Economic Roles of Social Networks in Rural India

by

Judit Johny

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Department of Resource Economics and Environmental Sociology
University of Alberta

Abstract

Rural populations in developing countries face problems of persistent poverty and imperfect markets associated with credit, capital and insurance despite many government efforts and initiatives. This study investigates the role that social networks can play in addressing some of these concerns and provide a new approach to achieving some of the development objectives. There are two main objectives developed for the study: a) to understand the structure and properties of social networks found among rural households and b) to examine the role of social networks in income diversification activities among the rural households. Understanding the structure of social networks can provide important insights into the patterns and regularities of interactions among these households. This in turn can provide new perspectives and recommendations to guide design and implementation of various development interventions in rural areas. Further, income diversification is particularly important for rural poor whose livelihoods primarily rely on rain-fed agriculture and are characterized by poverty, instability and inequality. Social networks could play an important role in influencing and promoting income diversification activities. Data on income diversification and social networks was collected from nine villages in Wayanad district of Kerala, India. Fundamental techniques of social network analysis were used to understand the structure of networks. In order to examine the role of social networks in income diversification, we developed a network econometric model based on a Spatial Autoregressive econometric approach by replacing the spatial matrix with a network matrix.

Results from social network analysis provide important insights into the structure and properties of the networks. There are no common demographic attributes among the households who function as central actors in each village. The density of village level networks ranged from a low of 15% for the village with the greater number of households to a high of 50% for the village with the lowest number of households. Analysis on differences in node-level centralities by demographic attributes revealed differences in centrality scores by caste of the households. Scheduled castes have highest mean values, followed by scheduled tribes, followed by other backward castes, and general. Results also show that social networks play a positive role in influencing and promoting income diversification. Social network effects were found to have greater influence on income diversification of agricultural households compared to non-agricultural households. Social network characteristics measured by node – level centralities were found to be positively correlated to diversification. Thus this study provides empirical evidence on the importance of social network effects in economic development context and adds to the recent economic development literature on role of social networks.

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The members of the examining committee are Drs. Brent Swallow* (Committee), Bruno Wichmann* (Committee), Sandeep Mohapatra* (Arm's Length), and James Rude* (Chair). *Department of Resource Economics and Environmental Sociology, University of Alberta.

Preface

This thesis is an original work by Judit Johny. The research project, of which this thesis is a part, received research ethics approval from the University of Alberta Research Ethics Board, Project Name "Role of social networks in diversification of income sources in rural India", ID. Pro00041819, amendments approved on November 8, 2013.

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Chapter 1 . Introduction

Social networks play vital roles in various aspects of our economic and social spheres. Networks can influence transmission of information about job opportunities, trade of goods and services, product consumption patterns, languages, criminal activity, education, and professional success (Jackson, 2008). Network research has evolved to become a cross-disciplinary subject with applications in many fields of social and economic life. Social network theory is largely used in sociology and organizational science for formulating and testing hypotheses about individual behaviors and social structures. It helps to describe patterns of relationships linking individuals (or other social units), to analyze the structure of these patterns and discover their effects on people, organizations and decisions (Martinez et al, 2003; Crespo, Desjardins and Vincente, 2014). In recent years, economists have explored social network effects on outcomes such as agricultural technology adoption (Maertens and Barrett, 2012), labor market function (Armengol and Jackson, 2004, 2007), diffusion of microfinance (Banerjee et al, 2012), academic achievement (Lin, 2010) and participation in retirement plans (Saez and Duflo, 2003).

1.1 Background and Motivation

The state of Kerala, situated in southwestern India is known for its remarkable achievement in social development. During the past four decades, public action, including both progressive state interventions and popular movements, has brought about high levels of social development and improved living conditions, in spite of low per capita income and nearly stagnant economic growth rates (Ramachandran, 1997). Development indicators such as high literacy, better demographic traits, government spending in service sector, remittance income were pivotal in the "Kerala Model" of development (Rajasenan, Abraham and Rajeev, 2013). When compared to the rest of the country, Kerala has very high levels of social development and compares favorably with middle income countries (Heller, 1996).

Rural populations in Kerala still suffer from problems of fragmented landholdings, poor infrastructure, lack of credit, capital and insurance markets, availability of information and unstable prices for agricultural products. Irrespective of high social development and reform movements within the state, issues of inter-caste disparity are still prevalent in the state (CSSEIP, 2010). These problems are aggravated in the case of the lower social strata or historically disadvantaged groups, particularly the scheduled tribes who tend to be the most marginalized among all groups. The socio-economic indicators of the tribes are much lower than the state average. As mentioned in CSSEIP (2013), tribal areas of Kerala are in fact considered as pockets of poverty, malnutrition and ill-health.

Over the years, the state has introduced various policies and programs particularly for the development of lower strata and tribal communities. Though these initiatives have helped to improve their conditions to an extent, improvements in human living conditions within and across these groups have been limited. The problems of persistent poverty and imperfect markets associated with credit, capital and insurance are particularly high among the lower social strata or historically disadvantaged groups of the society. These problems, to an extent, are aggravated by the highly stratified socio-cultural make-up of the society. While government initiatives and market solutions could address these issues to an extent, co-operative solutions or social networks could also help.

In some instances where markets fail, these networks can facilitate access to resources. For example, lack of access to credit and collateral restrictions often prevent the rural poor from getting a commercial loan. In such cases informal kinship and connections within the community can serve as an alternative by facilitating access to credit through mutual lending among people (Kim, 2011). Further, social networks can play a role in effective information dissemination. Availability of information regarding various services and opportunities can be critical for people to make use of them. One of the limitations faced by the small and marginal farmers in rural areas of India is the lack of initial capital and marketing channel to sell their products. Farmers can overcome this by pooling their resources together. Social networks can facilitate this by enabling group formation.

Social networks can also play an important role in promoting collective action. As mentioned in Smith (2001), in some cases farmers gain better access to information, training and equipment regarding agro-processing from Non-Governmental Organizations and development institutions by organizing themselves into groups. Farmers can acquire means of transportation by organizing themselves which can help them to overcome problems of mobility and enhance market acess (Kim, 2011). In other cases, farmers can organize themselves and negotiate price as a group directly with a big traders from cities. Through collective action people can strive for better provision of social services and effective implementation of programs in rural areas (Kim, 2011). Thus understanding these social networks and the possible cooperative mechanisms seems to be particularly important in our context.

Further, social networks also play an important role in influenicng various development outcomes. Rural livelihoods in developing countries primarily rely on rain-fed agriculture. They face several problems and challenges in terms of low prices, fragmented landholdings, seasonality of weather, poor infrastructure, unavailability of credit and segmented labor markets, which make it difficult for them to secure stable income from one source throughout the year. Given this context of rural survival, households tend to diversify their income sources. In other words households engage in multiple income earning activities as a strategy to stabilize or increase their income (Ellis, 1998). Thus Income diversification is viewed as an important strategy in rural areas. On one hand diversification is primarily driven by the households' poverty status where diversity acts as a safety valve for the rural poor. On the other hand, household income diversification can be a matter of choice and opportunity involving deliberate household strategies for improving living standards and accumulating wealth (Ellis, 1998; Reardon et al, 1992). Social networks through providing access to resources, facilitating collective action and influencing behavioral patterns could play a positive role in promoting income diversification.

1.2 Research questions and Objectives

Against this background, the focus of this study is on social networks found in rural areas of Wayanad District situated in Kerala. Given the large heterogeneity of the population in these villages, merely understanding the socio-cultural make-up does not tell us about the various types of interactions and networks formed among people. Jackson (2009, p.491) argues that "Many economic interactions are embedded in networks of relationships and the structure of the network plays an important role in governing the outcome". More generally an individual's choices can be influenced by the people they are connected to through various relationships or interactions. Thus it is important to understand the structure of these social networks. It enables us to understand to understand community as a social entity and gives us an idea of the social context faced by a given individual, for example, the extent to which his or her local environment is socially cohesive or the diversity of his or her personal contacts (Butts, 2008).

In particular, this study aims to gain a deeper understanding of the following aspects regarding social networks in rural India. What are the different types of networks found in villages of Wayanad? Are there any patterns or regularities that influence the structure of these networks? Are there any specific properties that enable collective action within the network? Can we identify networks that are more socially cohesive and have better chances at collective action? This understanding can be critical for the application of social networks in designing and implementing various interventions in rural areas.

Further, as mentioned before, social networks can play a critical role in achieving variety of development outcomes (eg, agricultural technology adoption, diffusion of microfinance). Rural populations in Kerala and many other developing countries are faced with poverty and high degree of income variability. In this context, income diversification is viewed as an important household strategy that allows us to deal with income variability and to ensure a minimum level of consumption (Ellis, 1998). This is particularly important for the rural poor and tribal communities in Wayanad who face high levels of poverty and malnutrition. Thus, another important question related to this study is about the role of social networks in income diversification. In particular, do social networks play a role in promoting diversification activities among the tribal communites and the rural poor in India? If social networks are important, what are its implications?

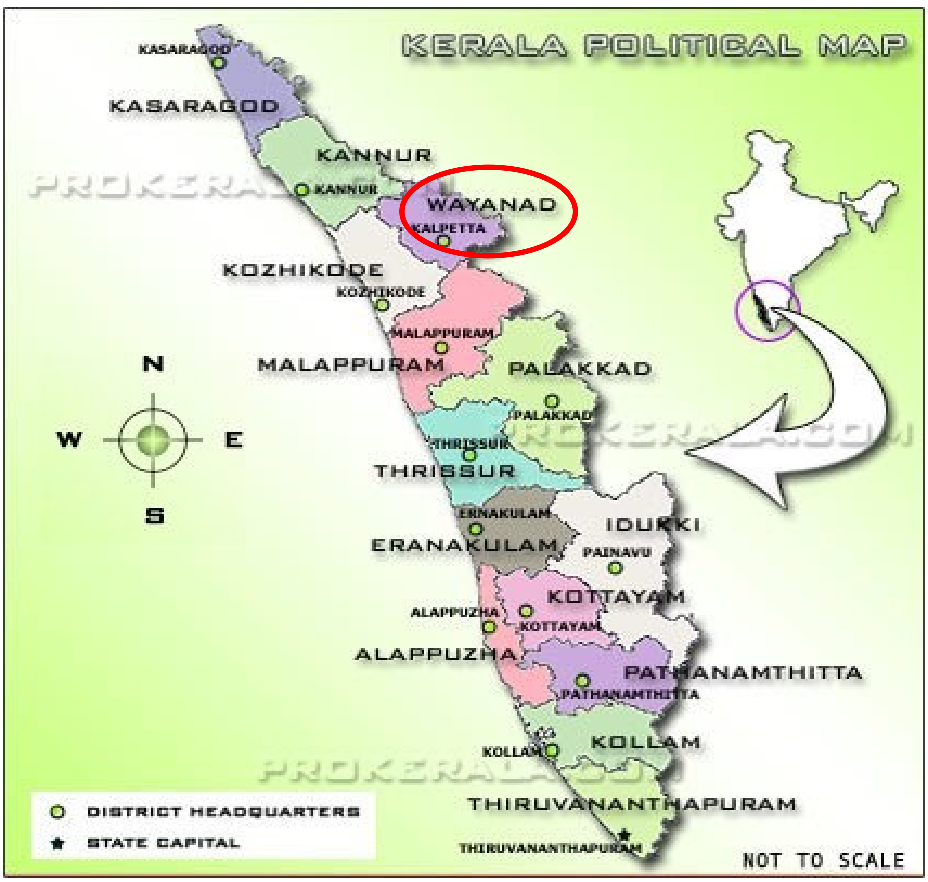
The specific objectives developed for this study are;

a) Gain a better understanding of rural India's social networks

b) Examine whether social networks play a role in diversification of income activities among rural poor.

1.3 <u>Study Location</u>

Figure 1.1: Map showing study location in Kerala, India



Source: www.prokerala.com

This study is part of a larger project, the “Alleviating Poverty and Malnutrition in Agrobiodiversity hotspots in India (APM)”. The study was conducted in nine villages of Meenangadi panchayat in Wayanad district of Kerala, situated in southern India. The location is one of the sites included in the APM project. It is recognized as one of the world’s 35 biodiversity hotspots due to the many endemic floral and faunal species and due to the threats to those species (APM Baseline Survey, 2013). Wayanad is primarily a rural district, in which 96 % of the total population lives in villages (Census Statistics, 2011). The district has a substantial concentration of minority (mainly Christians and Muslims) population. Majority of the Christians in the district have been migrants from the central and southern parts of Kerala. Agriculture is the main occupation of the people (Institute for Human development, 2008). Forty percent of the labor force is constituted by the agricultural laborers which are much higher compared to the state average of 19.6 % (Institute for Human development, 2008). The principal agricultural economy of the region includes plantation crops such as coffee, tea, cocoa, pepper and rubber, while seasonal crops such as rice, banana, tubers and fruits serve as the local food sources (APM Baseline Survey, 2013).

Traditionally, Indian society is highly stratified by the caste system. Mohindra, Haddad and Narayana (2006) describe caste as a hereditary, endogamous, usually localised group, having a traditional association with an occupation and a particular position in the hierarchy of castes. The different castes are categorized into four main groups namely Scheduled Tribes (ST), Scheduled Caste (SC), Other Backward Classes (OBC) and General caste (General). These classifications are recognized by the government and are commonly used (see, http://censusindia.gov.in, http://socialjustice.nic.in).

The scheduled tribes are the indigenous people of India, also known as Adivasis. As described in CSSEIP (2013), tribes are usually people living in a particular place, who enter into marriage relationship among themselves, who are traditionally or ethnically ruled by adivasi leaders, who speak a special language, and who have their own distinct beliefs, customs and traditions. Tribal communities usually live in relative isolation and are shyness about contact with the community at large (see Ministry of Tribal Affairs, Government of India). Scheduled castes are the disadvantaged sections of society and were historically considered as the untouchables. Other Backward Classes (OBCs) are constituted by communities who are generally considered as socially backward. These communities usually depend on agricultural and/or other manual labour for their livelihood, lack any significant resource base and have very low literacy rates. This category includes lower-caste Hindus as well as other sub-groups from other religious and ethnic minorities (see National Commission for Backward Classes, Government of India). The General Caste consists of people who belong to traditionally privileged higher castes. The Scheduled castes and Scheduled tribes are considered as the low-status castes and belong to the bottom of the caste hierarchy. Historically, they faced exclusion and were exploited by higher castes. Although the government of India adopted a policy of positive discrimination to correct the oppression, the caste disparities exist even today due to accumulated privileges and continued discrimination.

One of the important features of Wayanad is the presence of large proportion of tribal population. There are about 35 tribal communities in the state and Wayanad district has the highest concentration of tribal population in Kerala (Census statistics, 2011). The ST`s (Scheduled tribe) are the backward and disadvantaged sections of the society. The majority of the tribes (few exceptions) are mainly dependent on casual labor in agriculture, plantations and forestry for survival since they have little or no land.

