on agriculture productivity (Cobb-Douglas) using generated instruments.

	Model 1	**Model 2**	**Model 3**
Dependent	Log (Productivity)		
Degree Individual network			
Log (Information)	0.0396**		
	(-0.0199)		
Log (Friendship)		0.0428	
		(-0.0584)	
Log (Credit)			0.0166
			(-0.0378)
Neighbourhood characteristics			
Log (Avg. Productivity in t-1)	0.229**	0.0549	0.18
	(-0.108)	(-0.0538)	(-0.12)
Log (Avg. Age)	0.197**	-0.153*	-0.468***
	(-0.0989)	(-0.0849)	(-0.178)
Log (Avg. Education)	0.0325	0.0103	-0.0338
	(-0.0469)	(-0.0359)	(-0.0636)
Individual characteristics			
Caste[a]			
Other Backward Caste	-0.023	0.0124	0.0727
	(-0.0364)	(-0.0383)	(-0.0459)
Low Caste	-0.118*	-0.0346	-0.0377
	(-0.0714)	(-0.059)	(-0.0771)
Log (Age in years)	-0.0814	0.0126	0.207**
	(-0.0769)	(-0.0701)	(-0.0974)
Log (Education in years)	0.0168	0.0529	0.0939***
	(-0.0293)	(-0.0335)	(-0.0352)
Inputs			
Log (Fertilizer in kg)	-0.0196	-0.0199	-0.0483
	(-0.0283)	(-0.0384)	(-0.0574)
Log (Compost in loads)	0.0275	0.0221	0.0482
	(-0.0234)	(-0.0253)	(-0.0418)
Log (Labour in hours)	0.0276	0.0520*	-0.00757
	(-0.0233)	(-0.0305)	(-0.0263)
Log (Seeds in kgs)	0.0585	0.134	-0.0913
	(-0.0529)	(-0.0814)	(-0.0787)
Log (Machine Ratio)[b]	0.998***	1.083***	0.23
	(-0.313)	(-0.268)	(-0.3)
Land size[c]			
1-2 acre	0.015	0.0228	0.024
	(-0.0319)	(-0.0336)	(-0.0371)
2-4 acre	-0.0481	0.0355	0.014
	(-0.0493)	(-0.0498)	(-0.0533)
Village FE	Yes	Yes	Yes

Constant	4.638***	6.432***	7.343***
	(-0.925)	(-0.727)	(-1.106)
Observations	171	193	129
R-squared	0.204	0.240	0.269
F test for instruments (p-value)	0.00	0.00	0.00
Test for overidentification[d] (p-value)	0.12	0.09	0.20

***, **, * indicate significance at 1, 5 and 10 % respectively. Coefficients are obtained from instrumental variable regressions. Productivity (kgs), fertilizer, labour, seeds and compost are accounted as quantities per acre. [a] Base category is High (General) caste. [b] Ratio of number of mechanised activities out of total number of activities. [c] Base category is less than one acre. [d] Hansen's J-test. WMN and UMN indicate Weighted Multiplex Network and Unweighted Multiplex Network respectively. Robust standard errors in parentheses are clustered at household level. 1st and 2nd regression models are with instruments generated for information and friendship networks using Lewbel (2012) approach of 2SLS for triangular systems. 3rd regression model is with instruments generated for credit network using Lewbel (2012) simultaneous system approach.

Taking cue from the QAP correlation output, we assess the effect of our similarity index on agricultural productivity. A positive effect from this index can lead to higher flow of knowledge due to the strength of relationships of a farmer's neighbourhood. Our coefficient for similarity index is positive but not significant indicating the closeness of members through multiple relationships does not improve productivity significantly. Among other variables, the lagged average productivity of network members shows positive and moderately significant effect on productivity indicating the quality of the network. We have also accounted for the characteristics of the network members and individual characteristics, and they have no effect on productivity. Among inputs, machine ratio has a highly significant and positive effect indicating higher the mechanisation, higher the productivity. One percent increase in machine ratio increases productivity by more than 1 percent (1.01). Farmers who are not capable to buy machines can borrow/exchange it from their networks like friends and thus increase their productivity. Therefore, friendship network can act as a catalyst for the improvement of productivity with its facilitation role. This is very important during certain production activities such as transplanting and harvesting. Since in a village most of the farmers perform these activities at the same time, there will be higher demand for labourers. Therefore, networks can act as a source of machines/implements that can improve yield or reduce potential loss of yield that arises from lack of timely availability of labourers in critical periods of rice cultivation.

The significance of F test for instruments indicate relevance of generated instruments for both the regressions. The test for over-identification is not significant indicating the productivity model is not over-identified. The test for weak identification obtained the C-D Wald test statistic of 12.38 which is more than the Stock-Yogo critical value at 10 percent indicting the instruments are significant.

The identification of causal effects of social networks and the use of multiplex networks provide a very important input for the policy makers to better understand the role of social networks in improving rice productivity. It also provides an evidence for the potential channels for information and resource flows in villages that are central to the success of introduction of innovations such as improved varieties, machines and other improved agricultural practices. Our paper also provides a way for further academic inquiry of the role of multiple relationships in improving performance in agriculture and various sectors.

Table 5: Effect of multiplex networks on agriculture productivity (Cobb-Douglas) using generated instruments.

