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Social Networks and Agricultural Performance: A Multiplex Analysis of Interactions among Indian Rice Farmers[1]

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Abstract

Most network studies in agriculture examine uni-dimensional connections between individuals to understand the effect of social networks on outcomes. However, in most real-world scenarios, network members' exchanges happen through multiple relationships and not accounting for such multi-dimensional interconnections may lead to biased estimate of social network effects. This study aims to unravel the consequences of not accounting such multidimensional networks by investigating the individual and joint effects of multiple connections (relationships) that exist among households on agricultural output. We use census data from three villages of Odisha, India that enables us to account for three types of relationships viz. information networks (knowledge sharing), credit networks (resource sharing) and friendship (social bonding) between households. We estimate the social network effect by combining both econometric (IV regression) and network (directed networks) techniques to address the problems of endogeneity. The joint effect of multiple networks is estimated using the multiplex network framework. We find that information flows are crucial to improve agricultural output when networks are accounted individually. However, the joint effect of all three networks using multiplex shows a significantly positive influence, indicating complementarity across relationships. In addition, we found evidence for the mediating role of interpersonal relationships (friendship network) in enhancing gains from the information flow.

Keywords: Agriculture production, Social network, Multiplex networks, knowledge sharing, Resource sharing, Friendship.

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1 Introduction

For any nation state, food-security is a necessary condition for sustained development with continuous increments of national well-being. It follows that especially for any country experiencing increasing population and limited availability of land, improving agricultural productivity is essential. But in spite of major technological advances and efforts to reduce poverty, it is estimated that at least half a billion people live with hunger and suffer from undernourishment (McGuire, 2015). About three-quarters live in rural areas, with most dependent on agriculture for both their livelihoods and their food security (FAO-UN, 2020).

In India, agriculture is paramount for the economy, employing roughly 42 percent of the labour force (World-Bank, 2020b), and accounting for 14 percent of GDP (World-Bank, 2020a). The agricultural production structure is not characterized by intensive agriculture, rather, most agricultural output comes from several million small farming families. The state of Odisha (also known as Orissa) is a good example of a region with a long history of struggle with food scarcity, famine and malnutrition (Mishra, 2005; Mohanty, 2017), where small-holders account for the vast majority of production. Rice is the staple food-crop of the state. Through all stages of its production, (germination, seedling, tillering, panicle initiation, flowering and harvesting) the access to resources such as nutrients, machinery, and labour are vital to secure a successful crop. However, the poverty of the typical small holder creates a serious challenge when they try to access the many and varied inputs or resources needed throughout the production process. In recent decades, efforts from government, farmers and research organisations have successfully increased overall productivity of the sector throughout India; however, ensuring food security still remains a major challenge (Das, 2012; Janaiah and Xie, 2010; Kumar and Mittal, 2006).

Capital investment and technical change have played a big role explaining increments and differences in agricultural productivity between Asian countries (Nin-Pratt et al., 2010). For instance, during the Green Revolution (1986–2000), increments in rice productivity in India have been related to the development and adoption of machinery, irrigation systems, high yielding varieties, and hybrids (Singh et al., 2019). In addition, mineral fertilisers and pesticides have become widely used (unfortunately at the expense of soil degradation) (Janaiah et al., 2006). However, productivity increments from these inputs require financial investment and access to specialized knowledge. But agricultural markets from villages usually have poor access to the formal institutions that in other places provide credit, information and education. Consequently, farmers tend to rely on other 'informal channels' to access both knowledge and resources.

In India, many small farmers tend to produce surplus crops which they sell in local markets. However, not all farmers are able to produce high marketable surplus to make it remunerative. For instance, our agricultural data on rice farmers in Odisha show, many only produce for self-consumption with little surplus (39 percent of our sample households – see Table 2 where we define a variable "production orientation"). The difference between those who do and those who do not produce high surpluses, lies largely not in their willingness to sell on the market, rather in their capacity to generate a high enough yield. These capacity constraints arise not only from a lack of awareness of better agricultural practices and productivity enhancing inputs (knowledge and technology constraints) but also, when awareness is present, financial inability to purchase those inputs (liquidity constraints). In this regard, Odisha is particularly striking (Das, 2012). We argue that with a growing population and thus a growing demand, poorly developed credit and input markets, and a lack of access to formal institutions, farmers will access both information and inputs through informal channels. In other words, farmers benefit by using knowledge and resources from their peers.

Studies in different agricultural settings have provided evidence on flows of resources and knowledge from informal networks. For instance, research on adoption (Bandiera and Rasul, 2006; Banerjee et al., 2013a; Conley and Christopher, 2001; Maertens and Barrett, 2012; Munshi, 2004) and adaptation in agriculture (Dowd et al., 2014; Johny et al., 2017) shows how (local and informal) information flows facilitate the dissemination of knowledge and technology. Other work points out financial flows within rural agricultural networks, such as informal gifts, zero-interest loans and transfers (Fafchamps and Lund, 2003), micro-finance (Banerjee et al., 2013b), and micro-credit (Chuang and Schechter, 2015). Another body of literature pays attention to what facilitates such network flows. Lyon (2000), for example, points out that in the absence of formal institutions, trust is the key mechanism that allows small farmers to access resources (new markets and technologies, credit from traders and other farmers) from informal networks. Similarly, the study of Golovina et al. (2014), finds that benefits to agricultural production from farmers' memberships in cooperative networks depend on the degree of shared values — trust, loyalty, involvement, and satisfaction. The review of Murdoch (2000) identifies the existence of vertical (farmers, traders and consumers) and horizontal (farmers and cooperatives) linkages and argues that it is not the linkages alone but the objects and relations that flow through them that are important. Further, the work of Krishna (2001) shows that benefits from informal networks (labour-sharing, collective dealing with crop disease and natural disasters) and the mechanisms that facilitate coordination and cooperation (trust, reciprocity and solidarity) are magnified or reduced, depending upon how capable some network members are in attracting additional resources and disseminating information about government programs and market opportunities. Fafchamps (2006) discusses how networks of interpersonal relationships in rural settings can increase efficiency of social exchange[2] via trust and also reduce the cost of search (inputs, suppliers, markets, technologies) with word-of-mouth. More recently, Shiferaw et al. (2011) argued that rural-farming networks (producer organisations and collective institutions) can mitigate market inefficiencies, such as reducing transaction costs, enhancing access to technologies and input and output markets, by taking voluntary group actions to achieve common interests.

We depart from the previous studies in three ways. Firstly, we expect that rural farmers benefit from networks, provided that networks carry relevant resources for agricultural production. That is, connections from networks can be beneficial as a channel to access knowledge, information or capital: provided some agents have access to those resources, networks can mitigate production constraints, market and institutional inefficiencies. Therefore, in our study we define networks based on what flows through them. In this regard, we account for two informal networks that potentially carry information and financial flows. The information network serves as an informal source of knowledge about agricultural technologies, inputs, and improved practices that can enhance productivity directly. The credit network is a channel for obtaining informal loans ("hand loans") from network members and therefore acts as a potential provider of resources. Specifically, it eases liquidity constraints and provides timely access to credit. Our credit network only indicates

[2] The author defined two dimensions of exchange: material (money, inputs, goods) and immaterial (values, norms and institutions).

potential sources of credit the farmers have, and we do not have information on actual borrowing.

Secondly, the existing social relationship (interpersonal relationships) between individuals are shown in the literature to catalyse the network flows through trustworthiness, loyalty, reciprocity, and such links are characterized as voluntary strong ties. To capture this, friendship networks[3] can be seen as the relevant facilitator of resource flows. The friendship network enhances social cohesion or bonding and facilitates the exchange of information and resources among network members, and thus reduces transaction costs involved in information search and provision of credit. For instance, Ghobadian et al. (2007) point out that friendship increases trust and loyalty; Chung et al. (2016); Henttonen et al. (2013) show that the development of social bonding increases information sharing; Butt (2019) demonstrates that the absence of personal relationship can hinder the exchange of ideas and delay conflict resolution. Moreover, a farmer's production is most likely to benefit from resourceful connections, and hence we argue that the friendship network (or network of interpersonal relationships) has to be studied jointly with other networks that carry resources. Therefore, while we investigate the effect of all three networks, viz. information, credit and friendship networks, independently on agricultural productivity, we also consider the mediating effect of friendship in facilitating the flow of information and resources.