In the past, tribal communities did not have permanent houses and usually lived in dense forests which were remote and inaccessible. However, the changing times and affirmative action by the Government of India have enabled them to build permanent houses and own land. The settlement patterns of the tribes vary regionally. In Wayanad, it is seen that they usually settle in groups or clusters with houses closely located to each other. These clusters are commonly referred to as tribal settlements or colonies. Thus a village can have one or more tribal settlement. It is commonly observed that extended families tend to live in the same settlement. Further, people belonging to the same tribe tend to settle together.

There are different tribal communities found in Kerala. Of the different tribal groups in Wayanad, the three main tribes found in the study area are Kurumas, Kattunaikkans, and Paniyas. All of these tribes speak Malayalam along with their native language. Among these tribes, the Kurumas are generally recognized to be at the top of the caste hierarchy. Their native language is similar to Malayalam with a spattering of Kannada and Tamil words. They are the settled land-owning community that is primarily involved in agriculture. The main crop cultivated by the Kuruma tribe is paddy, mainly on the fallows and flat lands as well as on moderate slopes (Narayanan et al, 2011). The Kattunaikka tribe traditionally used to settle closer to the forests. Their native language is the Kattunaikka dialect, which is close to the Dravidian language, Kannada. The traditional occupations of the Kattunaikka include food and Non Wood Forest Produce (NWFP) gathering, hunting, fishing and trapping of birds and animals (Narayanan et al, 2011). The Paniyas rank the lowest in hierarchy among the different tribes.

They have a distinct language of their own, closely related to Malayalam. They are the most disadvantaged and backward sections and is almost entirely dependent on wage-labour in the paddy fields and farms of the land-owning classes for their livelihood (Narayanan et al, 2011). Traditionally the landlords used to sell them as bonded labor.

1.4 Thesis Structure

The thesis is organized in the following manner. Chapter 2 provides a detailed analysis of social networks found in Wayanad using some of the fundamental techniques of social network analysis. It provides a discussion on the importance of social network analysis, a brief description of the data and techniques used and a detailed description of social network for each village. Chapter 3 examines whether social networks play a role in income diversification activities . It provides discussions on the importance of income diversification, how social networks could be important for diversification, the econometric model developed for the study and the results found. Chapter 4 offers a conclusions based on entire study and implications of the results obtained.

Chapter 2 . Assessing social networks of villages in rural India

2.1 Introduction

Social networks can be viewed as connections or relationships formed through various interactions between people. The purpose of this chapter is to gain a better understanding of social networks found in villages of Wayanad using social network analysis. Social network analysis can be used to examine patterns and regularities of relationships that influence the structure of a network (Wasserman, 1994, p: 5-10). It also facilitates characterization of properties of individual actors within the network.

For example, some households can be critical to speed and improve the effectiveness of transfer of resources while others can have the power to influence other households in the village. Further, a household can act as a bridge between several disconnected households within a village and thus can be important for transferring resources across the entire network. Identifying these households can in turn have applications in the fields of information transmission regarding new agricultural practices, new technology, new government schemes and policies, spread of a new disease, or health services available in the rural areas. At the network level, social network analysis can provide insights into the overall stability or vulnerability of the villages. It gives us an idea about the connectivity and level of cooperation in the villages. Some networks might be more successful at collective action than others. Information transmission might be higher in networks with high level of solidarity.

Social network analysis can provide a unique perspective, approach and recommendation to guide design and implementation of various interventions in rural areas. Banerjee et al. (2012) in their study on diffusion of microfinance through social networks found if individuals who were initially informed about the program were connected to other important individuals in a network ,then they played an important role in determining the eventual participation rate of microfinance in a village. Thus, identifying central actors within the network can be critical to effective information dissemination in rural areas. Information can be made available to more number of people if transmitted through central actors within a network. In many instances, government organizations and other institutions tend to have few regular initial contact points to transfer information regarding training programs and other services that may or may not play an effective role in disseminating information.

Given the relevance and importance of social networks, the focus here is to understand the properties of social networks found in nine villages of Wayanad district, Kerala. In particular we aim to test whether there are any common attributes to households who occupy the leadership positions or positions of high centrality in each network. Further, given the context of inter caste-disparity in Wayanad; we aim to examine whether social network statistics, particularly centralities of households vary by the social strata they belong to.

The outline of this chapter is as follows. Section 2.2 gives a description of the data used. Section 2.3 explains how network data is commonly represented along with brief description of the common terms used in the literature. Section 2.4 consists of a brief explanation of the commonly used network descriptive statistics followed by section 2.5 which presents a description of the network for each village and figures that allow for network visualization. Section 2.6 includes a discussion on variation in node-level centralities based on attributes of the households. Section 2.7 offers concluding remarks.

2.2. Representation of Social Networks

A social network consists of a set of nodes or vertices with a relation between those entities. The nodes in question can be persons, groups, organizations or entities such as texts, artifacts and even concepts depending on the setting (Butts, 2008). We view social networks as connections and links among households within a village through which resources flow (Maertens and Barrett, 2012).

Networks can be represented in different ways depending on the objective of the study. Social network analysis is closely related to graph theory, the branch of mathematics which is concerned with discrete relational structures and network data is often represented using graph theoretical notation (Butts, 2008). However, matrix/vector format is one of the most common methods used by social scientists to represent social networks. In empirical contexts, network data is usually represented as an adjacency matrix, an $N X N$ matrix whose ij th cell is equal to 1 if node i has a link to node j, and 0 otherwise. In cases where a link can take on more than two values, it is referred to as a weighted graph. This representation allows us to track the intensity level of relationships. Typically, since self- links do not have any meaning, the diagonal of adjacency matrix A is set at zero ($a_{ii}=0$) for all nodes (Butts, 2008; Jackson, 2008).

The usual form of a network is an undirected graph, in which two nodes are either connected or they are not. In undirected networks, one node cannot be related to a second without the second being related to the first. For an undirected network with adjacency matrix **A**, it is clear that $a_{ij} = a_{ji}$ (i.e. the adjacency matrix must be symmetric). This structure holds in many social and/or economic relationships, such as partnerships, friendships, alliances, and acquaintances. However, there are other situations in which one node may be connected to a second without the second being connected to the first: this is referred to as a directed network or digraph. The distinction between directed and undirected networks is fundamental to social network analysis as the applications for both types are quite different (Butts, 2008; Jackson 2008).

2.3 Data

Data required for this study was collected from 301 households in nine villages. The unit of analysis is a household. Respondents were selected from a census of 1000 households in 31 villages that were previously included in the related study, "Alleviating Poverty and Malnutrition in Agrobiodiversity Hotspots." Out of the thousand households, households living in all small villages (<20 households) and all large villages (>100 households) were excluded. Of the villages remaining, nine villages of intermediate size (between 20 and 100 households) were selected. This focus on intermediate-sized villages was done to ensure a reasonable sample of villages and to ensure that households within the villages are properly connected. All households in each of the nine villages chosen were included in the study.

Networks within a village can be formed through various interactions among households. Households may interact with one another as neighbors, friends, relatives or members of same caste/community. Often households help each other to fulfill various needs. For example, in scenarios where there is an unexpected shortage of essential commodities like rice, sugar, or oil, female members of the household usually asks others for help. In other cases these households may borrow cash to meet sudden and unexpected hospital costs, for purchasing seeds or fertilizers, for hiring a pump for irrigation, for cultivation or sometimes for alcohol consumption (Choudhuri and Jana, 2014). From previous experience in the area and field studies, the senior author of this paper observed that households prefer to borrow cash from their relatives or close friends. Further, women in the area also actively participate in self -help groups, which forms another basis of interaction. Sometimes members of different households attend temple or church festivals together. People might ask opinions of other households while taking a decision regarding a marriage proposal or sometimes when resolving a local issue. Most of the adult males living in the area belong to a political party and actively participate in their activities. These regular interactions on any dimensions in the course of daily life provide opportunity for households to build stable ties among themselves.

To measure a household's important social networks a questionnaire was drafted based on the social network survey which was previously developed by Banerjee et al., (2012) in their study on diffusion of microfinance in villages of rural Karnataka, India. That site is located less than 200 km from our field site in Kerala. Some questions were changed based on interactions observed in the study area. The survey is comprised of questions on thirteen possible dimensions of interactions through which households within a village could be connected. The thirteen dimensions included in the survey are close relatives, watching television together, help with medical emergency, borrowing households goods such as kerosene, rice, wheat, sugar, oil, visiting places of worship together, borrowing money, advice on personal decision, participating in SHGs/ other savings groups and farmer's clubs, connections to leaders within the village, sharing produce from home gardens, connections developed through the sale of agricultural or non-agricultural produce, and point of contact for information regarding public policies and government schemes. The survey was administered in the local language to a member of the household who is above 18 years of age. In most cases the head of the household or spouse of head answered the questions and in some cases both spouses answered.[1]

Following Banerjee et al. (2012), there are a few important things to be mentioned about the social network data. This study represents villages of Wayanad as networks of households linked through social ties. In Wayanad, people end to live in villages. Further, the villages tend to be small enough for people to know each other but large enough to capture many forms of social interactions. Further, the data collected for this study is treated as an undirected network. In other words a household i is connected to j if any member in household i mentions a member in household j as a contact in response to one or more of the network questions. For example household i may report borrowing money or material goods from j although j did not borrow from i. However we assume that the one-way borrowing link would be sufficient to create a link between the two households through which information, services or skill could flow in either direction. The network data collected enable us to construct thirteen different matrices that take into account the connections between households along each of the dimensions included in the questionnaire. To model social networks for this study, we construct a matrix where two households are considered to be linked if they have a relationship along any of the thirteen dimensions. As justified by Banerjee et al. (2012) this is a proper measure since the emphasis

[1]The english version of the survey is included in section a.1 of appendix A

here is on the link between two households and any of the dimensions included in the survey can create an opportunity for contact. Finally, the network data only takes account of interactions within the village.

2.4 Descriptive Measures and Definitions

The most commonly used indices in social network literature can be broadly divided into two categories, namely node-level indices (NLI) and graph-level (GLI) indices

Node- level Indices

These indices facilitate characterization of the properties of individual positions in a network. They allow us to identify households in positions of prominence or whose position enables actions such as information dissemination. Node level indices give us an idea of the social structure faced by a given individual, for example, the extent to which his or her local environment is socially cohesive or the diversity of his or her personal contacts (Butts, 2008). The most well developed and commonly used node level indices are the centrality indices which capture the extent to which one node occupies a more central position than another. There are different notions of centrality (Butts, 2008).

a) Degree centrality - The degree of a node simply refers to the number of links that involve the node. A measure of degree centrality indicates how well a node is connected in terms of direct connections with other nodes (Butts, 2008). Different notions of degree are encountered in the case of undirected and directed networks. In the case of an undirected network degree is the number of direct connections of the node in question (Jackson, 2008). Formally degree centrality is measured as:

$$C_d\ (v, G) = N(v)/n - 1 \qquad (2.1)$$

where, C_d refers to degree centrality, v refers to a vertex or node, G is the graph or network, N is the number of edges or connections attached to the node and n is the number of nodes in the graph.

Degree centrality ranges from 0 to 1 and is one of the simplest measures of tracking position of a given node. For example, in a network of size 10 (10 nodes), if there exists a node with a degree of n-1 or 9, it would be directly connected to all other nodes and therefore very central to the network (Butts, 2008). An actor with high degree centrality maintains more ties and will have more influence on those around it and possibly on the whole network. Central actors are usually located at or near the center in network diagrams whereas a peripheral actor maintains few or no relations and thus is located at the margins of a network diagram (Wasserman and Faust, 1994).

b) Betweenness Centrality – This index quantifies how important a node is in terms of connecting other nodes. It measures the extent to which a particular node is well situated or occupies a "between" position on the geodesics or shortest paths connecting many pairs of other actors in the network and ranges from 0 to 1 (Butts, 2008). It is estimated as:

$$C_b\ (v_i, G) = \frac{P_i(kj)/P(kj)}{(n-1)(n-2)/2} \quad k \neq j : i \notin (k,j)\ . \qquad (2.2)$$

where $C_b\ (v_i, G)$ refers to the betweenness centrality of vertex i in graph G, $P_i(kj)$ denote the number of geodesics (shortest paths) between k and j that i lies on, and P(kj) is the total number of geodesics between k and j. The importance of i in terms of connecting k and j can be estimated by looking at the ratio $P_i(kj)/P(kj)$. If this ratio is close to 1, then i lies on most of the shortest paths connecting k to j, while if it is close to 0, then i is less critical to k and j. Averaging across all pairs of nodes, the betweenness centrality of a node i can be calculated by the above equation (Jackson, 2008).

Nodes with high betweenness scores tend to act as bridges for groups that are otherwise distantly connected. Thus these nodes might play a central role in effective information dissemination and exchange of resources, knowledge or skills within the network. These households that connect others that are otherwise disconnected can benefit from having access to diverse sources of opportunities, information and resources along with the ability to control the flow of information or exchange of resources (Wasserman and Faust, 1994; Carboni and Ehrlich, 2013).

c) Closeness centrality - A measure of closeness centrality captures the extent to which a given node has short paths to all other nodes within the network. This measure can be calculated only if the networks are connected (Butts, 2008). Closeness centrality ranges from 0 to 1and can be formally measured as:

$$C_C(v_i, G) = \frac{n-1}{\Sigma\, d(v_i, v_j)}\,, \qquad (2.3)$$

where n is the number of nodes in graph g and $d((v_i, v_j)$ is the geodesic distance from vertex i to vertex j. In this case, $C_C(v_i, G) = 0$ for any v lacking a path to any vertex and, hence, all closeness scores will be 0 for graphs having multiple weak components (Butts, 2008).

Closeness centrality reflects both direct and indirect relationships. A node that is not directly connected to every other node could be indirectly connected through many intermediaries. Closeness centrality reflects a node's potential to quickly interact with others in the network and is particularly relevant if the number of transmission steps matters. High closeness centrality indicates the node's ability to quickly transfer information to the entire network and not just to immediate neighbors as with degree centrality (Wasserman and Faust, 1994).

d) Eigenvector centrality - This centrality measure is based on the idea that a node's importance is determined by how important its neighbors are and takes into account a node's proximity to other important nodes (Jackson, 2008). Let $C^e(g)$ denote the eigenvector centrality associated with a network g. The centrality of a node is proportional to the sum of the centrality of its neighbors: $\lambda C_i^e(g) = \sum_j g_{ij} C_j^e(g)$. In matrix notation, it can be represented as follows;

$\lambda C^e(g) = gC^e(g)$, where λ is a proportionality factor. Thus $C^e(g)$ is an eigenvector of g, and λ is its corresponding eigenvalue (Jackson, 2008). [2] The measure ranges from 0 to 1.

If a node influences just one other node that consequently influences many others, then the first node is considered to be highly influential (Borgatti, 2004). These measures also tend to take account of situations in which a high degree position is connected to many low degree positions or a low degree position is connected to a few high degree positions (Bonacich, 2007).