	Model 1	**Model 2**
Dependent	**Log (Productivity)**	
Degree multiplex network		
Log (WMN)	0.0454*	
	(-0.026)	
Log (UMN)		0.0707*
		(-0.04)
Log Similarity index	0.0901	0.0715
	(-0.12)	(-0.119)
Neighbourhood characteristics		
Log (Avg. Productivity in t-1)	0.142*	0.161**
	(-0.0744)	(-0.0774)
Log (Avg. Age)	-0.114	-0.117
	(-0.134)	(-0.136)
Log (Avg. Education)	-0.00169	0.00721
	(-0.0484)	(-0.0491)
Individual characteristics		
Caste[a]		
Other Backward Caste	0.0153	0.0115
	(-0.0316)	(-0.0315)
Low caste	-0.0163	-0.0181
	(-0.0501)	(-0.0515)
Log (Age in years)	0.0791	0.0867
	(-0.0774)	(-0.0787)
Log (Education in years)	0.0389	0.0349
	(-0.0261)	(-0.0269)
Inputs		
Log (Fertilizer in kg)	-0.0111	-0.0121
	(-0.0291)	(-0.0295)
Log (Labour in hours)	0.0298	0.03
	(-0.0242)	(-0.0244)
Land size[b]		
1-2 acre	0.00464	0.00281
	(-0.0284)	(-0.0289)
2-4 acre	-0.000149	-0.000189
	(-0.0425)	(-0.0423)
Log (Seeds in kgs)	0.0958	0.0927
	(-0.0606)	(-0.0609)
Log (Machine Ratio)[c]	1.013***	1.001***
	(-0.25)	(-0.249)
Log (Compost in loads)	0.0287	0.0249
	(-0.0217)	(-0.0212)
Village FE	Yes	Yes
Constant	5.667***	5.386***
	(-0.739)	(-0.781)

Observations	250	250
R-squared	0.212	0.209
F test for instruments (p-value)	0.00	0.00
Test for overidentification[d] (p-value)	0.11	0.25

***, **, * indicate significance at 1, 5 and 10 % respectively. Coefficients are obtained from instrumental variable regressions. Productivity (kgs), fertilizer, labour, seeds and compost are accounted as quantities per acre. [a] Base category is High (General) caste. [b] Base category is less than one acre. [c] Ratio of number of mechanised activities out of total number of activities. [d] Hansen's J-test. WMN and UMN indicate Weighted Multiplex Network and Unweighted Multiplex Network respectively. Robust standard errors in parentheses are clustered at household level. All the regression models are with instruments generated for WMN and UMN using Lewbel (2012) instrumental variable approach.

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A Appendix Network Graphs

Figure 1: Credit Network

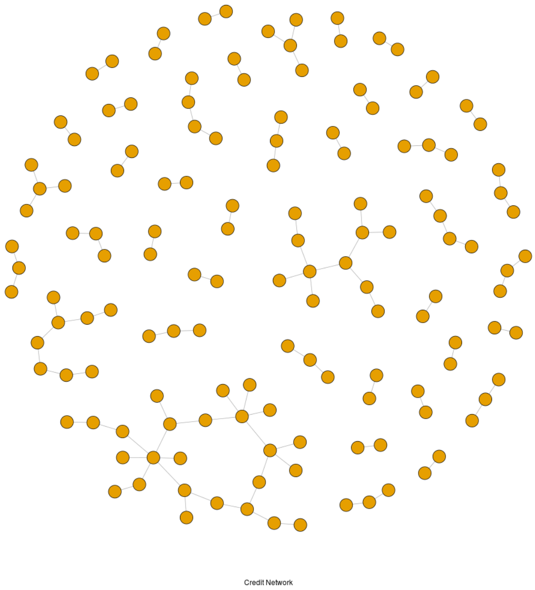

Figure 2: Friendship Network

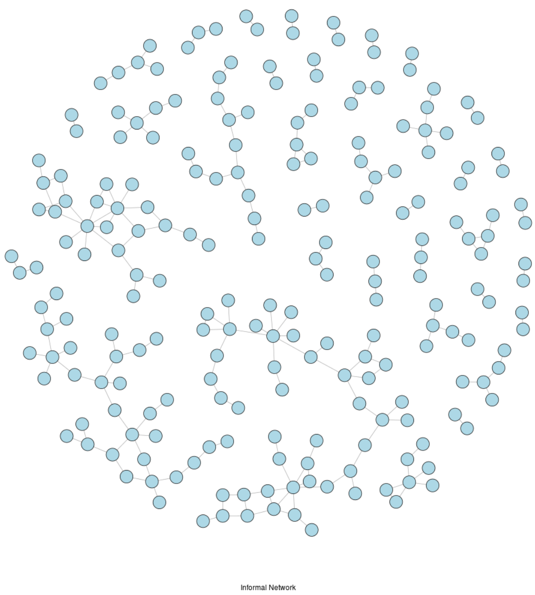

Figure 3: Information Network

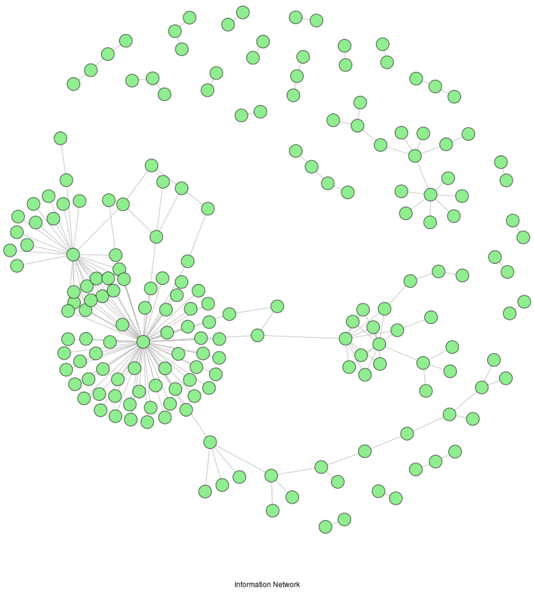

Figure 4: Multiplex Network