Thirdly, since the information, credit, and friendship networks are likely to be mutually embedded (Borgatti and Li, 2009), the core of our paper is not only to measure individual network effects but to understand how the overlap and interaction of connections among individuals between these networks affect agricultural productivity. Most studies on social networks in agriculture have considered only singular networks, that is, the network flow is limited to one network (the network of agriculture informants for example). A few studies have considered multiple networks that mostly vary by the type of interpersonal relationships between the members (friendship, kinship, geographical proximity, and so on). However, the multiple networks are typically either considered independently or by simply aggregating them. Further, in most work they are assumed to carry mainly

[3] Here we define friendship based on the closeness criteria. That is, a friend is someone who is perceived as closer by the household. Therefore, it could also be his kin, his neighbour or any other relative within the village. For the sake of common representation, we call it friendship.

information (Banerjee et al., 2013; Johny et al., 2017; Van den Broeck and Dercon, 2011). In fact, though, not only are individuals part of multiple networks but they also receive distinct things from different networks, such as information, resources advice, support and so on. In addition, given that most social connections among farmers tend to be confined to a community of geographic location, there tends to be an overlap of connections among the same members. That is, connections between two individuals exist for more than one reason: they maintain more than one type of relationship. For example, two farmers who exchange information might also be friends with each other. In such cases, accounting for networks in isolation can lead to incomplete understanding of network structure and its effects. Accounting for relationships that provide different things gives a richer and more complete understanding of the role of network structures. Further, overlap of connections through multiple relationships may strengthen the bond between individuals (Wellman and Wortley, 1990), and so change the effects of the separate links. Therefore, treating jointly the different networks in which individuals are involved will yield a holistic understanding of social networks, the nature of their flows and their aggregate impacts.

While it is important to account for multiple relationships and their interplay, the data at this level is limited. For instance, the study by Van den Broeck and Dercon (2011) which is close in spirit to our own study, quantified the effect of social externalities on banana production in Tanzania by considering information flows from kinship, neighbours and informal insurance networks. But they considered only the independent effect of these networks on productivity, disregarding the natural overlap and interaction of social connections and its flows. To address this gap, Cai et al. (2018) introduced a framework of network structure that can incorporate interconnections across multiple relationships to create a single composite multiplex network. We employ this framework to investigate the aggregated effect of the interaction of multiple networks at the individual level on agricultural productivity, accounting for the relative importance of each relationship.

In this study, we investigate the role of social networks on rice productivity by using unique primary data that provides information on multiple networks. Our data contains a full census of three villages with rice production details in two time periods. With these data, we are able to tackle three methodological problems that are common in network studies. Firstly, in the absence of full network data, wherein links between specific pairs of agents would be recorded, authors often use a proxy, inferring a direct, personal link between pairs of people who belong to the same community or village for example. Second, even when detailed network data are available, very often they include only one type of connection between agents, when in fact, in any setting there are typically several types of links that might join pairs of agents.

We address these shortcomings through precise, detailed network data for the entire population that helps to capture the relevant networks. In addition, by using multiple networks and the interaction of connections between different networks we account for the complex nature of interaction and its aggregate effect. This is largely missing in the literature. The third issue we address is endogeneity, which we tackle by using directed networks and the instrumental variable procedure of Lewbel (2012).

Our results confirm the presence of overlap of connections among the farmer households between different kinds of relationships. Focusing on the individual network effects, a farmer's rice productivity is positively influenced by his or her degree[4] in the information network. Credit and friendship networks exhibit non-significant effects on production. Our results on *individual* networks are consistent with the results from most studies which typically consider (only) the information or learning networks as a proxy for social interaction in agriculture. However, the results when we treat the three networks as one multiplex network show that productivity is jointly affected by all the networks. In other words, it shows that certain networks (friendship and credit) which seem irrelevant when treated individually exhibit influence when considered jointly with other networks. In addition, we found evidence for the mediating role of interpersonal relationships (friendship) on enhancing the effect of information flow.

The rest of the paper is organised as follows. Section 2 presents the description of sampling and methods used. Section 3 describes the results. In Section 4 we discuss its implications and concluding remarks.

[4] An agent's "degree" is defined as the number of direct connections he or she has in the network (colloquially, the number of friends you have).

2 Sampling and Methods

2.1 Data collection

Our data constitute cross-sections from three Indian villages. The data was collected in 2016 from the villages Taraboisassan, Kanijpur and Kunarpur in Odisha state, as part of the Small Farmers Large Field (SFLF) project's baseline survey by the International Rice Research Institute (IRRI), India.[5] The unit of our analysis is a household. The information on social networks, agricultural production activities and socioeconomic characteristics were collected from the entire population of the three villages and therefore, our data constitute a full census of households. In the context of network analysis, population data are more reliable than samples in capturing the complex relationships within the true network structure (Costenbader and Valente, 2003; Lee et al., 2006). Agriculture production data was collected concurrently for 2016 and retrospectively for the 2015.

The network data was gathered at the household level and it consists of three different types of interactions: the agriculture information network which represents each household's informal agricultural information sources; the friendship network that includes the individuals who are personally close to the household; and the credit network representing informal credit sources. All these are the self-reported intra-village social networks, and all the networks involve the same households. All surveyed households were asked to mention a maximum of five members that they are related to in each network.[6] For each network link the information on the direction of the network flow was also collected. Credit network captures only the potential sources of credit for each member and not the actual borrowing. However, it does capture the ease with which borrowing could occur. The survey questions used to build the networks are presented in Table 1.

[5] This project is designed to allow small and marginal rice growing farmers to benefit from economies of scale (reduced cost of inputs and machinery use for example), by pooling their small farms into large fields of 50-500 hectares (Mohanty et al., 2018). Our study is part of the collaboration with IRRI to understand the role of social networks in the project villages.

[6] The limit of the network members was introduced to capture only the most relevant ties in each network. In this we follow Banerjee et al. (2013) - in their study on the information diffusion of micro-finance also used a limit of 5 to 8 network neighbours.

Table 1: Survey questions on networks

Networks	Description of questions
Information	Who provides you the information regarding public programs, agricultural technologies, inputs, loans, insurance, subsidies and training programs?
Credit	Who are the people you think you can borrow money from (less than INR 1000)?
Friendship	Who do you go with visiting places of worship, attending local festivals, marriages, procuring ration?

The data obtained from the above questions provide information on the network flow directed towards each individual household, i.e., ties that are directed to a node. Therefore, the network structure that we build accounts for the directionality of the links. Further details on the network building are described in the next section.

2.2 Network Framework

We define three networks for each village. In the context of a single village, in all networks the set of vertices V, is the set of households in the village. Each network is then defined by two sets: vertices and edges: $G^m = (V^m, E^m): m \in \{\alpha, \beta, \gamma\}$ for the information, credit, and friendship networks respectively. For estimation reasons, detailed in Section 2.3, we measure the inflow of network externalities that affect households unidirectionally (we exclude their feedback), creating a directed network. Thus, E^m is a set ordered pairs of nodes (v_i, v_j), representing a flow from i to j, $v_i \to v_j$. Each network has a corresponding adjacency matrix A^m whose entries are defined as $a_{ij}^m = \{1 \; if \; (v_i^m, v_j^m): (i \neq j) \in E_m, 0 \; otherwise\}$.

To study the joint effects of direct resource exchange from multiple networks, we measure the degree centrality that characterizes immediate interactions between households within a village.[7] This measure indicates the social position or influence, i.e., how well a household is connected in terms of direct connections with other households (Butts et al., 2008; Jackson, 2010). Since we are interested in the in-flow of the networks, we measure in-degree for each household, indicating the volume of

[7] We are aware of the applicability of other centrality measures such as eigenvector and betweenness centrality. However, the interest of our study lies on estimating the marginal effect of an additional direct connection in a multiplex space and not from different positions in the network structure. The potential benefits from network structural positions (for instance, reach, betweenness or eigenvector centrality) is thus less relevant for the current study.

ties directed towards a household. In our study, a household with higher in-degree represents a well-connected household who potentially receives higher information or resources from other households. As a first step, we measure the degree centrality independently for each network G^m. Concretely, we estimate the in-degree (d_j^m)of each household for all three networks as the sum of the rows for each column in A^m.

$$d_j^m = \sum_i A_{ij}^m$$

To study the multiple connections, we use a multiplex network in which a fixed set of nodes (V set of households) are interconnected by different types of links. In our case, it represents interconnections among households across three different relationships, the information, credit, and friendship networks, respectively. Formally, we define the multiplex as a set $M = \{v_i, v_j, l_m\}$ of triplets that contains pairs of farming households (v_i, v_j) and a third element that represents the link or type of connection from a set of layers: $l_m \in L = \{l_\alpha, l_\beta, l_\gamma\}$.