[2] Given an $n \times n$ matrix T, an eigenvector v is a nonzero vector such that $Tv = \lambda v$ for some scalar λ, which is called the eigenvalue of v (Jackson, 2008). As described by Jackson (2008), eigenvectors are vectors that, when acted upon by the matrix T, give back some rescaling of themselves, rather than being distorted to some new vector or new direction. So they serve as a sort of fixed point of the transformation T, and for many matrices (but not all), there will be as many eigenvector-eigenvalue pairs as there are dimensions.

Graph- level Indices

Graph level indices quantify structural properties of the network as a whole and are extensively used in the modelling of network structure. Identifying the particular pattern of graph level scores associated with a given network makes it possible in some cases to infer properties of the social process which gave rise to it (Butts, 2008) We use some of the commonly used graph level indices to examine network structures in nine villages of Rural India.

a) Density - The density of a network can be defined as the fraction of potentially observed links which are presented within the networks. In other words it is the number of actual connections observed within a network divided by the number of potential connections denoted by the number of nodes (Butts, 2008). Density can be formally represented as follows:

$$\frac{\text{Average degree}}{n-1} \qquad (2.5)$$

High density within a network tends to ease the flow of information, create trust among members and enables them to cooperate with each other leading to solidarity and collective action (Peng, 2004).

b) Diameter - The diameter of a network is the largest geodesic between any two nodes in the network. The term geodesic is used to denote the length of (number of links) the shortest path between two nodes (Jackson, 2008). If the diameter is *n*, no two individuals are more than *n* steps away from each other. It is a very basic measure of how well connected the network is. Generally, nodes in a network with a smaller diameter are connected to each other through fewer intermediates, and transfer between individuals is potentially faster than in a group with larger diameter (Wey et al., 2008).

c) Average path length - The average path length is the average of all geodesics in the network (Jackson, 2008). This measure also gives a general idea of the network's overall connectedness, and a shorter average path length again suggests potential for quicker transfer among all nodes in the network (Wey et al., 2008).

d) Transitivity – One of the common properties of social networks is clustering or network transitivity. Intuitively weak transitivity can be observed when two nodes that are both linked to the same third node have a high probability of also being linked to one another(Butts, 2008). In other words there is high probability that two of one's friends are friends themselves (Jackson 2008). It can be denoted formally as follows:

$$((i,j),(j,k)\epsilon\ E \ \Leftrightarrow (i,k)\epsilon\ E) \qquad (2.6)$$

where i, j and k refers to nodes in a network.

This measure ranges from 0 to1 and is 1 on a fully connected graph (everyone knows everyone else) and has typical values in the range of 0.1 to 0.5 in many real-world networks (Girvan and Newman, 2002). Weak transitivity is preferred for most applications (Butts, 2008).

e) Centralization – These indices measure the extent to which centrality is concentrated within a small number of nodes. One of the most commonly used centralization indices are the Freeman centralization indices (Butts, 2008). It is a network level measure of the node-level centralities discussed above. It quantifies the difference between the maximum observed centrality score and the average centrality of all nodes or in other words how much variance there is in the distribution of centrality in a network. It can be formally represented as follows (Butts, 2008):

$$C(G) = \sum_{i=1}^{n} ((max_j\, c(j, G)) - c(i, G))$$

where c is a centrality index.

The centralization measures capture the tendency of a single point to be more central than all other points in the network (Freeman, 1979). This tendency of a single point to be outstandingly central could influence how nodes within the network perceive leadership structure as well as the speed and efficiency of a network in solving problems (Leavitt, 1951). The index depends on the size of the network and can be computed based on all centrality measures (degree, betweenness, and closeness). This index obtain its maximum value 1 in the case of a star graph for most known centralities and is 0 for a network in which there is no variation in centrality among nodes (Butts, 2008) .

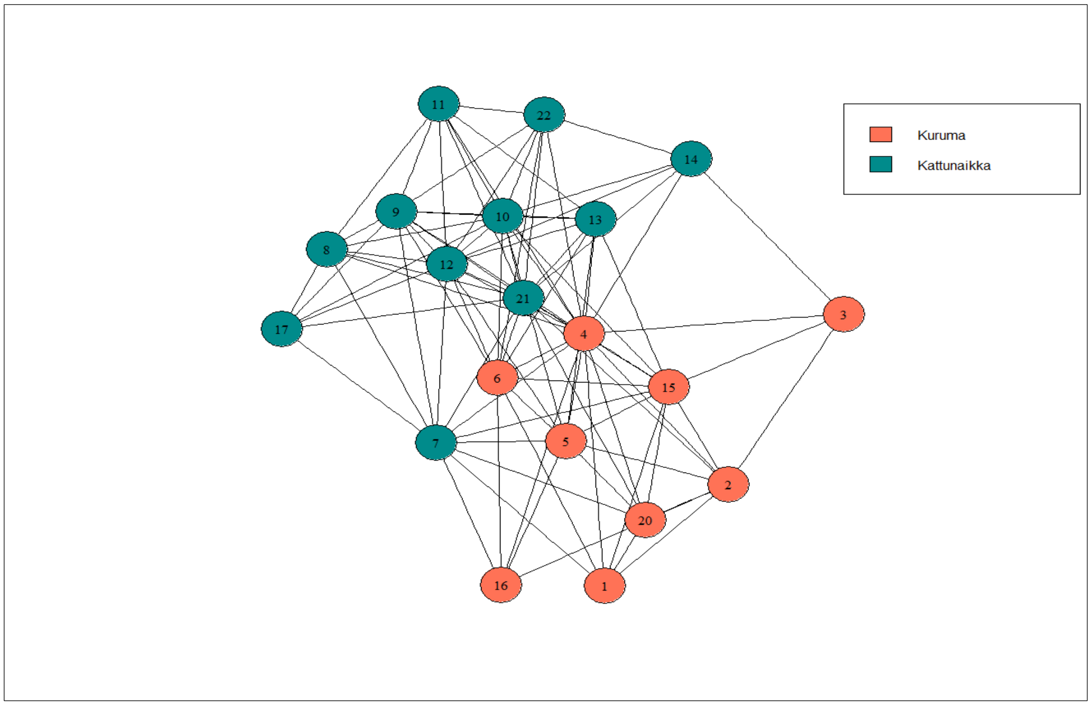
2.5 Description of networks.

This section includes representation of the networks using figures along with a description of each network based on node and graph level indices. The figures are constructed in R software using Fruchterman-Reingold layout. This layout is developed based on two main principles that vertices or nodes connected by an edge (link) should be drawn near each other and that vertices should not be drawn close to each other (see Fruchterman and Reingold, 1991). The network figures are color coded to represent different attributes of the households which in most cases is the caste of the households. Further, impressions and observations obtained during data collection by the senior author are also used to support the description of the networks. The graph level statistics for all nine networks are reported in table 2.10.

Network 1

This network represents a tribal village which is constituted by two different tribal groups, the Kurumas and Kattunaikkas. The figure below represents a visualization of network 1. Nodes are represented using different colors to differentiate between the two tribes. Although the two tribes have traditional differences in their occupation and wealth status they interact well with each other. Households tend to interact with each other on various dimensions such as kinship, friends, for borrowing money and household goods, attending temple festivals together, advice regarding marriages, passing information regarding government schemes and participation in self-help groups.

Figure 2.1: Visualization of social network for village 1 in Meenangadi, Wayanad.



Source: Author's analysis

It is the smallest network constituting twenty households with an average degree of 9. Thus the number of links for each household is high showing that most of the households are connected and interact with each other. This network has the highest density among all nine villages and this is possibly because of relatively high levels of solidarity and trust within the network, which may lead to a better flow of information. The average path length is used to measure the average of all shortest path length (number of links) and the diameter of a network is the length (number of links) of the largest geodist connecting any two nodes in a network. These measures give an idea of how well connected the network is. Network one has the smallest average path length and a small diameter, relative to other villages, showing that number of edges or links that need to be traversed to get from any two households within the network is small. Table below shows node-level centrality scores. Nodes with highest score for each of the four centrality measures are reported.

Table 2.1: Nodes with highest centrality scores in village 1 of Meenangadi, Wayanad.

Centrality	Node	Score	Node	Score
Degree	4	0.947	21	0.789
Betweenness	4	0.045	21	0.133
Closeness	4	0.950	21	0.826
Eigenvector	4	0.356	21	0.321

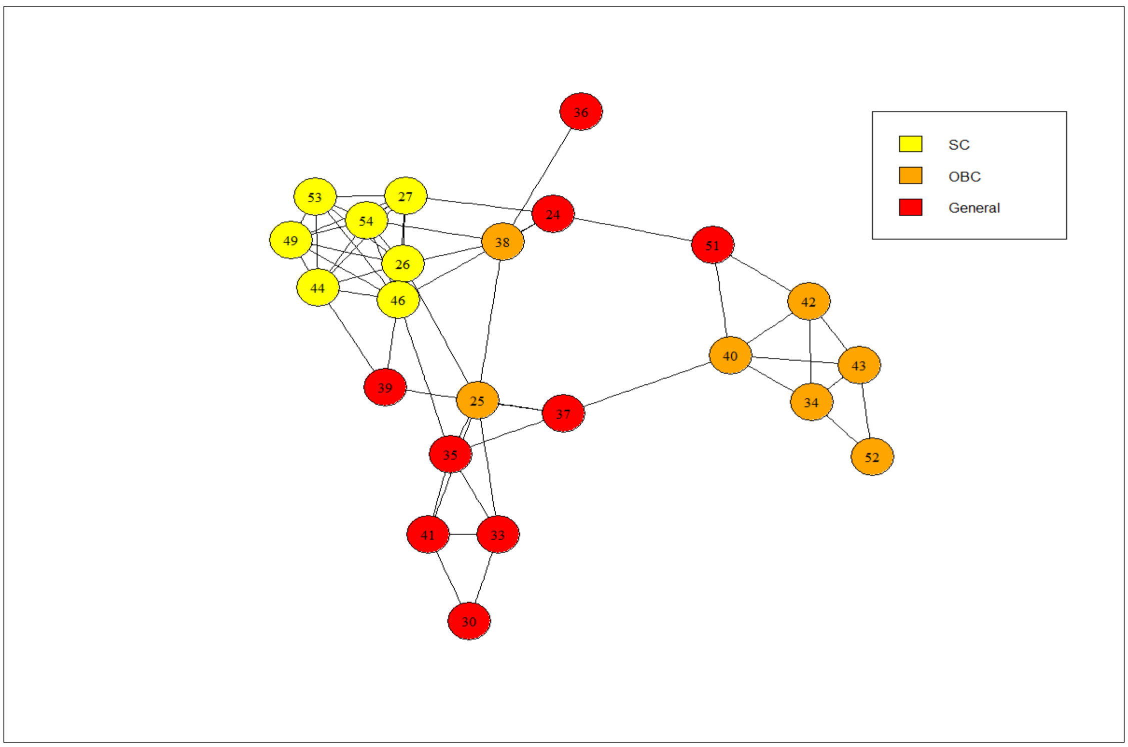
Source: Author's analysis

Household 4 (node 4) has the highest score for all centrality measures. This shows that the household is important in terms of the direct connections with other households, for connecting disconnected groups, in terms of ability to interact quickly with others and has connection to other households with high centralities. Observations from the field support the results above. Household 4 is well connected to all other households in the village and every household (across the two tribal settlements) listed household 4 as their connection on several dimensions. Members of this household always took the initiative to circulate information. Further, during the data collection, household 21also appeared to be important and popular within the network. Other households in the village (across the two tribal settlements) considered the head of the household 21 to be influential. One of the members of this household is actively involved in politics and another is a representative for their tribal group. This observation is reinforced by the node level centrality scores. Household 21 is shown to have the second highest score for all centrality measures. Furthermore it is important to note that household 4 and household 21 belong to different tribes and play a crucial role in maintaining ties across these two settlements. The figure above shows that these two households occupy central positons in the network.

Network 2

Network two represents village 2 and is constituted by 23 households. The figure below represents a visualization of the network.

Figure 2.2: Visualization of social network for village 2 in Meenangadi, Wayanad.



Source: Author’s analysis

The majority of the population in village 2 belongs to scheduled castes and general caste category. It can be seen from the network figure below that households belonging to the scheduled caste category are well connected and form a distinct cluster. Most of the households within this cluster are related through kinship connections and there is a high level of interaction and cooperation among these households.

Network level statistics show a relatively low average degree or number of links between households in village 2. The overall density of the network is relatively low. The network also has the highest diameter and average path length among the nine. This indicates that the village as a whole may is not well connected. The table below represents nodes with highest score for each of the four centrality measures.

Table 2.2: Nodes with highest centrality scores in village 2 of Meenanagadi, Wayanad.

Centrality	Node	Score
Degree	46	0.409
Betweenness	37	0.085
Closeness	25	0.500
Eigenvector	46	0.388

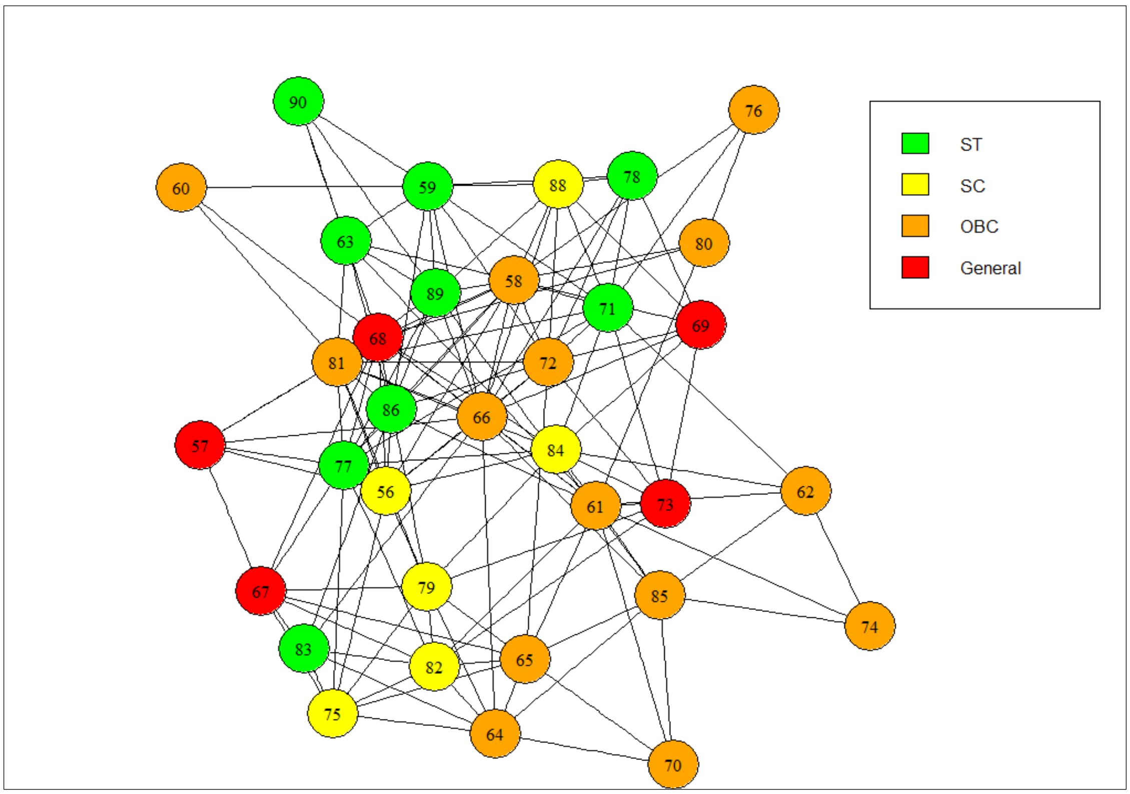
Source: Author's analysis

Node level centrality statistics shows that household 46 has the highest degree centrality indicating its importance in terms of number of direct connections with other households. Household 37 has the highest betweenness centrality score and plays an important role in linking otherwise disconnected groups. Household 25 is found to have the highest closeness centrality score which captures the extent to which a given node has short paths to all other nodes within the within the village. Household 25 has a business venture within the village and this creates a wider accessibility and point of contact to other households within the village. Household 46 is shown to have the highest eigenvector score indicating that the household have connections to other influential or important households.

Network 3

Village 3 is comprised of 34 households. Figure 2.3 below represents a visualization of the network. It can be seen that households within the village are a mix of other backward caste, scheduled tribe, scheduled caste, and general. From observations in the field and the network visualization, the village appears to be well connected and to have high levels of cooperation and trust among the households.

Figure 2.3: Visualization of social network for village 3 in Meenangadi, Wayanad.



Source: Author's analysis

The majority of the households in the village knows each other and interacts with one another on various dimensions.

The network figure illustrate that all households in the village are linked properly without any outliers. On average the households in this network have a degree of 8. The network has a medium density score, small average path length and small diameter, relative to the other villages. This supports the observations from the field mentioned above. Table 2.3 presents the nodes with highest centrality scores within the village. Node level centrality scores show that household 66 has the highest score for degree centrality and closeness centrality. This shows that household 66 is important for maintaining the maximum number of direct connections as well as for having the shortest path or links to other households in the village

Table 2.3: Nodes with highest centrality scores in village 3 of Meenangadi, Wayanad.

Centrality	Node	Score
Degree	66	15
Betweenness	61	0.095
Closeness	66	0.647
Eigenvector	58	0.280

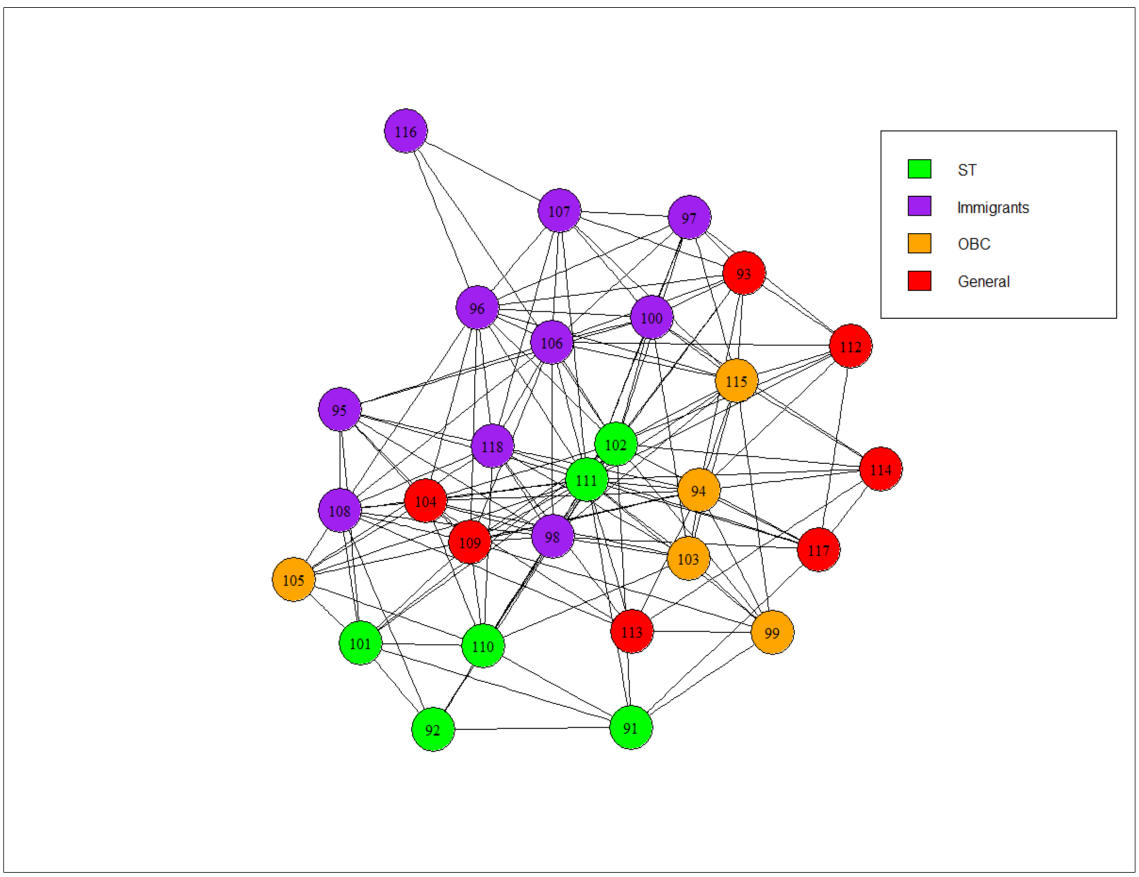
Source: Author’s analysis

Household 61 has the highest betweenness centrality score showing that it acts as a bridge between disconnected households. During the data collection it was noted that almost all households within the village had links to this household. This could be due to the fact that the head of the household owns a rickshaw and everyone in the village has access to it when they need transportation. Household 58 is also shown to be important within the network in terms of having links to other households with high centrality. This supports the observations from the field. Other households in the village considered household 58 to be influential in common decisions regarding the village and in solving issues that arise within the village.

Network 4

Network 4 is comprised of 28 households and is the only village among the nine with immigrants from a neighboring state, Karnataka. These immigrant households are displayed as purple nodes in the network figure 2.4 below. Most of the immigrant households are relatives and have high degree of kinship links. The village also has a tribal settlement with few households who are well connected.

Figure 2.4: Visualization of social network for village 4 in Meenangadi, Wayanad.



Source: Author's analysis

A high degree of interactions between the tribal and non-tribal households was observed in the village. Households interact with others on several dimensions. Most of the financial interactions are through kinship networks and private money lenders who come to the village. Field observations gave the impression that households prefer to approach kinship networks for borrowing household goods followed by their close friends. The village as a whole is well connected as illustrated in the network figure.

The network has an average degree of 10 which is high compared to the nine villages. It also has a very small average path length and diameter along with relatively high density. This indicates that households in the village are tightly linked and that there is a high degree of interaction. This could lead to better solidarity and trust in the village which could in turn promote collective action. The table below display information about the nodes with highest centrality scores within the network.

Table 2.4: Nodes with highest centrality scores in village 4 of Meenangadi, Wayanad.

Centrality	Node	Score	Node	Score
Degree	111	0.926	102	0.704
Betweenness	111	0.098	102	0.062
Closeness	111	0.931	102	0.771
Eigenvector	111	0.369	102	0.287

Source: Author's analysis

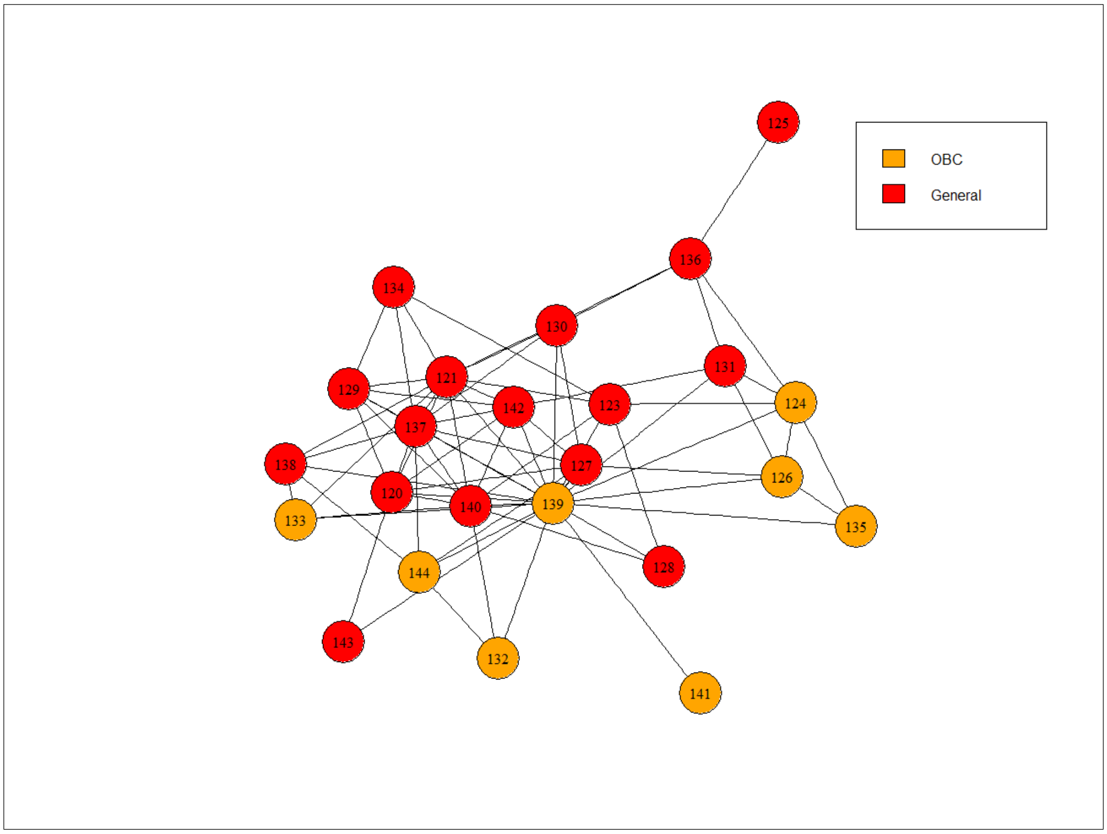
Household 111 has the highest score for all centrality measures which shows that it plays very important roles in the village in various aspects. It has the highest number of direct connections, acts as bridge between disconnected groups, has shortest paths to all other households and has connections to other influential households. This is possibly because the locally-elected representative of the Panchayat belongs to this household. Household 102 also plays a central role in the village. It has the highest score for all centrality measures after household 111. This might be due to the fact that the female head of 102 is a local supervisor for the MGNREGA, a government employment scheme and thus has the opportunity to interact with other female household members who are involved in the program directly. The female head here has better access to information regarding various matters and often takes the initiative to circulate among household in the village. Further almost all households in the village mentioned household 111 and 102 as their contact in one or more dimensions. Thus the observations during the data collection further reinforce the results found through network analysis.

Network 5

Village 5 is comprised of 24 households and represents network 5 as shown in figure 2.5. This village has large population of general caste households. There are no scheduled castes or scheduled tribe households in the village.

Network Figure 2.5 indicates that most of the households in this village are well connected with a few outliers. There is less number of kinship networks observed within this village compared to the rest of the villages. Observations from the field gave the impression that the households know each other and there are good interactions along various dimensions. Graph level statistics given in table 2.10 reports an average degree of 6 for the network. The network has a medium density, diameter and average path length. The average path length is used to measure the average of all shortest path length (number of links) and the diameter of a network is the length (number of links) of the largest geodist connecting any two nodes in a network. These measures are an indication of how well connected the network is. Based on the statistics we can to say that the village is fairly- well connected.

Figure 2.4: Visualization of social network for village 5 in Meenangadi, Wayanad.



Source: Author's analysis

Table 2.5 display nodes with the highest centrality scores in the network. From the node level centralities, household 139 is found to have the highest score for all centrality measures. Thus household 139 plays a vital role in connecting people within the village, maintaining direct number of connections with other households as well as connections with other influential households. This could indicate that household 139 is particularly important for disseminating information, skills and services within the village.

Table 2.5: Nodes with highest centrality scores in village 5 of Meenangadi, Wayanad.

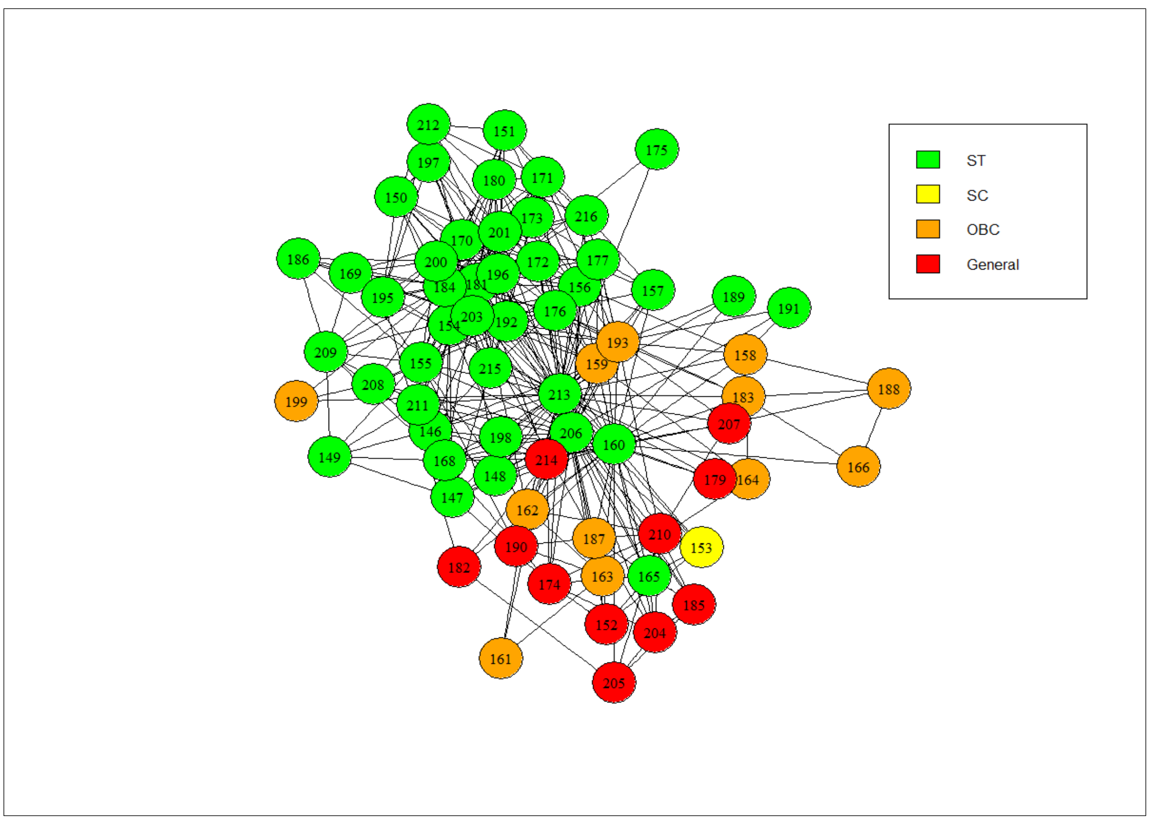
Centrality	Node	Score
Degree	139	0.870
Betweenness	139	0.167
Closeness	139	0.852
Eigenvector	139	0.437

Source: Author’s analysis

Network 6

Network 6 is the largest village consisting of sixty seven households. The village has two tribal settlements.