Following Boccaletti et al. (2014) we define a multiplex network as a supra-adjacency or block matrix whose off-diagonal blocks are identity matrices I_n of size *n*, and diagonal blocks are adjacency matrices A^m for each network in N. Our sample size is $n = |\cup_{i \in m} V_i|$. This matrix helps to simultaneously capture the interaction of households within and across different networks. From this matrix we elicit a multiplex degree for each household that represents an individual's position considering his or her connections across multiple networks.

$$A^{Multiplex} = \begin{pmatrix} A^\alpha & I_n & I_n \\ I_n & A^\beta & I_n \\ I_n & I_n & A^\gamma \end{pmatrix}$$

The multiplex degree that we obtain from the above block matrix gives by default equal importance to connections in all networks, i.e., every connection carries equal weight. We must consider the possibility though, that in a given context different types of connections can be more or less important. Therefore, to incorporate the relative importance of connections in each network G^m and across networks and estimate its effect on agricultural productivity, we calculate a set of weights. Following Cai et al. (2018), we define weights from equation 1 where r^θ are the *r*-squared values of a univariate regression analysis taking the in-degree of each network N as explanatory variable for agricultural productivity.

$$w^{\alpha\beta} = \frac{r^{\alpha} r^{\beta}}{\sum\limits_{\theta \in m} (r^{\theta})^2} \tag{1}$$

Fourthly, we define a *weighted* multiplex network as a block matrix where the vectors of corresponding weights w^{ij} are multiplied to the respective elements in the matrix.

$$A_w^{Multiplex} = \begin{pmatrix} w^{\alpha\alpha} A^{\alpha} & w^{\alpha\beta} I_n & w^{\alpha\gamma} I_n \\ w^{\beta\alpha} I_n & w^{\beta\beta} A^{\beta} & w^{\beta\gamma} I_n \\ w^{\gamma\alpha} I_n & w^{\gamma\beta} I_n & w^{\gamma\gamma} A^{\gamma} \end{pmatrix}$$

From $A^{Multiplex}$ and $A_w^{Multiplex}$, the unweighted and weighted multiplex degrees of each household respectively is aggregated by the following equation (Cai et al., 2018).

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

Where, k_j is the multiplex degree that is derived for each individual from the block matrix that contains m layers (types) of connections among the N households.

The essence of our study is to understand the effect of interaction and overlap of multiple social connections on agricultural productivity. The multiplex degree that we estimated accounts for the interaction of households across different networks. The simple multiplex degree hides information however: suppose the degree of node j is 3, it could be that j is connected to k in three different networks (or layers of the multiplex network) or that j is connected to three different agents, each in a different (or the same) layer. Connection "overlap" between layers could be important. For example, the connection between two households is stronger, and thus possibly lending efficacy to any of the individual connections, if they are linked through multiple relationships such as sharing information, providing credit, and being friends. To capture the effect of such connection (tie) strength in the multiplex framework, we adapt Jaccard index or similarity index. This index measures the similarity of connections between different networks. In other words, it indicates the extent of common links out of total links across all networks.

We define the open neighbourhood of a vertex as $VG_m(v_i) = \{v_i \in V_m \mid (v_i, v_j) \in E_m\}$ from which the similarity index for the multiplex is given by

$$S(v_i) = |m|^{-1} \sum_{k \neq p \in m} \frac{|\nu_{G_k}(v_i) \cap \nu_{G_p}(v_i)|}{|\nu_{G_k}(v_i) \cup \nu_{G_p}(v_i)|} \tag{3}$$

Similarly, we construct two other similarity indices to account for the role of interpersonal relationships in facilitating the exchange of information and credit. That is, we construct a similarity index of the friendship network with the information network and with the credit network. In total, we have constructed three similarity indices for each household.

2.3 Econometric Framework

In this section, we ask which aspects of the multiplex network are important for determining productivity among rice farmers in Odisha. Most importantly, we first treat each network independently, but then examine their joint effect using the multiplex structure we have just described.

To answer this, we model farmer's output (production per acre) using a standard Cobb-Douglas (C-D) production function. The C-D production function is the most commonly used functional form to explain agricultural productivity (Bravo-Ureta et al., 2020; Van den Broeck and Dercon, 2011). In addition, with the introduction of network analysis to agricultural productivity, there is now growing evidence that the relationship between degree centrality and performance is also non-linear (Badar et al., 2015).

The specific form we use is:

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

where, y_t is output per acre, D_k is the degree of the farmer capturing network effects, X is a vector of inputs, K is a vector of observable individual characteristics and F is a vector of neighbourhood characteristics including the average productivity of neighbours in the previous period. From equation 4, the variables of interest are the in-degree $D = \{D_1, D_2, D_3, D_4\}$ of the information, credit, friendship, and multiplex (weighted and unweighted) networks. If there exist social network effects, then we expect the coefficients of degree (β) to be positive and significant.

Identifying social network effects is not straightforward as it involves several econometric challenges, and we address three of those in our analysis. Firstly, *the simultaneity problem (Reverse causality)*: There often exists simultaneity in the relationship between an individual's productivity and the number of individuals directly connected to him (degree of his network). For example, a farmer's productivity may increase with the number of direct connections he has because it provides him a larger pool of potential information sources. On the other hand, high productivity farmers are most likely to be contacted by other farmers (eg: for information or credit). We tackle this problem using directed networks and specifically the in-degree of households. Section 2.1 presents the questions that we used to build the networks and all the questions provide information with the direction of flow of factors. For example, in the information network, the question specifically indicated where the information comes from (or who gives the information). In this case, the number of farmers (households) from whom the information is received is less likely to depend on the productivity of the receiving farmer.[8] Similar logic applies to the credit 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. Productivity and network formation could be affected by common unobserved factors. For instance, individuals can choose peers based on similar characteristics such as age, caste, gender, etc. that could also explain their agriculture outcomes. This is generally addressed using the instrumental variable (IV) approach. We did not find good instruments for our network variables that satisfy the exclusion restriction condition. Therefore, we address this issue by following Lewbel (2012)'s IV approach in which it identifies and estimates the endogenous regressor model using heteroscedasticity present in the auxiliary equation (equation for degree centrality of social networks). A Breush-Pagan test (Breusch and Pagan, 1979) confirms the presence of heteroscedasticity in our models for social networks. The Lewbel IV method can be used in the absence of external IVs and also in combination with external IVs (Chau et al., 2017; Gutmann et al., 2020; Kelly and Markowitz, 2009; Mozhaeva et al., 2019; Shahe Emran and Shilpi, 2012). Here the instruments are generated by using the variables that are in the productivity (main) equation (excluding endogenous variables).[9] Therefore, we specify our linear triangular model as,

[8] One may question that a household's in-degree could be related to his/her previous season's productivity. To test this, we check correlation between in-degree of the information network and productivity of households in the previous season and found it is weak and insignificant.

[9] We implemented Lewbel's IV approach using the Stata command ivreg2h developed by Baum and Schaffer (2012)

$$log(y_t) = \alpha_1 + \beta_1 log(D_k) + \Gamma_1 log(X) + \delta_1 log(K) + \eta_1 log(F) + \epsilon_1 \quad (5)$$

$$log(D_k) = \alpha_2 + \Gamma_2 log(X) + \delta_2 log(K) + \eta_2 log(F) + \epsilon_2 \quad (6)$$

This IV procedure uses $(Z_k - \overline{Z_k})\varepsilon_2$ as the identifying instruments where Z is the vector of all the explanatory variables X, K and F (both continuous and discrete) in equation 6. Lewbel demonstrates that this instrument identifies the endogenous regressor models when $Cov(Z, \varepsilon_2^2) \neq 0$ and $Cov(Z, \varepsilon_1\varepsilon_2) = 0$.

Third, estimating the joint effect of multiple social networks is challenging econometrically for two reasons. The first is due to correlation between these networks since they represent links between the same set of people. The respondents in the survey were asked to name a maximum of five people that they are connected in each of three networks, and we expect high correlation in their estimated degree. Secondly, classical econometric ways of interacting the degrees of different networks leads to the problem of inference of the joint variable as the degrees are measured in a continuous scale, and also the problem of correlation across all the individual networks. We address this issue by employing the multiplex network framework (Cai et al., 2018) which helps in constructing one large network using all three different networks. That is, a composite network measure is used to overcome the inference problem of joint effect of different networks on productivity.

In addition to addressing the aforementioned concerns, we also account for the quality of the networks by using lagged average productivity of the household's neighbourhood in equation 4.

Overall, we combine both econometric procedures (IV) and network methods (Directed in-degree) along with detailed network data to tackle the problem of identification of social network effects.

3 Results

3.1 Descriptive statistics of sampled households

Table 2 provides the summary statistics of our sample households. Our respondents are household heads (the person who makes decisions about agriculture production), and all individual characteristics described here pertain to them. Most of our respondents are male with an average age of about 51 years, and with 8 years of education. There is a fair amount of social heterogeneity in our sample with the majority (67.1%) of them belonging to Other Backward Castes followed by General (Upper) Castes (21.7%) and Scheduled (Lower) Castes (11.2%).[10]

Table 2: Descriptive statistics

	n	Mean	Std. Dev	Min	Max
Dependent					
Productivity (kg/acre)	256	1822.31	337.01	1000	2875
Independent					
Degree centrality (Directed)					
Information network	152	1.23	0.49	1	4
Credit network	164	1.09	0.33	1	3
Friendship network	152	1.22	0.51	1	4
Multiplex (Unweighted)	256	8.15	1.06	7	13
Multiplex (Weighted)	256	0.04	0.04	0	0.20
Individual characteristics					
Age (years)	256	50.58	11.94	20	82
Gender	256	1.96	0.19	1	2
(Female=1; Male=2)					
Education (years)	256	7.85	3.29	1	16
Caste	256	0.89	0.56	0	2
(General=0, *OBC*[1]=1, SC=2)	256	0.61	0.49	0	1
Production orientation					
(Consumption=0, Market=1)					
Inputs					
Seed type	256	1.07	0.36	1	3
(*HYV*[2]=1, Hybrid=2, Traditional=3)					
Seed quantity (Kg/acre)	256	22.26	3.54	10	33.33
Labour (hrs/acre)	256	237.47	98.46	33.75	772.5
Fertilizer (kg/acre)	256	118.09	31.31	0	245
Compost (loads/acre)	256	0.42	0.84	0	6.25
Land area (acre)	256	1.05	0.67	0.16	3.5

Note: [1]OBC – Other Backward Castes. [2]HYV– High Yielding Varieties.

The average rice productivity is 1822 kg per acre with most of the farmers (96.5%) using high yielding rice varieties with very few farmers using hybrids (less than 1%) and traditional varieties (2.7%). This indicates homogeneity of the type of seeds used for production. The average land holding is about one acre, indicating the prominence of marginal farmers. 61% of our sampled households produce rice mainly for market sales and we define it with a variable "production orientation". If a household sells more than 50 percent of what he/she produced we consider his production as market

[10] Caste is a system of the social hierarchy followed in India. The caste of an individual is determined by his/her birth and is unchangeable. The castes which are at the top of the hierarchy are called General castes, and the one at the bottom of the hierarchy are Scheduled Castes (SC and ST) with Other backward castes (OBC) occupying the middle space. An individual's caste, therefore, determines his social status.

oriented, and self-consumption otherwise. It indicates the motivation of households' production. The average (in-)degree for all the three networks viz., information network, friendship network and credit network are below 1.23 indicating there are fewer than two agriculture informants, friends and credit providers for every household.

The number of observations in the individual networks are different from each other [*n(info)*= 152; *n(credit)*=164; *n(friendship)*=152] and less than the multiplex network (256) because we only included members who have a degree of at least 1 in the individual networks for the regression analysis. If a household has zero degree in a network, it can mean one of two things: either it is completely isolated in that network, or it has only "out-degree", that is, in the information network for example, it only gives information but never asks for it. Thus, regarding effects on productivity, zero in-degree has opposite implications: on the one hand it would be correlated with low degree because the farmer has no source of information about how to increase productivity; but on the other hand it would be correlated with high productivity because the farmer has a high knowledge level, (which drives high productivity), and so is a source of information but never needs to ask. Because of this discontinuity, and double effect at degree zero, for the multiplex network we include members who have at least one link in any one of the networks and drop members who have no links in any network.[11]

3.2 Network Correlations

As all our networks are obtained from the same population, we expect our households to have multiple types of connections among themselves. That is, there is a likelihood to have links between the same two nodes (households) in different networks. We measure that in Table 3 which presents the dyadic correlation across all the three networks obtained by a Quadratic Assignment Procedure (QAP)[12] (Krackardt, 1987). QAP calculates the correlation between two adjacency matrices (two networks) by

[11] Because of the ambiguity in the implication of zero degree, we drop households with zero in-degree from our regression analysis. But they are included in constructing network-based variables as dropping them completely will bias the estimation of social network effect as it would alter the degree centrality of other nodes who have them in their neighbourhood.

[12] QAP helps to examine the similarity of network structure among social networks. Since all three networks are formed among the same set of people, we expect the links between individuals to be nested and embedded, thus violating the assumption of statistical independence of observation to carry out the conventional correlation analysis. Therefore, QAP - a variant of conventional correlation analysis serves as a better measure of correlation in social networks analysis (Moolenaar et al., 2012; Raider and Krackhardt, 2017).

comparing each element in those matrices. Correlations are obtained and presented village-wise, as our networks are bounded by the village. Village 1 shows a significant dyadic correlation of 0.12 between the information and friendship networks, meaning that if two households are connected by information network, they are more 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 magnitude of coefficients indicate that the correlations are weak.

Table 3: QAP correlation for individual social networks

Correlation between households' social networks in village 1			
Networks	Information	Friendship	Credit
Information	1.00***	0.12***	-0.013
Friendship	0.12***	1.00***	-0.014
Credit	-0.013	-0.014	1.00***
Correlation between households' social networks in village 2			
Networks	Information	Friendship	Credit
Information	1.00***	0.0003	-0.005
Friendship	0.0003	1.00***	-0.005
Credit	-0.005	-0.005	1.00***
Correlation between households' social networks in village 3			
Networks	Information	Friendship	Credit
Information	1.00***	0.03	0.22***
Friendship	0.03	1.00***	0.04
Credit	0.22***	0.04	1.00***

Note: ***, **, * indicate significance at 1%, 5% and 10% respectively.

High correlation indicates higher overlap between different layers (networks) and thus it may make those layers redundant or uninformative in attempts to understand the structure of the system and to explain its effects on agricultural outcomes. In such cases, one can aggregate those layers and only keep distinct layers for building the multiplex network, which allows for the better characterization of the complex network and its functioning (De Domenico et al., 2015). Given that all our three individual networks (layers) have very low correlation, we consider them as distinct layers and build the multiplex network accordingly.

3.3 Regression Output

The estimation of social network effects on rice productivity are performed for individual and multiplex networks separately following equation 4. We begin with the estimation of individual network effects and then proceed to multiplex networks. All regression models account for neighbourhood characteristics such as average age and average education; the individual specific characteristics such as age, education, gender, caste, and orientation of production. Among inputs, we have controlled for the use of fertilisers, compost (organic manure), labour hours, seeds and machinery. We have also accounted for the village fixed effects (See Table A1 in the Annex for the description of all the variables). All estimations are from IV regressions using the Cobb-Douglas production function.

3.3.1 Individual networks and productivity

Table 4 presents the estimation results for the effect of individual social networks on rice productivity. Our analysis for the individual networks involves households who have at least one network link ($D_k \geq 1$) in the respective networks. Regression models 1, 2 and 3 provide estimations for the information, credit and friendship networks respectively, while 4 and 5 present estimations for the information and credit networks taking into account their respective overlaps with the friendship network. The significance of the F test for instruments for all the estimations indicates that the generated instruments are relevant. The test for overidentification is insignificant indicating the productivity model is not over-identified. The weak identification test shows the Cragg-Donald Wald F statistic of 9.54, 37.25, 13.00, 9.62 and 35.69 for regressions 1 to 5 respectively which is more than the Stock-Yogo critical value at 10 percent for all the regressions except for the models with information network (models 1 and 4). This suggests that the generated instruments are strong and relevant for the models 2, 3, and 5. Given that the generated instruments for the information network are relevant but weak, we test for the weak instrument robustness inference using Anderson-Rubin Wald test. We obtained the *p* value of less than 0.01 which indicates that it is robust for the presence of weak instruments.