Figure 2.5: Visualization of social network for network 6 in Meenangadi, Wayanad.



Source: Author’s analysis

It also has households belonging to scheduled castes and general category. Households within the tribal settlements are well connected and interact on various dimensions. Within the rest of the village there appeared to be clusters of households which are well connected. The network figure 2.6 below represents a visualization of the network.

The network has a low density score showing a low fraction of potentially observed links in the networks. Results in table 2.10 report high diameter and average path length relative to the other networks. Diameter represents the longest path in the network and thus suggests that households in network 6 are connected through a fairly large number of intermediaries. The average path length also gives a general idea of the network's overall connectedness, and a high average path length suggests potential for slower transfer between households.

Table 2.6: Nodes with highest centrality scores in village 6 of Meenangadi, Wayanad.

Centrality	Node	Score
Degree	213	0.667
Betweenness	213	0.957
Closeness	213	0.750
Eigenvector	213	0.322

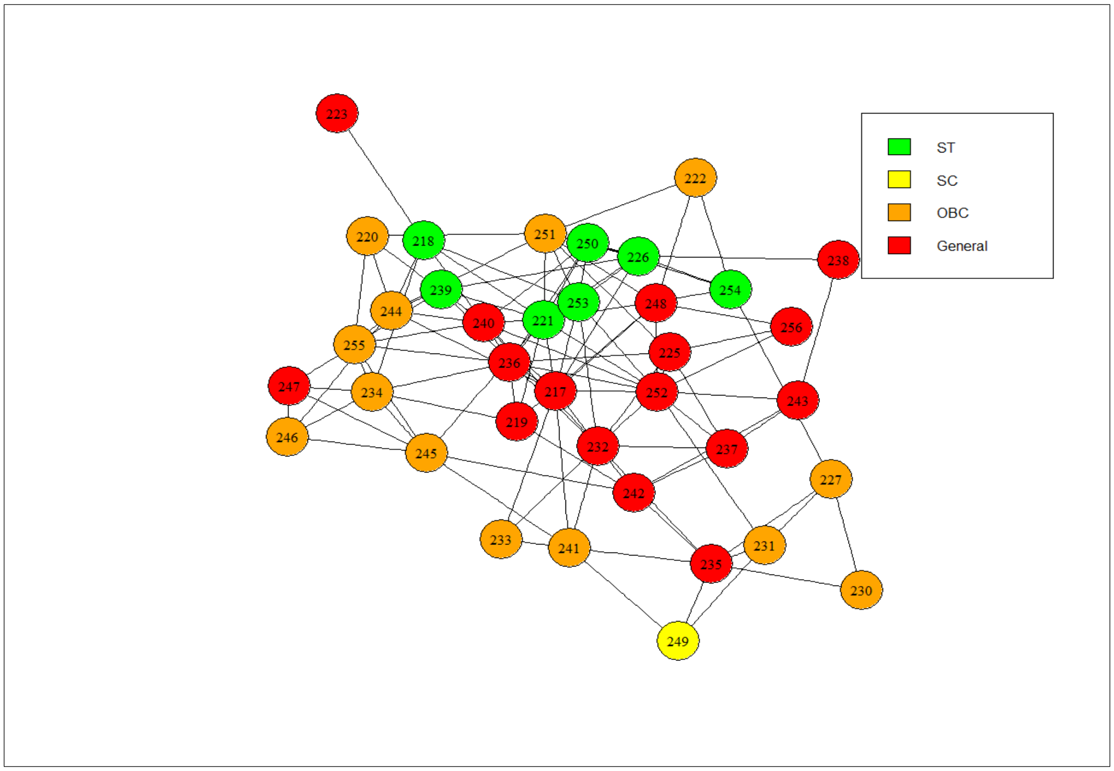
Source: Author’s analysis

Household 213 is shown to have the highest score for all centrality measures. This suggests its importance in the network with respect to aspects such as number of direct links, ability to quickly interact with other households, for linking disconnected households and for having connections to other households with high centralities.

Network 7

Village 7 is comprised of 37 households. This village has people who belong to different caste categories with a large population of general caste households.

Figure 2.6: Visualization of social network for village 7 in Meenangadi, Wayanad.



Source: Author's analysis

Field observations gave the impression that majority of the interactions were between households belonging to the same caste. Some of the households in the village are landowners and two households have their own business venture (factory). They often employed members of the tribal households to work on the fields or the factory. This created opportunities for cross caste interactions within the village. However on the whole, it was observed that households preferred to maintain ties with members of their own caste.

The network has an average degree of 6 and a small density score. This is possibly because of the lack of cooperation and limited interactions within the village. Low of density might in turn lead to lower levels of information dissemination. Results in table 2.10 also suggest that the network has a relatively high diameter and average path length. This indicates that the number of links connecting any two households is relatively large. Nodes with highest centrality scores are reported below.

Table 2.7: Nodes with highest centrality scores in village 7 of Meenangadi, Wayanad.

Centrality	Node	Score
Degree	221	0.36
Betweenness	252	0.145
Closeness	221	0.58
Eigenvector	221	0.34

Source: Author’s analysis

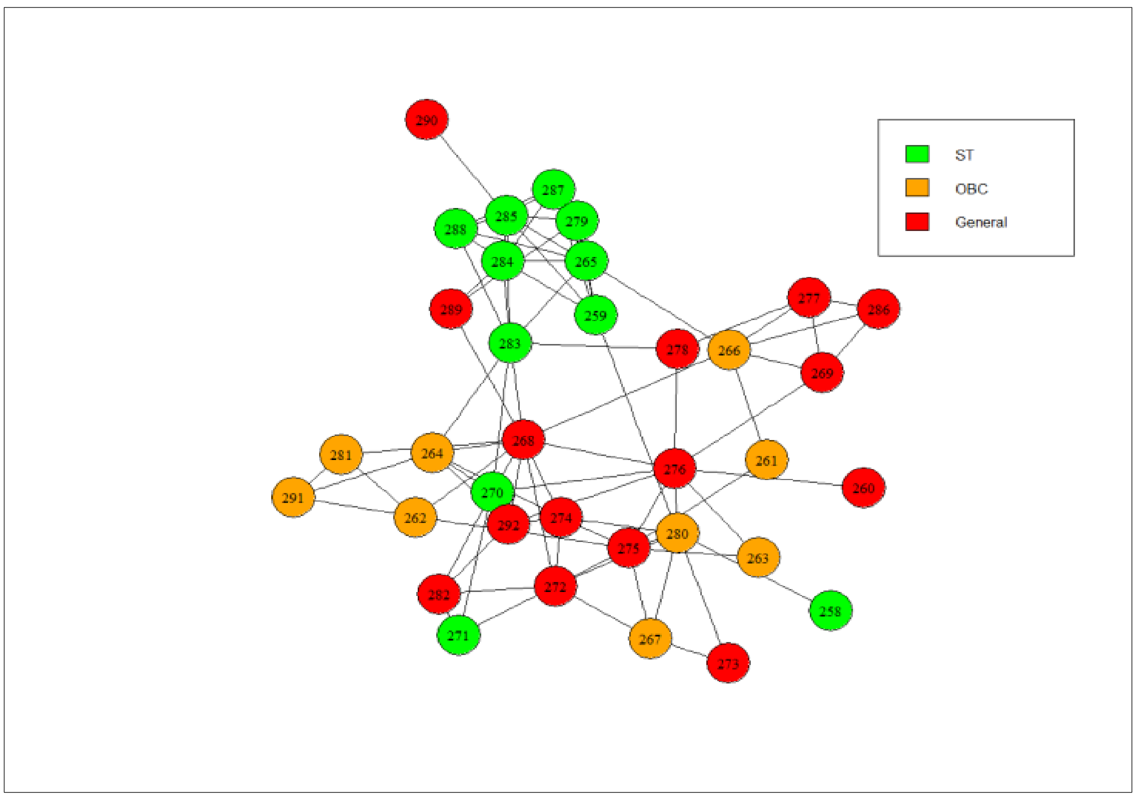
Household 221 has the highest number of direct links to other households. It also has the highest closeness and eigenvector centrality scores. This suggests that it has the shortest path length to all other households in the network and also has connections to other influential households within the network. Further, household 252 is found be important in terms of acting as a bridge to other disconnected households.

Network 8

Village 8 has 35 households and represents network 8 as shown in figure 2.8. Though all households within the village do not have direct links or interactions with one another, the majority of them tend to know each other through intermediaries. This village has a Paniya household represented by household 258. Paniya people tend to be the most backward and disadvantaged among the tribal groups. The generally tend to have very limited interactions with other households. It can be seen from the figure that household 258 is isolated with only one direct link with the rest of the network.

The network has a relatively low density, high diameter and high average path length. This is possibly because of lower levels of solidarity and cooperation. High average path length and diameter indicates a fairly large number of intermediaries between any two households.

Figure 2.7: Visualization of social network for village 8 in Meenangadi, Wayanad.



Source: Author’s analysis

Table 2.8 reports nodes with highest centrality scores in the village. The results show that household 268 has the highest scores for all centrality measures. This is possibly because the female head of the household is an ASHA (Accredited Social Health Activist), community health worker introduced as part of the National Rural Health Mission (NRHM), a scheme instituted by the government of India's Ministry of Health and Family Welfare (MoHFW). The primary role of an ASHA worker is to visit other households in the village to promote health education and services. This in turn facilitates connections to other households in the village.

Table 2.8: Nodes with highest and lowest centrality scores in village 8 of Meenangadi, Wayanad.

Centrality	Node	Score
Degree	268	0.324
Betweenness	268	0.209
Closeness	268	0.548
Eigenvector	268	0.305

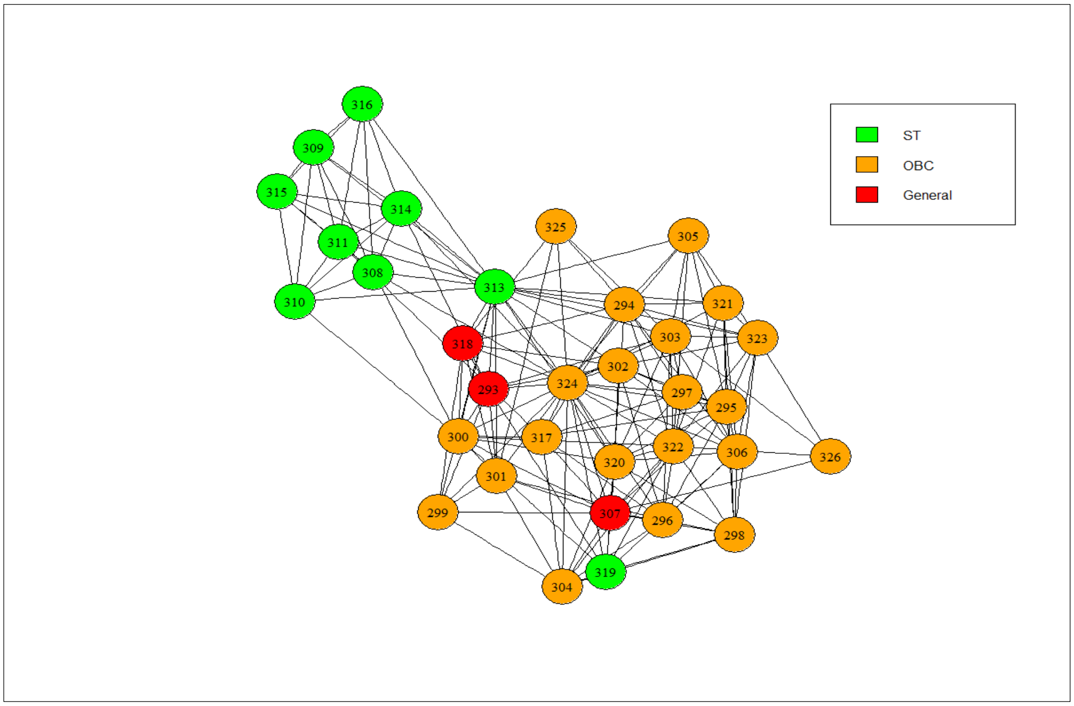
Source: Author's analysis

Network 9

Village 9 is comprised of 33 households and has one tribal settlement. The network figure above shows that the tribal households form a distinct cluster. Household in tribal settlements generally tend to be well connected with interactions on several dimensions.

The village has high average degree and density along with low average path length and diameter. This suggests that the network is well connected with few intermediaries between households. This indicates better levels of cooperation and solidarity within the village.

Figure 2.8: Visualization of social network for village 9 in Meenangadi, Wayanad.



Source: Author's analysis

Table 2.9 reports the highest score for all centrality dimensions.

Table 2.9:Nodes with highest centrality scores in network 9

Centrality	Node	Score
Degree	324	0.750
Betweenness	313	0.098
Closeness	324	0.800
Eigenvector	324	0.364

Source: Author's analysis

Household 324 plays an important role in the network in terms of maintaining direct links with other households, being able to quickly interact with others. It also has connections to other important households. Further, household 313 has the highest betweenness centrality score and therefore plays a significant role in connecting households in the network. The position of household 313 in the network figure above reinforces this result.

Graph level statistics

Table 2.10 reports summary statistics for all nine networks.

Table 2.10: Graph level statistics of nine villages in Meenangadi, Wayanad.

Village	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Number of nodes	20	23	34	28	24	67	37	35	33
Average degree	9.4	4.783	8.471	10.5	6.083	11.104	6.162	4.971	10.182
Average path length	1.511	2.676	1.904	1.624	1.859	2.009	2.308	2.497	1.784
Diameter	3	6	3	3	4	4	5	5	3
Density	0.495	0.217	0.257	0.389	0.264	0.168	0.171	0.146	0.318
Transitivity	0.62	0.607	0.406	0.505	0.445	0.348	0.339	0.402	0.495
Centralization(degree)	0.503	0.21	0.21	0.578	0.66	0.514	0.201	0.188	0.46
Centralization(betweenness)	0.157	0.174	0.095	0.17	0.422	0.256	0.103	0.183	0.196
Centralization(closeness)	0.598	0.241	0.24	0.65	0.639	0.502	0.287	0.294	0.486

Source: Author’s analysis

Transitivity scores between 0.3 and 0.6 have been estimated for the networks. This is consistent with what is usually observed in real world networks (Butts, 2008). Transitivity represents the idea that if A has a relationship with B, and B has a relationship with C, then A has a relationship with C as well. Greater transitivity could suggest a greater potential for transmission within a network (Wey et al., 2008). Results show a connectedness value of 1 for all networks indicating that networks are connected. In other words every pair of households within a network is connected by a path.