The information network shows a significant and positive effect on productivity, while the credit and the friendship networks show negative but insignificant effects. In a C-D production function the coefficients can be interpreted as elasticities and thus a 10 percent increase of degree in the information network will increase rice productivity by more than 1 percent. The effect size is similar for the credit network though it is negative and insignificant. We will come back to this point below.

Table 4: Effect of individual networks on agricultural productivity (C-D production function)

Dependent Variable: Productivity	1 Information	2 Credit	3 Friendship	4 Information	5 Credit
In-Degree	0.101**	-0.111	-0.0714	0.103**	-0.104
	(0.0479)	(0.0698)	(0.0531)	(0.0433)	(0.0714)
Similarity Index[a]				0.363***	0.0697
				(0.125)	(0.115)
Neighbourhood characteristics					
Avg. productivity (in t-1)	0.00003	0.0255***	0.00592	0.00522	0.0244**
	(0.0113)	(0.00960)	(0.00779)	(0.0112)	(0.00992)
Avg. Education (years)	0.0306	-0.0533	0.00562	0.0275	-0.0521
	(0.0351)	(0.0350)	(0.0237)	(0.0346)	(0.0348)
Avg. Age (years)	-0.0280	-0.0113	-0.0812**	-0.0362	-0.0113
	(0.0412)	(0.0311)	(0.0325)	(0.0398)	(0.0310)
Individual characteristics[b]					
Production orientation (Market=1, Self-consumption=0)	0.0616**	0.0918***	0.100***	0.0589**	0.0905***
	(0.0259)	(0.0288)	(0.0308)	(0.0244)	(0.0293)
Inputs					
Land size[c]					
1-1.99 Acre	0.0130	-0.0229	-0.0294	0.0182	-0.0221
	(0.0293)	(0.0322)	(0.0311)	(0.0280)	(0.0324)
2-4 Acre	-0.0530	-0.0384	-0.0335	-0.0459	-0.0386
	(0.0468)	(0.0438)	(0.0449)	(0.0460)	(0.0439)
Fertiliser (kgs)	0.0101	0.0914***	0.103***	0.00453	0.0910***
	(0.0264)	(0.0173)	(0.0181)	(0.0252)	(0.0174)
Labour (hours)	0.0306	0.0102	0.0344	0.0287	0.0127
	(0.0230)	(0.0278)	(0.0340)	(0.0232)	(0.0285)
Seeds (kgs)	0.0447	0.0323	0.0627	0.0559	0.0258
	(0.0858)	(0.0832)	(0.0732)	(0.0842)	(0.0859)
Machine use[d]	0.473*	0.866***	0.808***	0.395*	0.848***
	(0.242)	(0.237)	(0.234)	(0.225)	(0.246)
Compost (loads)	0.0146	-0.0043	0.0308	0.0129	-0.00506
	(0.0310)	(0.0320)	(0.0311)	(0.0308)	(0.0320)
Village FE	Yes	Yes	Yes	Yes	Yes
Constant	6.957***	6.084***	6.250***	7.039***	6.109***
	(0.377)	(0.451)	(0.507)	(0.365)	(0.459)
Observations	152	164	152	152	164
R-squared	0.225	0.351	0.429	0.266	0.352
F test for instruments	11.98***	24.67***	12.25***	15.79***	28.53***
Test for over-identification[e] (p value)	0.18	0.42	0.66	0.31	0.45

Note: ***, **, * indicate significance at 1%, 5% and 10% respectively. All the continuous variables are in their log forms. Coefficients are obtained from Lewbel (2012)'s instrumental variable regressions. Productivity (kgs), fertiliser, labour, seeds and compost are accounted as quantities per acre. [a]For information and credit networks this index is calculated by only considering their respective intersection with friendship network. [b]Included few more regressors, but not presented in the table. See the Annexure Table A2 for complete results. [c]Base category is less than one acre. [d]Ratio of number of mechanised activities out of total number of activities. [e]Hansen's J-test. Robust standard errors in the parentheses.

As discussed in the beginning, friendship or interpersonal relationships are only likely to be useful for the production process if they carry knowledge or resources. Interpersonal relationships facilitate the exchange of knowledge and resources from other networks. We test this by including similarity indices for both the information network (ratio of common connections between the friendship and the information networks to the total connections in both) and the credit network (ratio of common connections between the friendship and the credit networks to the total connections in both) which captures the mediating effect of friendship on the flow of information and credit. In regression models 4 and 5 we can see that the similarity index shows a positive relationship with productivity for both the information and credit networks. However, it is significant only for the information network with the effect size 0.36. It implies that for a 10 percent increase in the similarity index productivity increases by 3.6 percent. The effect size is over three times that of the degree of the information network.

Similarity between credit and friendship networks has a positive (though insignificant) effect on productivity. Credit itself has a negative, or possibly null effect. It is important to recall that the credit network does not indicate actual borrowing activity (use of credit facilities) but rather potential creditors.[13] Therefore, the null effect of credit degree might be due to the possibility that not many households managed to receive credit from their links, though in need. This could be due to the possibility that the credit links in general are not always resourceful as these links are just other farming households but not professional money lenders. Therefore, even if the creditors are friends, it did not significantly influence the production of the household (thought the sign is positive).

Among neighborhood characteristics, the lagged average productivity of network members has a positive effect on productivity for all individual networks but is significant only for the credit network. The coefficient implies that if the past productivity of the household from whom one might take credit increases by 10 percent, then the current season's productivity increases by 0.24 percent. One explanation is that higher past productivity of one's (credit) neighbours implies that

[13] It is possible that some households may have borrowed (at least once) from these nominated creditors (which might have prompted them to name them), however we do not have information on their actual borrowing activities.

they have more resources and therefore there is a higher chance that they have actually lent the credit which translates into higher productivity for the focal (borrowing) farmer. Furthermore, Manski (1993) recommends accounting for exogenous neighborhood characteristics to verify if there exist any contextual effects. Accordingly, we controlled for age and education of network members but mostly found non-significant effects except for the average age which showed significantly negative effects for the friendship network. Friends can act as informants, credit providers or facilitators of any such transactions. In addition, friends also act as providers of labour especially during the scarce periods. Anecdotal evidence from interviewing the key informants in those villages suggests that the interpersonal relationships play a crucial role in accessing technologies (hiring agriculture machines for example), and labourers during the peak harvest periods of rice production. Given that young tend to be more innovative (Hamilton et al., 2015), a negative coefficient reflects a weak support system for production as aged farmers might be less up to date with novel technologies or it might be difficult for them to support as laborers in the critical periods of production, thus affecting productivity negatively.

3.3.2 Multiplex network and productivity

Table 5 displays the results for the effect of multiplex network on productivity. As in the analysis of individual networks, we estimate the causal effect using Lewbel's IV regression. A household that has a link at least in one of the three networks is considered for the multiplex regression analysis. The estimation of the joint effect of all three networks is presented in regression models 6 and 7 for the weighted and unweighted multiplex degree measures, respectively. The F test for the instruments is significant in both models, indicating the relevance of the generated instruments. Hansen's J test for the over-identification is non-significant indicating that the models are not over-identified. Similarly, the test for weak identification is significant for both regressions suggesting the strength of generated instruments.

The results show that both weighted and unweighted degree measures have significant and positive effect on productivity with the effect of weighted measure being larger and more significant than the unweighted measure: better connected farmers have higher productivity. The coefficients carry similar interpretations (elasticities) as in previous cases. The significant effect indicates the importance of assessing the network effect by accounting for multiple connections. That is, multiplex networks allow us to exploit correlations and interactions of households across different networks (layers) which is not possible in the analysis of single layers taken in isolation. Therefore, it extends our understanding of the role of different networks on productivity.

Table 5: Multiplex networks and agricultural productivity (C-D production function)

Dependent Variable: Productivity	6 Multiplex (Weighted)	7 Multiplex (Unweighted)
In-Degree	1.452*** (0.402)	0.307* (0.162)
Similarity Index[a]	0.148 (0.110)	0.0948 (0.106)
Neighbourhood characteristics		
Avg. productivity (in t-1)	0.00951 (0.0214)	0.0155 (0.0204)
Avg. Education (years)	0.00964 (0.0296)	0.0451 (0.0304)
Avg. Age (years)	-0.0271 (0.0410)	-0.0569 (0.0403)
Individual characteristics[b]		
Production orientation	0.0726***	0.0757***
(Market=1, Self-consumption=0)	(0.0227)	(0.0232)
Inputs		
Land size[c]		
1-1.99 Acre	-0.00646 (0.0249)	-0.00770 (0.0275)
2-4 Acre	-0.00520 (0.0367)	-0.00939 (0.0383)
Fertiliser (kgs)	0.0455* (0.0271)	0.0471 (0.0340)
Labour (hours)	0.0476** (0.0229)	0.0520** (0.0236)
Seeds (kgs)	0.0891 (0.0660)	0.0720 (0.0720)
Machine use[d]	0.778*** (0.189)	0.788*** (0.196)
Compost (loads)	0.0335 (0.0268)	0.0218 (0.0261)
Village FE	Yes	Yes
Constant	6.155*** (0.341)	5.543*** (0.492)
Observations	256	256
R-squared	0.300	0.271
F test for instruments	15.46***	9.93***
Test for over-identification[e] (p value)	0.39	0.18

***, **, * indicate significance at 1%, 5% and 10% respectively. All the continuous variables are in their log forms. Coefficients are obtained from Lewbel (2012)'s instrumental variable regressions. Productivity (kgs), fertiliser, labour, seeds and compost are accounted as quantities per acre. [a]This index is calculated by the ratio of intersection to the union of connections across all three networks. [b]Included few more regressors, but not presented in the table. See Table A3 in the Annex for complete results. [c]Base category is less than one acre. [d]*Ratio* of number of mechanised activities out of total number of activities. [e]Hansen's J-test. Robust standard errors in the parentheses.

The higher significance of weighted multiplex degree indicates the need to account for the relative importance of different relationships to explain productivity.[14] The positive coefficient signifies the complementarity between interaction of households across different networks and the factors they carry.[15] As the multiplex networks also encompass the overlap of connections across different networks, we include this effect with another similarity index. Here the similarity index is the ratio of number of common links from all three networks out of total number of links in the network which is measured for each household. The coefficient for similarity index is positive, however, not statistically significant for both weighted and unweighted multiplex measures. An increase in productivity for the higher level of this index can be explained by the following example. Let us imagine that a farmer has taken some credit from his friend, and he also asks for some information related to agriculture activities like information on rice hybrids, pest management, fertiliser application etc. In this case, the farmer giving credit has a strong incentive to provide relevant or good information for two reasons. First, to safeguard the reputation of friendly relationship with the asking farmer. Second, to safeguard the credit provided. That is, if he provides poor information to his friend, it might affect the production and thus the repayment capacity of the credit received farmer. These things reinforce each other and thus affect productivity positively. The lack of significance might be due to the null effect of similarity between credit and friendship network seen in the separate equations in Table 4. Among neighborhood characteristics, we did not find any significant effects. For further discussions on other variables, in the sections that follow, we follow the regression output for the weighted multiplex measure.

Lastly, we also report in Table A4 in the Annex, the results of the productivity model for the weighted multiplex network by only including households who have links in all three networks. It is to test whether there exists any bias due to including households who have a link at least in one of the networks. The regression model is over-identified due to a relatively smaller sample size for the generated instruments. Therefore, we only consider the sign of in-degree coefficient for our interpretation.

[14] The weights calculated for the construction of multiplex degree are as follows. $w^{\alpha\alpha}=0.05$; $w^{\beta\beta}=0.95$; $w^{\gamma\gamma}=0.0000025$; $w^{\alpha\beta}=0.22$; $w^{\alpha\gamma}=0.0004$; $w^{\beta\gamma}=0.002$.

[15] We cannot directly compare the effect sizes of the degree between the individual networks and the weighted multiplex network because the measurement units are different (Weighted multiplex degree is measured in decimals and the individual networks are measured in integers).

The results from the sub-sample analysis are qualitatively similar to the main analysis, suggesting no bias introduced due to our selection criteria.

3.3.3 Socio-economic factors and inputs

Among individual characteristics, years of education has a positive and significant effect with the coefficient of 0.0586 (see Table A3 in the Annex). Education improves productivity through increased knowledge, and higher ability to process available information. Another variable, production orientation,[16] also exhibits positive and significant effect. It implies that if the household is market oriented (that is, it sells at least 50 percent of what he produces) then its productivity is higher than one that produces mainly for self-consumption. This variable may proxy for the motivation or desire to produce. Even those with better access to knowledge and resources from their social networks a lack of motivation for market sales may adversely affect productivity. One might expect that market-oriented farmers are more entrepreneurial and thus more innovative. For instance, market sales are generally exposed to price risks and therefore to offset its effects, market-oriented farmers are more likely to work hard, pro-actively learn and adopt or make productivity-enhancing innovations. Among inputs, fertilisers, labour, and machinery use have the expected positive influence on productivity. Also, consistent with other studies though not significant, productivity decreases with land size.

Finally, we revisit the credit network and examine for the possibility of an alternative explanation for its negative but null results. Credit network centrality could be affected by productivity through wealth. That is, a less productive farmer (so probably poor) is likely to have more links in the credit network as he is most likely to depend on others for resources and which is why we have a negative coefficient. By contrast, a high productivity farmer (so probably rich) might have many links in the credit network as credit providers may trust him given his repayment capacity. Although both these arguments are plausible and cancel out each other, we test to ensure that there is no such effect. Since we have already accounted for endogeneity using directed networks and IV regression (takes into account self-selection issues), we test for the correlation between access to credit (in-degree) and wealth using land-size as a proxy. The result showed a small and non-significant correlation. Moreover,

[16] We reiterate the definition of this variable: If a household consumes more than 50 percent of rice produced, it is considered as self-consumption and if less than 50 percent is consumed, it is considered as market oriented.

we also re-run our analysis by removing wealthy farmers and found similar results and therefore reject our wealth proposition.

4 Discussion and Conclusions

The role of social networks in agricultural development have received much attention in the literature. However, there are ongoing discussions about how data can be collected effectively to capture social interactions from networks (Bandiera and Rasul, 2006; Banerjee et al., 2013; Maertens and Barrett, 2012; Van den Broeck and Dercon, 2011). However, most of these studies considered singular networks, disregarding the existence of multiple networks, or considered multiple networks in isolation, disregarding interconnections across different networks. We address this gap by using a multiplex framework that incorporates the interconnections among households across networks. It was possible only due to the availability of a rich census data of rice farming households from Odisha, India that included information about three different types of networks (information, credit and friendship networks) including information on the direction of the network flows, as well as further household characteristics.

Our econometric analysis generated several results. First, among the three networks considered individually, only the information network is found to influence rice productivity. This shows that households who have direct links with a higher number of advisors (information providers) on agricultural matters benefit in terms of their production. This is in line with the consensus in the literature which assumes that social network effects on agriculture reflect information sharing or learning (Bandiera and Rasul, 2006; Conley and Christopher, 2001; Maertens and Barrett, 2012). However, by looking at networks separately, the absence of other networks' effects may tempt one to conclude that they are irrelevant, this may be too hasty.

Second, there are mediating effects of friendship. Interpersonal relationships are known to ease barriers of interaction among individuals. In our data, the friendship network has no direct influence on productivity, but we ask whether it might serve as a factor in effective utilization of other relationships, and we find that it does: the effect of a connection in the information network is made stronger if that connection also exists in the friendship network. This indicates the possibility of two things: in the first place, it reflects the importance of the strength of relationship (due to closeness or acquaintance) between households, and stronger relationships facilitate faster and more efficient flow of information. In the literature, strength of ties is generally measured through the frequency of contact between ties. Mere frequent contacts may not develop reciprocity, emotional intensity, and intimacy which are building blocks of tie strength (Marsden and Campbell, 1984). Our measure of friendship is based on closeness of ties and therefore, friendship ties may serve as a better proxy for capturing strength of ties compared to measures like frequency of contacts. Secondly, one can expect higher trust in such relationships and trust within a tie is thought to be a good proxy for the tie strength (Zagenczyk et al., 2015). Therefore, the trustworthiness of information or advice from a friend may be higher due to the potential ramifications on friendship dynamics had the advice gone wrong. This allows for the exchange of more credible and valuable information across ties. The social exchange of information and informal dissemination of agricultural technologies between friends are very common in rural areas (Matous et al., 2014), and given the strong social norms prevailing in the community such networks are valued highly (Magnan et al., 2015). For example, the majority of farmers in the study region rely on informal sources for seeds rather than the seed market or other formal sources or sale points. Such interpersonal relationships therefore can help in facilitating transfer of information and technological inputs with lower transaction costs.