Centralization measures capture the tendency of a single household to be more central than all other households in the network. In other words it provides insight into whether there is a huge variance between the most central household and others in terms of degree, closeness and betweenness. Networks with high degree centralization are subject to fragmentation if the highly connected nodes are removed. Betweenness centralization indicates the presence or absence of nodes that are high in betweenness and lie between all other nodes as gate keepers of the network. Closeness centralization is key in representing the node's ability to pass information to all other nodes in the network quickly. Removal of the most central household in all cases could affect flow of information, resources, skill or services. In the case of degree centralization the variance is high for networks 1, 4 and 6. Network 4 has the highest variance for betweenness centralization. In terms of being able to reach others quickly, the variance is relatively higher for networks 1, 5 and 6 showing that closeness centrality in these networks is concentrated within a small number of households.

2.6 Node –level centralities and household attributes

The techniques of social network analysis used above facilitate characterization of structural properties of a network and this in turn allows us to identify the important actors within a network as well any pattern or regularities that might influence the structure of the network. However, given the large heterogeneity of the population in these villages it is worthy to examine whether any demographic attributes influence network properties such as centrality of households. In particular, given the inter caste-disparity that exists, we aim to examine whether centralities differ by social strata or caste of the households. Analyses are also done to examine whether social network properties could be influenced by attributes such as, education age and gender.

A set of analysis was done using t-tests to determine if there are any differences in network measures by attributes such as caste of the household, gender of the head, age-group of the head and education of the head. The network measure used is eigenvector centrality which is proportional to the sum of the centrality of its neighbors.

Table 2.11: P-values of two-sided t-tests of differences in mean eigenvector centrality scores by caste of the household in Meenangadi, Wayanad.

	ST (167.07)	**SC** (213)	**OBC** (127.54)	**General** (136.38)
ST (167.07)	-	0.035	0.001	0.013
SC (213)	-	-	0.000	0.002
OBC (127.54)	-	-	-	0.491
General (136.38)	-	-	-	-

Note; Mean eigenvector centrality in parenthesis.
Sample sizes: ST =106, SC=16. OBC=95, General= 86
H0: mean (row) = mean (column)

Results show that the mean eigenvector score of households belonging to scheduled tribe is greater than households belonging to other backward classes. Further the mean eigenvector score of households belonging to scheduled caste were found to be greater than the mean scores of households belonging to scheduled tribe, other backward classes and general caste. Scheduled castes have highest mean values, followed by scheduled tribes, followed by other backward castes, and general.

Table 2.12: P-values of two-sided t-tests of differences in mean eigenvector centrality scores by gender of head of household in Meenangadi, Wayanad.

	Male (n=242)	**Female** (n=57)	**P-value**
Mean	150.30	142.03	0.517

H0: mean (male) = mean (female)

Table 2.13: P-values of two-sided t-tests of differences in mean eigenvector centrality scores by age-group of head of household in Meenangadi, Wayanad.

	20-34 (124.91)	**35-49** (146.96)	**50-64** (156.67)	**65 above** (140.20)
20-34 (124.91)	-	0.266	0.129	0.491
35-50 (146.96)	-	-	0.394	0.649
50-64 (156.67)	-	-	-	0.289
65 above (140.20)	-	-	-	-

Note; Mean eigenvector centrality in parenthesis.
Sample sizes: 20-34yrs =22, 35-49yrs =114, 50-64yrs =121, 65yrs and above = 44
H0: mean (row) = mean (column)

Table 2.12, 2.13, reports the results of t-tests between mean eigenvector values of households by age-group and gender of the head of household for the whole sample, respectively. Results show that centrality scores of households are not influenced by age-group and gender of the head.

T-tests were also done to examine if there were differences in eigenvector score based on the education level of the head of household. Education levels were grouped into four main categories for this purpose. Category I include 1st to 5th grade of schooling, category II include 8th to 12th grade. Category III include any level education after 12th grade (eg, diploma, masters) and category IV consists of heads that are illiterate. Results are reported in table 2.14. Education level of the head of households is shown to have no impact on their eigenvector centralities.

Table 2.14:P-values of two-sided t-tests of differences in mean eigenvector centrality scores by education level of head of household in Meenangadi, Wayanad.

	I (148.16)	**II** (148.05)	**III** (131.2)	**IV** (152.61)
I (148.16)	-	0.9925	0.555	0.742
II (148.05)	-	-	0.564	0.753
III (131.2)	-	-	-	0.491
IV (152.61)	-	-	-	-

Note; Mean eigenvector centrality in parenthesis.
Sample sizes: I =138, II =89, III =10, IV = 59
H0: mean (row) = mean (column)

2.7 Conclusion

Social network analysis has been applied in diverse fields for identifying patterns of relationships linking individuals within a network and analyzing structure of these patterns. This chapter has used social network analysis to describe social networks in nine villages of rural India. The study views villages of rural India as networks of households connected by social ties.

Households in positions of prominence within each village were determined using the node level network measures such as degree, betweenness, closeness, and eigenvector centralities. There were no common demographic attributes identified with these households across the villages. However, in most of the villages, central households were the ones who were well known to other households due to their occupation or strong association with a political party. For example, in village 2, the central households were actively involved in politics and had links to influential individuals within the political party. In village 3, one of the central households owned a rickshaw which was commonly used for transportation by all others in the village. In village 4, one of the households had a member who was a locally elected representative of the panchayat and the other central household held a supervisory position with the government employment initiative (MGNREGA). In village 5, the central household owned a business venture. In village 8, the central household had a member working as an ASHA, as a part of the government health service initiative.

At the village level, network measures provided insights into the overall structure and possible stability or vulnerability of villages. Networks with high density, small diameter and small average path length are perceived to have better connectivity and cooperation and hence more successful at collective action than others. Results showed that level of cooperation and solidarity are higher in villages 1, 3, 4, 5 and 9. Transfer of resources is likely to be faster and efficient in these villages.

A set of analysis using two sided t-tests were done to determine any significant differences in centrality scores of households based on attributes such as caste of the household, age of the head of household, gender of the head of household and education of the head of household. Results revealed differences in centrality scores by caste of the households. Scheduled castes have highest mean values, followed by scheduled tribes, followed by other backward castes, and general. This suggests that scheduled tribes and scheduled castes are more successful at maintaining ties with other important households within the village. On one hand, this tendency to maintain network ties could be due to positive response to developmental initiatives and on the other hand, it could be characteristic of the network itself.

There were no significant differences in centralities by gender[3], age group and education of the head of households. This indicates that the households belonging to lower castes are more successful at maintaining ties with other households and performing network functions such as connecting disconnected groups, reaching others quickly and influencing other households.

These analyses provide a deeper understanding of the structure of rural India's social network and how social interactions influence network structure and dynamics. It is important to recognize that there are difference in interactions and patterns among households across the villages although they are located closely. These intuitions at the node level and network level can offer a better foundation for developing and implementing any regional level initiative by the government, NGO's or development projects.

[3] It is possible that women in general have higher centrality scores than men in these villages. However, this cannot be examined since our unit of analysis is a household.

Chapter 3 . Social Networks and Diversification of Income Sources

3.1 Introduction

Rural livelihoods in developing countries primarily rely on rain-fed agriculture and are characterized by poverty, instability and inequality. Given this context of rural survival, households tend to diversify their income sources. In other words households engage in multiple income earning activities as a strategy to stabilize or increase their income (Ellis, 1998).

One of the factors that can play a role in income diversification is the social networks of the households. A household's social network may help it gain ideas, skills, information and services which could influence their decision to start a new initiative or maintain an existing one. Further, networks can facilitate diversification through collective action and transfer of resources. For example, the Self Help Group (SHG) model which is one of the most important networks found among women in rural India, is a good example of how connections made through networks can promote a favourable atmosphere for diversification. The SHG provides opportunities for collectve action and risk sharing along with a platform to share information, knowledge, skills and develop more contacts within the community.

There are very few studies that have focused on the role of social network or other forms of social capital on rural income diversification (Schwarze and Zeller, 2005; Smith et al., 2001; Baird and Gray, 2014).The few studies that been done have mainly looked at one or more specific social intercation and its possible links to diversification, for example involvement in community groups and exchange of material goods between communities. Much of the diversification literature is focused on determinants, patterns and links to household welfare through income and consumption (Ellis, 1998, 2000; Barret et al., 2001; Ersado, 2003; Abdulai and Crolerees, 2001).

The focus of our study is to depict social networks as connections or links between the households within a village formed through various interactions and examine its role in diversification activities using a network econometric model. Further, the results from chapter 2 revealed that scheduled castes and scheduled tribes have higher centrality scores. Thus, in our analysis we account for any influence that social strata or caste could have on diversification of income sources.

The outline of this chapter is as follows. Section 3.2 provides brief background about the Indian context. Section 3.3 includes a discussion on the various motives and factors that influence income diversification. Section 3.4 provides a discussion on why social networks might be important for diversification. Section 3.5 gives a brief account of the data used. Section 3.6 discusses the econometric methodology following by section 3.7 which discuss challenges in estimation of the models. Section 3.8 presents results followed by section 3.8, a brief conclusion to the chapter.

3.2 Background

India, being the world's second most populous country, is also home to a large number of poor and malnourished people. Poverty is engrained in many areas, particularly in remote villages with high proportions of tribal communities and rural poor. Seventy percent of the nation's population lives in rural India and sixty percent of the rural workforce remains primarily involved in agriculture (Himanshu et al., 2013). In recent years, there has been a continuous decline in the share of agriculture and allied sectors to the overall Gross Domestic Product

(GDP) of the country from 30 percent in 1990-91to 13.7 percent in 2012-13 (Government of India, 2013). However, this decline has not been accompanied by a matching reduction in the percentage of population dependent on agriculture. With the slow growth of the agricultural sector, rural employment challenges are increasing fast. It is seen that the rural non-farm economy and migration to urban areas serve as key alternative sources of new jobs. Based on the National Sample Survey Organization (NSSO) statistics between 1983 and 2009/10, Himanshu et al, (2013) find evidence indicating a process of diversification out of agriculture that is slow but accelerating. Further, village based studies on income diversification in India indicate that majority of households have diversified incomes and non- farm income is an important component (Lanjouw and Shariff, 2001; Deb, et al., 2002; Vatta and Sidhu, 2007; Anderson et al., 2005; Rawal et al., 2008.).

3.3 Diversification of Income sources

Diversification of income sources for rural households can be considered in different ways. Minot et al, (2006) gives a detailed account of the various concepts of income diversification used in the literature. Two of these concepts of diversification are most commonly used in diversification studies. Income diversification is used to denote an increase in the number of sources of income or the balance among the different sources. Thus, a household with two sources of income is considered more diversified than a household with just one source. Further, a household with two income sources, each contributing half of the total, is also considered to be more diversified than a household with two sources where one accounts for 90 percent of the total (see Joshi et al. 2002; Ersado 2003). Another frequently used concept considers income diversification as expansion from farm into non-farm activities and is measured by taking into account the share of non-farm income in the total household income (see Reardon 1997; Escobal 2001). According to this concept if a household increases the share of income from nonfarm sources from 30 percent to 75 percent, this represents diversification into nonfarm activities but not income diversification in terms of the number and balance of income sources (as described by Minot et al, 2006). This concept is commonly used to capture the change in structural composition of rural incomes or to take account of the decline in share of agricultural income. This study applies the first concept of income diversification. It takes into account multiple sources (agricultural or non-agricultural) through which a household earns its income and the balance among those sources. The concept of income diversification is formally defined in section 3.5.

Income diversification among rural households has been studied extensively in the literature. The majority of studies are focused on the determinants and patterns of income diversification (Corral & Reardon 2001; DeJanvry & Sadoulet 2001; Lanjouw & Shariff 2002; Barrett et al. 2001a, 2001b; Abdulai and CroleRees 2001; Ellis 2000; Reardon, Delgado, and Matlon 1992), while others have examined the impact of income diversification on investment, poverty and inequality (Reardon et al. 2000; Schwarze and Zeller, 2005; Démurger, Fournier, and Yang 2010). Based on these studies, the main factors which influence income diversification can be categorized as: individual and household characteristics such as age, gender, education, marital status, household size; farm characteristics that commonly includes amount of cultivated land, membership in a farm organization, access to agricultural extension services; location, which is usually captured by quality of roads, availability of electricity, distance from towns; and market barriers which is captured by accessibility of credit and market information.

Some of the wealth of studies that discuss determinants of income diversification categorizes motives for diversification as "push" or "pull". Push factors include income diversification due to risk reduction, response to diminishing factor returns in any given use, such as family labor supply in the presence of land constraints driven by population pressure and fragmented landholdings, reaction to crisis and liquidity constraints, high transactions costs that induce households to self-provision in several goods and services (Ellis, 1998., Barrett et al, 2001a; Barrett *et al.*, 2001b). Pull factors such as the realization of strategic complementarities between activities that have strong backward and forward linkages. For example, recognizing the advantages of crop-livestock integration or taking advantage of local engines of growth such as commercial agriculture or proximity to an urban area (Ellis, 1998; Barrett et al., 2001a). Thus rural households diversify their income sources either to cope with livelihood risks or to exploit new opportunities. The ability to diversify is especially important for rural poor to deal with unexpected shortfalls in annual income (see Ellis, 1998). Evidence from empirical studies suggests that that income diversification is generally associated with higher income and food consumption as well as more stable income and consumption over time (Reardon et al 1992; Reardon 1997; Barrett et al. 2001a; Block & Webb 2001; Canagarajah et al. 2001).

3.4 Social networks and Diversification of Income sources.

Along with the several factors that have been previously identified, this study views social networks as one of the important factors that can influence diversification. Networks are particularly important for information dissemination, facilitating collective action and exchange of material goods, services, skills, ideas that can be critical for diversifying incomes. Jackson (2008) mentions that social relationships play a critical role in individual behavior. Social networks affect people's opinions, the information they obtain, and are also key in accessing resources. The amount of information, trust in the information and information dissemination are key factors in influencing behavior. As mentioned in Anderson and Feder, (2007) in rural areas, farmers often rely on their social connections as their most trusted and reliable source of information regarding the suitability, profitability, and use of new technologies. Kim (2011) suggests that social networks can facilitate access to key resources and thereby influence diversification. For example, in cases where collateral restrictions prevent the poor from getting a commercial loan, community networks act as alternative sources of credit through mutual lending.