Third, we examine the interaction of networks (or network multiplexity). Our estimations from the multiplex network suggests the presence of complementarity across all three networks which produces synergistic effects on rice productivity. It indicates that some networks which may not influence productivity independently show their effects when included jointly with other networks. Further, by using weights we account for the relative importance of each network on productivity, and this allows us to construct a multiplex network measure which captures more relevant information that we can derive from such complex interactions. Our analysis has defined different layers of the network based on what flows from household to household within a layer. This has permitted us to see how the different layers, or types of inter-household relations interact. Specifically, we have evidence for how friendship helps in enhancing the effect of information flow. A study by Matous et al. (2014) on how mobile technologies help individuals to better access information found that the links of information-communication and the links based on interpersonal relationships were intertwined. That is, different links were formed in a multiplex fashion. They therefore argue that the formation of knowledge sharing networks can be better modelled by including communication networks based on personal social relationships.

Further, capturing the complexity of social networks and its effects is a daunting task which not only requires better data but also good estimation techniques to address the challenges such as self-selection and simultaneity. We address them using a combination of econometric (IV regression) and network techniques (directed networks). The identification of causal effects and the application of multiplex networks provides a crucial input for the better and holistic representation and understanding of the role of social networks in influencing agriculture productivity. It also provides evidence for the existing potential channels for information and resource flows in villages. These channels are central to the success of introduction of innovations such as improved varieties, machinery, and other agricultural practices. Farmers in developing countries face several challenges due to weak institutional and technological developments threatening the productivity levels. Therefore, such networks not only help in improving productivity levels but also facilitate resilience through coordinated actions that yield higher overall benefits.

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A. Annexure Figures

Figure 1: Information Network

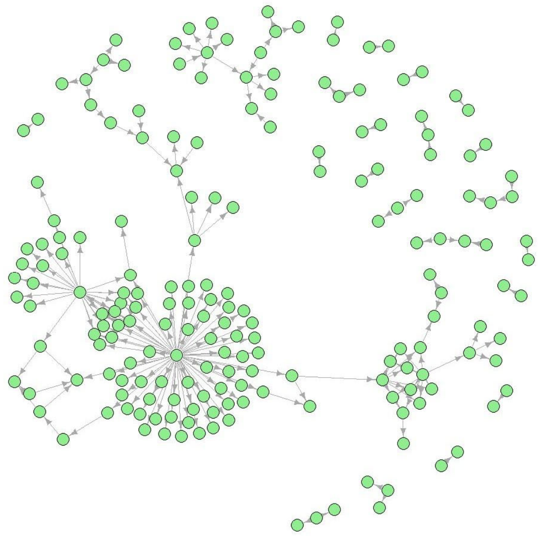


Figure 2: Credit Network

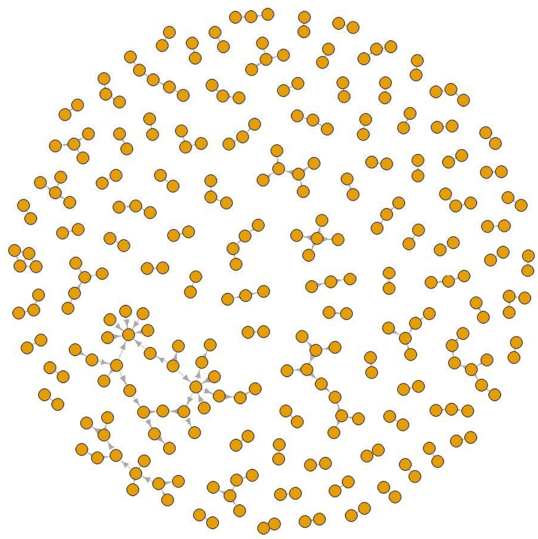


Figure 3: Friendship Network

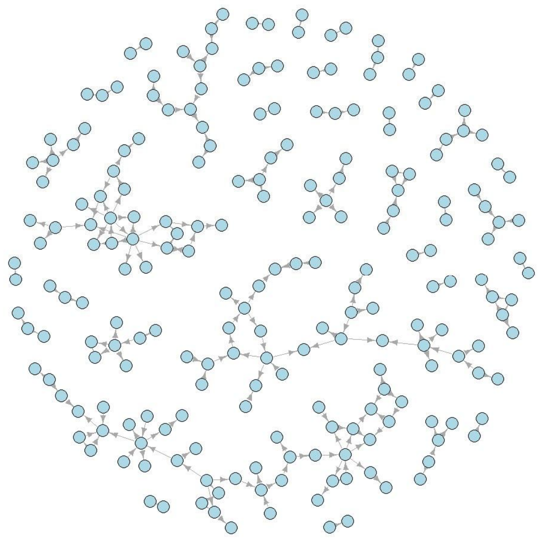
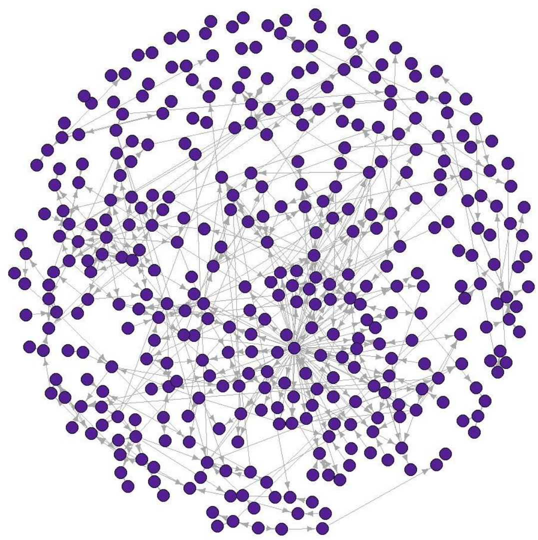


Figure 4: Multiplex Network



B Annexure Tables

Table A1: Description of variables

Variable	Description	Type
Productivity	Rice produced per acre by a household in kg per acre.	Continuous
Average productivity	Average productivity of a household's neighbourhood in kg per acre.	Continuous
Average education	Average years of schooling of a household's neighbourhood in years.	Continuous
Average age	Average age of a household's neighbourhood in years.	Continuous
Education	Number of years of schooling of the household head.	Continuous
Age	Age of the household head in years.	Continuous
Male	Gender of the household head (Female=0; Male=1).	Dummy
Caste	Caste of the household head (General Caste=0; Other Backward Caste=1; Scheduled caste=2).	Dummy
Production orientation	Share of total produced rice used for self-consumption and market sales. If a household consumes more than 50 percent of rice produced, it is considered as self-consumption (coded as 0) and if less than 50 percent is consumed, it is considered as market oriented (coded as 1).	Dummy
Land size	Area of land cultivated by the household in acres (<1 acre=0; 1-1.99 acre=1; 2-4 acre=2).	Dummy
Fertiliser	Total amount of fertilisers used (N, P, K) by the household in a cropping season in kgs.	Continuous
Labour	Total amount of labours used in hours by the household in a cropping season (family labour + hired labour).	Continuous
Seeds	Total quantity of seeds used by the household in a cropping season in kgs.	Continuous
Machine use	Ratio of number of mechanised activities out of total number of activities in a cropping season.	Continuous
Compost	Number of loads of compost (organic fertilizer) used by the household in a cropping season.	Continuous
Village	Village of the household head.	Dummy

Table A2: Effect of individual networks on agricultural productivity (C-D production function) – Full model