Further, problems of mobility and lack of proper infrastructure might limit market access and this can act as a strong hindrance to income diversification. Social networks through shared goasl and collective action can help to overcome these limitations (Kim, 2011). Social networks can also help people to access inputs from trusted providers or markets for outputs which inturn may faciliate diversiifcation into new activities. Further, the significance of the non-farm sector in rural areas has been growing over the past few years and households increasingly diversify into various non-farm activities (see Lanjouw and Murgai, 2008). For people who generate income from the non - farm sector, social contacts outside the farm are often a primary reason to enter into the sector and maintain these off-farm activities (Meert et al., 2005).

3.5 Data

Two sets of data were used to analyze the effect of social networks on diversification of income sources. Social network data collected for this study (see chapter 2) captures the links between households within a village. A household's social network consists of all households within their home village that it interacts with on various dimensions.

Data required to measure household income diversification were obtained from a survey conducted in 2013 as part of a related project (the APM Monitoring and Evaluation Survey). Household incomes in the survey are categorized into different sources namely, sale of surplus staple crops, fruit and vegetables, livestock products, crop by products, income from services by livestock, agricultural wages, off-farm activities, migration and salaried employment. Annual income in rupees earned from each of these sources was obtained from recall questions posed to the household respondents. The survey also obtained information on household demographics such as age, household size, education of the household, religion and ethnic background. Data regarding household shocks, availability of information, credit and infrastructure were also obtained.

Descriptive Statistics

Tables 3.1, 3.2 and 3.3 below provide descriptive statistics based on sources and share of household incomes.

Table 3.1: Average percentage share of income obtained from the different income earning sources identified in Meenangadi, Wayanad.

S.No	Sources of Income	Average percentage share of Income
1.	Sale of market surplus staple crops	10.87
2.	Sale of surplus fruits and vegetables	0.08
3.	Sale of crop by-products	0.33
4.	Sale of livestock, birds	0.86
5.	Sale of livestock products	5.32
6	Income from services by livestock	0.02
7.	Income from agricultural wages	4.72
8.	Income from off-farm activities (business, trade, non - ag wages).	52.81
9.	Income from migration	6.97
10.	Salaried employment	13.82
11.	Income from other activities	3.88

Source: Monitoring and Evaluation Survey, APM 2013
1 USD = Rs.59

Table 3.2: Average total income, average agriculture income and average non-agriculture income of all households, households who have diversified and who have not diversified in Meenangadi, Wayanad.

	All Households	Diversified	Non-diversified
Total Income(Rs)	155991.7	161656.5	127554.2
Agriculture Income(Rs)	37091.1	43733.16	3748
Non-agriculture Income(Rs)	118900.6	117923.4	123806.2

Source: APM Monitoring and Evaluation Survey, 2013
1 USD = Rs.5

Table 3.3:Total number of households who receive their main share of income from agricultural and non-agricultural sources in Meenangadi, Wayanad.

Main source of income	Total number of households	Number of households who do not diversify	Number of households who diversify
Agriculture	54	2	52
Non-agriculture	247	48	199

Source: APM Monitoring and Evaluation Survey, 2013

Table 3.1 shows the major share of income comes from off-farm activities (business, trade, non - agriculture wages) at 52.8%, followed by income from salaried employment at 13.8% and crop production at 10.9%. As presented in table 3.2, the average annual income of the households is Rs.155992 (1 USD = Rs.59). Further, average annual income for households who have diversified is slightly greater than for households who have not diversified. Based on the descriptive statistics we can classify households into two main categories, those who receive their main share of income from agriculture and those who receive their main share of income from non-agriculture. Table 3.3 shows that out of 301 households sampled, 247 households receive their main share of income from non- agricultural sources and 54 households receive their main share of income from agriculture. It is interesting to note that almost all agricultural households earn income from multiple sources while 20 percent of the non-agricultural receive their income from only one source.

3.6 Econometric Model

In this study, villages of rural India are represented as networks of households connected by social ties. These ties or links between the households are captured by an n x n matrix W where element $w_{ij} = 1$ if household j is connected to household i and zero otherwise. It is assumed that $w_{ii} = 0$, in other words that household i is not connected to itself and that every household has at least one connection. Given this, then matrix A is a row normalization of W such that element $a_{ij} = w_{ij} / \sum_j w_{ij}$. The element a_{ij} in the row normalized network A can be interpreted as the fraction of all network weight on household i that can be attributed to j.

Equation 2 below represents the model used in the study.

$$Y_i = \beta_0 + \beta_1 AY_i + \beta_2 X_i + \varepsilon_i \tag{3.1}$$

In the equation above, households or nodes are indexed by i = 1…..n. Y_i represents income diversification of household i. X_i represents exogenous factors that affect diversification. A is an n x n row normalized network matrix. The term AY_i in the model represents the average outcome (diversification) of household i's network. It allows us to examine how an actor's outcome can be influenced by the average outcome of its network. β_1 and β_2 are the parameters to be estimated and ε_i is the error term.

We build a network econometric model, based on the Spatial Autoregressive approach, by replacing the spatial matrix with a network matrix. Conceptually, our model is based on Manski's theory of social interactions which suggests that the outcome of each individual depends linearly on his own characteristics and on the mean outcome of his reference group (Manski, 1993). Bramoulle et al (2009) applies this theory to develop an econometric model for identification of peer effects through social networks. The model developed in this study closely follows the work of Bramoulle et al (2009).

A household's diversification behavior can be influenced by the average diversification of its network. This presence of positive social interactions suggests the existence of a social multiplier where aggregate effects will amplify the individual effects (Glaeser et al., 2003). This amplification is known as a social multiplier effect. Glaeser et al., (2003) has explained this using an example of criminal behavior. Crime deterrence is expected to be affected by changes in policing or punishment. However, if one person's inclination towards crime influences his neighbor's criminal behavior, then a change in policing will have both a direct effect on crime and an indirect effect through social influence. This presence of positive spillovers or strategic complementarities creates a "social multiplier" where aggregate coefficients will be greater than individual coefficients (Becker and Murphy 2000). This can be better explained using the equation 3.2 which represents the reduced form model of (3.1).

$$Y_i = (I - \beta_1 A)^{-1}(\beta_0 + \beta_2 X_i + \varepsilon_i) \qquad (3.2)$$

In the equation above β_2 captures the effect of X on Y. The term $(I - \beta_1 A)^{-1}$ represents the multiplier. It multiplies the effect of β_2. The social multiplier (η) is approximated as η= 1/ 1- β_1

and is interpreted as how much on average the network interactions intensify the effect of exogenous variation on outcome (Wichmann, 2014). It captures the ripple effect of exogenous variation (or varying X) on diversification. For example, facilitating income diversification activities for a group of women by providing training opportunities and initial support may lead their neighbors to do the same. This could take place as a result of information transmission, so that the choices of any single household modify the information available to the rest of the agents in its network (Maurin and Moschion, 2006).

Income diversification is commonly measured in the literature using indices such as Simpson Index, Herfindahl Index or Shannon Index, which takes account of both the number of sources and the balance among them (Ersado, 2003; Joshi et al. 2003; Minot et al., 2006; Babatunde and Qaim, 2009). We use the Simpson Index of diversity which is defined as $SID = 1 - \sum P_i^{\,2}$ where Pi is the proportion of income coming from source i. The value of SID always falls between 0 and 1. If there is just one source of income, Pi = 1, so SID = 0. As the number of sources increases, the shares (Pi) decline, as does the sum of the squared shares, so that SID approaches 1. If there are k sources of income, then SID falls between zero and 1 – 1/k (Minot et al., 2006). The Simpson Index is closely related to the Hirschman–Herfindahl index of concentration (HH), specifically, SID = 1 – HH/10,000 (Minot et al., 2006).

The explanatory factors (X_i) in the model are household demographics including age of the head, gender of the head (male =1), whether the head has completed primary education (yes=1), caste or social category of the household (schedule tribe=1, otherwise =0) and size of the household. The other variables are income, access to credit measured by whether the household has accessed formal or informal loans in the past year, access to infrastructure represented by use of electricity (=1), access to information which captures whether the household know about the availability of information services regarding agricultural extension services, weather, market prices, crop insurance services and whether the housheold has faced any shocks in the form of crop failure in the past year.

3.7 Econometric Challenges and Estimation

The model specified above suffers from the issue of endogenity due to reverse causality. We suspect that income variables could be influenced by diversification (Ersado, 2003; Dimova and Sen, 2010). Further, the variable that captures the average diversification of the social network (AY) could also be endogenous. A household's diversification is influenced by the average diversification of the network which in turn is influenced by the household's diversification.

The ordinary least squares (OLS) estimation of equation (1) will provide biased and inconsistent estimators due to the presence of endogenous variables (Wooldridge 2002).[4] Thus the Instrumental variable (IV) method is used to address this issue. The IV approach with endogenous variables requires an observable variable (Zi) not in equation (1), and satisfies two conditions: (a) Zi must be uncorrelated with the error term ε_i and (b) Zi must be correlated with income. In diversification studies, assets are commonly used as a proxy for income (Dimova and Sen, 2010; Ersado, 2003). In this study, we have tried to address the endogenity of income by using ownership of household assets as instruments. Assets used include irrigation pumps, truck or tractor, computer and fridge. These assets can influence household income but is unlikely to

[4] OLS results are provided in table a.2 of appendix A.

affect diversification activities directly. The correlation between income and instruments Zi can be tested by estimating simple regressions of income on instruments (Sokcheng and Kimsun, 2013). Diversification index was also regressed on these instruments to make sure that they are not directly correlated.[5]

Following Kelijian and Prucha (1998), the endogenity of average diversification of the social network (AY) is addressed using the average exogenous factors (such as household characteristics) of the household's network. The average exogenous factors of a household's network (AX), average exogenous characteristics of household's network's network (A^2X), and the third degree connection, that is the average exogenous characteristics of a household's network's network's network (A^3X) are used as instruments in the model. The intuition behind this is that the exogenous factors such as the household characteristics of the network are correlated to the diversification behavior of the network (endogenous variable AY) but are not correlated with unobservable factors of household's diversification. In other words, our identifying assumption is that X is exogenous, which would make AX a valid instrument.

[5] Regression tables are provided in table a.3 of appendix A.

3.8 Results and Discussion

The first step of analysis involves examining the effect of social networks on diversification of income sources for the whole sample. The results are provided in Table 3.4[6].

The average diversification of the network is shown to have positive effects on income diversification. This indicates the importance of network effects. As mentioned before, positive effects of network diversification on household's diversification can create social multiplier effects by amplifying the influence of exogenous variation on diversification. In other words, apart from the direct effect of the exogenous factors on a household's diversification, network interaction can further amplify these effects. Social multiplier can be calculated using the network effect parameter, (1/ 1- β_1). A social multiplier of 2.39 is estimated showing that the network effects intensify the effects of exogenous factors on diversification by 139 percent. Further, results also show that whether the household has faced any recent crop failure have statistically significant positive effects on diversification. Recent crop failure is to found to have a significant and positive effect on diversification showing that the households will prefer to diversify in order to minimize or cope with risks.

It is difficult to anticipate how age might affect diversification and there are mixed explanations in the literature. On one hand, as a person gets older, he or she may accumulate the skills that lead to greater specialization.

[6] Note that the main purpose of these analyses was to estimate the effects of social networks on income diversification. Different specifications of the model included different asset and income variables. While results for only one model are reported here, the estimates of the effects of social networks on diversification were robust across different specifications.

On the other hand, more experience and accumulation of assets may allow households to diversify into alternative enterprises (Minot et al., 2006; Block and Webb, 2001). In this case, age has no effect on diversification for households.

Gender (male=1) of the head is found to have no significant impact on diversification. Studies have found mixed results regarding gender of the household head and its effect on diversification (see Teshome and Edriss, 2013; Minot et al., 2006; Block and Webb, 2001). In some cases male headed household tend to diversify more while in other cases female headed household tend to diversify more. Education and size of the household were found to have no effects on diversification.

Lastly, social category, household's access to credit, and access to information is found to have no significant effects on diversification. In many cases, access to infrastructure is an important determinant for self-employment opportunities or small businesses (Minot et al, 2006). In the study area, almost all households have access to electricity and very few households are involved in self-employment. Access to information in the model captures whether the households are aware about the availability of various information services and is found to have no significant effect. While this is important for diversification, it might not accurately capture households' access to information.

Since the data is colleceted from nine different villages, it is also important to account for the unobservable village level charecteristics that might possibly have an impact on diversification. A village fixed-effects model was estimated to take account of the possible village level characteristics that might influence diversification differently among households. Results are indicated in table 3.4. It is shown that none of the village dummies are significant which in turn confirms that there are no particular unobservable village level characteristics that influence diversification of households differently across villages. Social network effects are found to be important for income diversification. Effects of recent crop failure on diversification are also found to be similar after accounting for village level fixed effects.

Although rural economies are generally perceived to be primarily dependent on agriculture, the descriptive statistics based on the data shows that a majority of the sample receive their main source of income from the non-farm sources. Several studies have identified this rise of non-farm sector and growing importance of its share in total income (Reardon, *et al*., 2006, Rawat et al, 2008). While it is interesting to see that social network matters for diversification, it is equally important to consider whether these explanatory variables affect agriculture households (who receive their main share of income from agricultural activities) and non-agriculture households (who receive their main share of income from non- agricultural activities) differently. For example social network effects could be more important for agriculture households than non-agriculure houseolds. To analyze whether factors affect diversification of agriculture and non-agricultural households differently, a set of analysis has been done by classifying the sample into two categories, households who receive their main share of income from agricultural sources (agricultural households) and households who receive their main share of income from non-agricultural sources(non-agricultural households). It is important to note that categorization of households as agricultural and non-agricultural households does not indicate that they diversify only into agriucltural activities or non-agricultural activities respectievely. The concept of diversification used in this study takes into account all sources of income. The results are reported in table 3.

Table 3.4: Instrumental variable regression results for all households with and without fixed effects, agricultural households and non-agricultural households.