Dependent Variable: Productivity	1 Information	2 Credit	3 Friendship	4 Information	5 Credit
In-Degree	0.101**	-0.111	-0.0714	0.103**	-0.104
	(0.0479)	(0.0698)	(0.0531)	(0.0433)	(0.0714)
Similarity Index[a]				0.363***	0.0697
				(0.125)	(0.115)
Neighbourhood characteristics					
Avg. productivity (in t-1)	0.00003	0.0255***	0.00592	0.00522	0.0244**
	(0.0113)	(0.00960)	(0.00779)	(0.0112)	(0.00992)
Avg. Education (years)	0.0306	-0.0533	0.00562	0.0275	-0.0521
	(0.0351)	(0.0350)	(0.0237)	(0.0346)	(0.0348)
Avg. Age (years)	-0.0280	-0.0113	-0.0812**	-0.0362	-0.0113
	(0.0412)	(0.0311)	(0.0325)	(0.0398)	(0.0310)
Individual characteristics					
Education (years)	0.0576	0.0765**	0.0858**	0.0482	0.0765**
	(0.0355)	(0.0336)	(0.0378)	(0.0336)	(0.0336)
Age (years)	-0.0351	0.0812	0.0409	-0.0475	0.0799
	(0.0528)	(0.0586)	(0.0616)	(0.0507)	(0.0587)
Male	0.0407	-0.0120	-0.0625	0.0429	-0.0146
	(0.0432)	(0.0475)	(0.0876)	(0.0415)	(0.0475)
Caste[b]					
Other Backward Caste	0.0227	0.0178	0.0252	0.0128	0.0146
	(0.0315)	(0.0384)	(0.0348)	(0.0304)	(0.0388)
Scheduled Caste	-0.0462	0.0856*	-0.00345	-0.0497	0.0834*
	(0.0488)	(0.0471)	(0.0485)	(0.0466)	(0.0475)
Production orientation (Market=1, Self-consumption=0)	0.0616**	0.0918***	0.100***	0.0589**	0.0905***
	(0.0259)	(0.0288)	(0.0308)	(0.0244)	(0.0293)
Inputs					
Land size[c]					
1-1.99 Acre	0.0130	-0.0229	-0.0294	0.0182	-0.0221
	(0.0293)	(0.0322)	(0.0311)	(0.0280)	(0.0324)
2-4 Acre	-0.0530	-0.0384	-0.0335	-0.0459	-0.0386
	(0.0468)	(0.0438)	(0.0449)	(0.0460)	(0.0439)
Fertiliser (kgs)	0.0101	0.0914***	0.103***	0.00453	0.0910***
	(0.0264)	(0.0173)	(0.0181)	(0.0252)	(0.0174)
Labour (hours)	0.0306	0.0102	0.0344	0.0287	0.0127
	(0.0230)	(0.0278)	(0.0340)	(0.0232)	(0.0285)
Seeds (kgs)	0.0447	0.0323	0.0627	0.0559	0.0258
	(0.0858)	(0.0832)	(0.0732)	(0.0842)	(0.0859)
Machine use[d]	0.473*	0.866***	0.808***	0.395*	0.848***
	(0.242)	(0.237)	(0.234)	(0.225)	(0.246)
Compost (loads)	0.0146	-0.0043	0.0308	0.0129	-0.00506
	(0.0310)	(0.0320)	(0.0311)	(0.0308)	(0.0320)
Village FE	Yes	Yes	Yes	Yes	Yes
Constant	6.957***	6.084***	6.250***	7.039***	6.109***

	(0.377)	(0.451)	(0.507)	(0.365)	(0.459)
Observations	152	164	152	152	164
R-squared	0.225	0.351	0.429	0.266	0.352
F test for instruments	11.98***	24.67***	12.25***	15.79***	28.53***
Test for over-identification[e] (p value)	0.18	0.42	0.66	0.31	0.45

Note: ***, **, * indicate significance at 1%, 5% and 10% respectively. All the continuous variables are in their log forms. Coefficients are obtained from Lewbel (2012)'s instrumental variable regressions. Productivity (kgs), fertiliser, labour, seeds and compost are accounted as quantities per acre. [a]For information and credit networks this index is calculated by only considering their respective intersection with friendship network. [b]Base category is High (General) caste. [c]Base category is less than one acre. [d]Ratio of number of mechanised activities out of total number of activities. [e]Hansen's J-test. Robust standard errors in the parentheses.

Table A3: Multiplex networks and agricultural productivity (C-D production function) – Full model

Dependent Variable: Productivity	1 Multiplex (Weighted)	2 Multiplex (Unweighted)
In-Degree	1.452*** (0.402)	0.307* (0.162)
Similarity Index[a]	0.148 (0.110)	0.0948 (0.106)
Neighbourhood characteristics		
Avg. productivity (in t-1)	0.00951 (0.0214)	0.0155 (0.0204)
Avg. Education (years)	0.00964 (0.0296)	0.0451 (0.0304)
Avg. Age (years)	-0.0271 (0.0410)	-0.0569 (0.0403)
Individual characteristics		
Education (years)	0.0586** (0.0287)	0.0571** (0.0283)
Age (years)	0.0207 (0.0460)	0.0352 (0.0477)
Male	-0.000693 (0.0381)	-0.00975 (0.0375)
Caste[b]		
Other Backward Caste	0.0325 (0.0273)	0.0275 (0.0276)
Scheduled Caste	0.00376 (0.0373)	0.0108 (0.0374)
Production orientation (Market=1, Self-consumption=0)	0.0726*** (0.0227)	0.0757*** (0.0232)
Inputs		
Land size[c]		
1-1.99 Acre	-0.00646 (0.0249)	-0.00770 (0.0275)
2-4 Acre	-0.00520 (0.0367)	-0.00939 (0.0383)
Fertiliser (kgs)	0.0455* (0.0271)	0.0471 (0.0340)
Labour (hours)	0.0476** (0.0229)	0.0520** (0.0236)
Seeds (kgs)	0.0891 (0.0660)	0.0720 (0.0720)
Machine use[d]	0.778*** (0.189)	0.788*** (0.196)
Compost (loads)	0.0335 (0.0268)	0.0218 (0.0261)
Village FE	Yes	Yes
Constant	6.155*** (0.341)	5.543*** (0.492)
Observations	256	256
R-squared	0.300	0.271
F test for instruments	15.46***	9.93***
Test for over-identification[e] (p value)	0.39	0.18

***, **, * indicate significance at 1%, 5% and 10% respectively. All the continuous variables are in their log forms. Coefficients are obtained from Lewbel (2012)'s instrumental variable regressions. Productivity (kgs), fertiliser, labour, seeds and compost are accounted as quantities per acre. [a]This index is calculated by the ratio of intersection to the union of connections across all three networks. [b]Base category is High (General) caste. [c]Base category is less than one acre. [d]Ratio of number of mechanised activities out of total number of activities. [e]Hansen's J-test. Robust standard errors in the parentheses.

Table A4: Effect of Multiplex network (weighted) on agriculture productivity (only for households with links in all three networks)

Dependent Variable: Productivity	1 Multiplex
In-degree	2.476
	(1.780)
Similarity index[a]	0.394***
	(0.134)
Neighbourhood characteristics	
Avg. productivity (in t-1)	0.400***
	(0.0956)
Avg. Education (years)	0.0418
	(0.0498)
Avg. Age (years)	-0.319***
	(0.0791)
Individual characteristics	
Education (years)	-0.0302
	(0.0459)
Age (years)	-0.114
	(0.0876)
Male	0.245***
	(0.0640)
Caste[b]	
Other Backward Caste	0.00243
	(0.0393)
Scheduled caste	-0.203***
	(0.0762)
Production orientation	0.0668*
(Market=1, Self-consumption=0)	(0.0367)
Inputs	
Land size[c]	
1-1.99 Acre	0.0720**
	(0.0332)
2-4 Acre	0.0411
	(0.0671)
Fertiliser (kgs)	0.0661
	(0.0529)
Labour (hours)	-0.00311
	(0.0363)
Seeds (kgs)	-0.123
	(0.0826)
Machine use[d]	0.256
	(0.312)
Compost (loads)	-0.0216
	(0.0240)
Village FE	Yes
Constant	5.777***
	(0.816)
Observations	53
R-squared	0.748

***, **, * indicate significance at 1%, 5% and 10% respectively. All the continuous variables are in their log forms. Coefficients are obtained from Lewbel (2012)'s instrumental variable regressions. Productivity (kgs), fertiliser, labor, seeds and compost are accounted as quantities per acre. [a]This index is a measure of the intersection of the urespective network with friendship network. [b]Base category is General (High) caste. [c]Base category is less than one acre. [d]Ratio of number of mechanised activities out of total number of activities. Robust standard errors in the parentheses.

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