Explanatory Variables	Fixed- effects (All households)	All households	Non-Agriculture (HH)	Agriculture (HH)
Average diversification of the network	0.611** (0.296)	0.585** (0.184)	0.389** (0.146)	0.467** (0.155)
Total income (change in every Rs.10000)	0.001 (0.002)	0.002 (0.002)	-	-
Agriculture Income (change in every Rs. 10000)	-	-	0.068*** (0.012)	-0.002* (0.001)
Non- Agriculture Income (change in every Rs.10000)	-	-	-0.010*** (0.002)	0.012*** (0.003)
Age of household head	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	-0.003*** (0.001)
Gender of household head(male=1)	-0.017 (0.034)	-0.019 (0.034)	-0.038 (0.031)	0.000 (0.033)
Education level of household head	0.010 (0.009)	0.008 (0.009)	0.001 (0.008)	-0.036** (0.012)
Size of the household	0.005 (0.009)	0.001 (0.009)	0.000 (0.009)	-0.007 (0.013)
Social strata (Scheduled tribe=1, Scheduled caste=1)	0.031 (0.036)	0.038 (0.032)	0.014 (0.029)	-0.045 (0.031)
Access to information	0.010 (0.029)	0.001 (0.028)	-0.002 (0.024)	-0.030 (0.027)
Access to credit	0.011 (0.026)	0.010 (0.025)	0.035 (0.022)	-0.010 (0.026)
Crop failure	0.118*** (0.036)	0.119*** (0.036)	0.112** (0.047)	-0.038 (0.036)
Village 2	-0.042 (0.076)	-	-	-
Village 3	-0.059 (0.071)	-	-	-
Village 4	0.017 (0.065)	-	-	-
Village 5	-0.005 (0.078)	-	-	-
Village 6	-0.028 (0.061)	-	-	-
Village 7	-0.060 (0.066)	-	-	-
Village 8	-0.061 (0.066)	-	-	-
Village 9	-0.024 (0.073)	-	-	-
Constant	-0.015 (0.130)	0.012 (0.108)	0.096 (0.088)	0.626*** (0.076)

*,**, *** represents statistical significance at 10%, 5% and 1% respectively

The results show that the average diversification of the household's network has a positive effect on diversification of the household in both categories. This is consistent with our proposition that social networks play an important role in income diversification. This again indicates the presence of social multiplier effects. A social multiplier of 1.65 is estimated in the case of agriculture households and 1.87 in the case of non-agriculture households. Thus the network effects intensify the exogenous effects on diversification by 65% in the case of non- agricultural households and by 87% in the case of agricultural households.

While social multiplier effects are present in both categories, it is interesting to note that the effects are greater in the case of agricultural households. There could be two factors that explain why social network effects are lower in the case of non-agricultural households. For households who receive their main source of income from the non-agricultural sector, the largest share of income comes from off-farm activities followed by salaried employment. In India, with 75 percent of nation's population living in rural areas, poverty and employment challenges seen in the study location are common. In order to address these issues, the government has initiated various programs and policies for rural employment, including the Mahatma Gandhi Rural Employment Guarantee Act (MGNREGA) which offers minimum 100 days of employment per year per household for eligible persons. Within the off-farm activities MGNREGA employment is one of the main source of jobs and a large majority of the households included in the study benefit from this policy. Further, many of the people who obtain formal wages are engaged in government jobs. In both of these scenarios there are certain fixed conditions based on education, social category and poverty status that need to be met to be eligible. This being the case, a person's social interactions or connections may not have a large impact.

Income of the household is an important factor and has a statistically significant effect on diversification activities. As discussed in Dimova and Sen (2010), a negative effect of income indicates that diversification activities are motivated by risk minimization or survival strategies and a positive effect of income indicates that diversification is motivated by accumulation strategies. In other words a household who diversify for risk minimization will initially diversify at lower income levels and as income increases diversification will decrease owing to stability and increased incomes. On the other hand, as income increases, a household that is driven by wealth accumulation purposes will diversify further in order to take advantage of strategic complementarities and to exploit opportunities. In rural areas it can be seen that households often diversify for both reasons.

In this model, income is entered as agricultural income and non- agricultural income. Results show that diversification among households is initially motivated by risk minimization and then accumulation strategies. For example, in the case of non-agricultural households their main source of income (non-agricultural income) has a negative effect on diversification and additional income has a positive effect. This could mean that a household initially diversifies for risk minimization and as their income level increases contributed by the increase in additional agriculture income, they tend to diversify for accumulation purposes. This pattern is observed in the case of agriculture households as well. It is interesting to note that diversification among households in Wayanad is motivated by both risk minimization and accumulation strategies.

Age has a negative effect on diversification for agricultural households while no impact is found in the case of non-agricultural households. As discussed above, it is difficult to anticipate how age might affect diversification and there are mixed explanations in the literature. On one hand, as a person gets older, he or she may accumulate the skills that lead to greater specialization. On the other hand, more experience and accumulation of assets may allow households to diversify into alternative enterprises (Minot et al., 2006; Block and Webb, 2001).

Education is found to have a negative effect on diversification for the households who are mainly involved in agriculture. An increase in education level could lead to increased knowledge about the crop or farming practice. This in turn can lead to a preference for specialization rather than diversification. On the other hand education is not statistically significant for non-agricultural households.

Access to credit is found to have a positive and significant effect for non-agricultural households. This suggests that having access to credit facilitate entry into new income earning activities for the non-agriculture households (Ellis, 1998). Credit has no statistically significant effects on diversification the case of agricultural households.

Effects of recent crop failure on diversification are positive and statistically significant for non-agricultural households. It is reasonable to expect that non-agricultural households who undertake farming as an additional activity will want to diversify and avoid risk if they face a crop-failure. Crop failure is shown to have no effect on diversification of agricultural households. This is possibly because households that are involved in agriculture for a long time when faced with crop failure might not immediately diversify away from their primary activity. This is very commonly observed among farmers in Wayanad. Farmers who face crop loss do not stop farming in the next season even if they are in debt.

Lastly, size of the household, gender of the head (male=1), caste or social classification, household's access to credit, and access to information are all found to have no significant effects on diversification.

Social network Statistics and Diversification

Results above indicate that network interactions, specifically average diversification of the network, play an important role in income diversification. While this already suggests the importance of social network effects on diversification, it will be worthy to examine whether node level centralities estimated in chapter 2 play a role in diversification activities. The node level centralities provide insights into whether social network properties matter for diversification and this will further help us to reinforce the results found above. Moreover, examining the effect of centrality of households on income diversification can guide the design and implementation of initiatives that are developed to facilitate diversification in rural areas. For example, if household centralities matter, then information regarding new diversification opportunities, support and training programs that might assist people in starting a new activity and any necessary skills or resources that might help sustain that activity can be transmitted through central actors within a network. This in turn can be critical to effective information dissemination in rural areas and might create stronger ripple effects.

To analyze the effect of these social network characteristics simple correlations of each of the node level indices, namely degree centrality, betweenness centrality, closeness centrality and eigenvector centrality on diversification are estimated. As described in chapter 2, degree centrality captures the number of direct connections of the household, betweenness centrality captures the ability of a household to act as a bridge within the network, closeness centrality captures the ability of a household to quickly reach other households and eigenvector centrality captures the ability of the household to be influential (in terms of having connections to households with high centrality measures. Results are provided in table 3.5.

Results show that all node-level centralities are positively correlated to diversification of income sources. This suggests that households with more number of direct connections, shortest path to other households and connections to other important households might have better access to information, skill and services that can facilitate diversification activities. This results could also be used in future studies to examine whether centrality of the first informed households are important for income diversification. These results further support our hypothesis that social network effects play a significant role in income diversification

Table 3.5: Correlation coefficients of node-level centralities and income diversification .

	I	II	III	IV
	Degree Centrality	Betweenness Centrality	Closeness centrality	Eigenvector centrality
Income Diversification	0.152 **			
Betweenness Centrality		0.158 **		
Closeness centrality			0.160 **	
Eigenvector centrality				0.200 **

** signifinace at 5%, obs= 301

3.9 Conclusion

In developing countries, diversification of income sources is a norm and specialization in one activity is an exception (Reardon, 1997). The link between social networks and diversification is a relatively unexplored area. The main focus of this study was to examine whether social network effects play an important role on income diversification activities among rural households in Wayanad. We represent villages as networks of households connected through social ties. In order to examine the effects of social networks, we used a network econometric model, based on the Spatial Autoregressive approach, by replacing the spatial matrix with a network matrix. Although there has been a recent growth in the use of network econometric models to examine social network effects (see Bramoulle et al., 2009), it is a relatively new approach in development economics. Thus our study adds to the growing literature.

The main results found are as follows. Average diversification of a household's social network has a positive effect on its diversification. This suggests the importance of ripple effects created through the network interactions. Given the relevance of diversification among rural households, it is important to recognize that social network effects can be critical in promoting diversification activities. Further, social network effects were found to be greater for agricultural households. Results found also indicate that a household initially diversifies for risk minimization and as their income level increases, contributed by the additional source, they tend to diversify for accumulation purposes.

Further, node – level centralities are also found to be positively correlated to income diversification. This suggests that households in positions of prominence or central households may have positive influence on diversification. Central households tend to have better access to resources due to their position in the network structure. On the other hand this information can also be used to target households (with high centrality) within networks to disseminate important information regarding training opportunities, government initiatives, and availability of skills & services that can facilitate and promote diversification in rural areas.

Chapter 4: Conclusions and Limitations

Kerala is known for its remarkable achievement in social development during the past four decades. The high level of social development in the state is a result of public action, including both progressive state interventions and popular movements, in spite of low per capita income and nearly stagnant economic growth rates (Ramachandran, 1997). Over the years, the state has also introduced various policies and programs particularly for the development of lower classes and tribal communities. However, human development patterns within and across these lower sections of the society have been limited despite these efforts. The problems of persistent poverty and imperfect markets associated with credit, capital and insurance are particularly high among the lower sections of the society. These problems, to an extent, are aggravated by the highly stratified socio cultural make-up of the society. While government initiatives and market solutions could address these issues to an extent, co-operative solutions or social networks could also help.

Social networks have specific functions that might be particularly important in our context. On one hand, networks could facilitate access to and effective transfer of resources among the rural population.. On the other hand, they could influence important development outcomes (such as income diversification, agricultural technology adoption, diffusion of microfinance, academic achievements, and labor market functions) through behavioural influences and multiplier effects caused by network interactions. However, given the large heterogeneity of the population and highly stratified socio-cultural make-up, it is important to gain a deeper understanding of the various types of interactions among people and the different types of networks. Given this context, there were two main objectives developed for this study. First, to gain a deeper understanding of the social networks found in Wayanad District using some of the fundamental techniques of social network analysis. Second, to examine whether household's social networks influence income diversification in rural India.

4.1 Social Network Analysis.

Social network analysis can be used to study relational ties between various interactive units within a network, to identify its importance and to examine patterns and regularities in their structure (Wasserman, 1994, p: 5-10). The main techniques of social network analysis used in the study include node-level indices, graph level indices and network visualization using Fruchterman-Reingold layout. Node- level indices facilitate characterization of the properties of individual positions in a network. It allows us to identify households in positions of prominence or whose position enables actions such as information dissemination and also give us an idea of the social structure faced by a given household. Graph-level indices provide insights into the overall structure of the network, for example, stability or vulnerability of the villages. The key findings from social network analysis are;

a) There are no common demographic attributes connecting central actors of each network. However, in most of the villages, central households were the ones who were well known to other households due to their occupation or strong association with a political party, for example, being a supervisor in the government's MGNREGA scheme, owing a business ventures, being a health activist. In other cases, the central households are those who take the initiatives in the village.

b) At the village level, network measures indicate that the level of inter-household interaction is highest in villages 1, 3, 4, 5 and 9. This suggests that these villages might be more successful at collective action than others. Further transfer of information and other resources is likely to be more inclusive and efficient in these villages.

c) Analysis on differences in node-level centralities by demographic attributes revealed differences in centrality scores by caste of the households. Scheduled castes have highest mean values, followed by scheduled tribes, followed by other backward castes, and general. There were no significant differences in centralities by gender, age group and education of the head of households. This indicates that the households belonging to lower social strata are more successful at maintaining ties with other households and performing network functions such as connecting disconnected groups, reaching others quickly and influencing other households.

These findings suggest that, although the nine villages are in the same location, there are differences in interactions and patterns among households. Thus it is important not to make generalizations regarding the social network structure of these villages or other villages in the nearby areas. Further social network analysis provides intuitions regarding households in prominent positions in each of these networks. These intuitions can be used to target important agents within the network for effective information dissemination with a wider outreach. This can guide the implementation of government initiatives by local institutions. For example, information on centralities of households or individuals can be useful while choosing a representative for the scheduled tribe and scheduled caste communities or while choosing a social health activist (ASHA). Further rural communities still have very limited access to information. Whether it is regarding improved farming techniques, research output on new fertilizers and pesticides, subsidies on machinery and fertilizers or training programs organized by the local government and non-government institutions, rural population find it difficult to gain access to information. Effective dissemination of information through central actors could play a critical role in addressing this issue. Further, lower social strata tend to have stronger social networks, which assist them to diversify incomes. This may be a result of the stratification process; people with more limited opportunities work together to progress, or it could be a result of successful social development policies and programs in the area.

4.2 Social networks and Diversification of Income sources.

Diversification of income sources is viewed as a norm in rural areas of developing countries (Reardon, 1997). The ability to diversify is particularly important for rural poor in order to maintain stable income throughout the year. This study considers social networks as one of the important factors that can influence diversification activities of the household. In order to analyze the effect of social networks on diversification, a network econometric model was developed, based on the spatial autoregressive approach, by replacing the spatial matrix with a network matrix. Some of the key findings from the study are;

a) Household's diversification is positively influenced by the average diversification of its network.
b) Social network effects were found to be greater in agricultural households compared to non-agricultural households.

c) Results indicated that income diversification was motivated by both risk minimization and wealth accumulation strategies across the population[7].

d) Social network characteristics measured by node – level centralities were found to be positively correlated to diversification.

These findings suggests that it is important consider the role that social network effects can play while studying income diversification. Diversification activities could be promoted through network interactions and collective action in rural areas. Initiatives by government and non-government organizations can support this by encouraging group activities and providing platforms for collective action. Initiatives can also be designed to actively promote diversification which can in turn lead to ripple effects. For example, facilitating income diversification activities for a group of women by providing training opportunities and initial support may lead their neighbors to do the same. This could take place as a result of information transmission, so that the choices of any single household modify the information available to the rest of the agents in its network (Maurin and Moschion, 2006). Further, the centralities of households could also have important implications for promoting diversification activities. We can target households (with high centrality) within networks to disseminate important information regarding training opportunities, government initiatives, and availability of skills & services that can further promote diversification in rural areas.

[7] Although the results provide evidence to indicate that income diversification is motivated by both accumulation and risk management strategies, we cannot really sort out the relative importance of each.

Thus this study provides empirical evidence on the importance of social network effects in development context. It is intuitive to think that social networks can affect several dimensions of an individual's welfare. Although social network effects have been studied for a long time, the economic development literature only recently started to produce empirical evidence to support this claim. Our study adds to this literature by providing empirical evidence on the importance of social network effects.

4.3 Limitations and Future study

The limitations of this study are summarized below.

- Given the time and resource constraints, this study only takes into account the relational ties of households within the village. Social networks outside the village could also have important implications.
- Limited sample size. Although the data collected include information on different types of interactions (kinship, borrowing money, borrowing material goods, networks formed through community groups), our study views networks as links formed through any of these interactions. With data for more households, analysis could be done on networks formed through each of the different type of interactions.

Future studies on social networks can be done on various issues. Some of the topics are summarized below.

a) Social network analysis can have important applications in monitoring and evaluation of networks and this could in turn facilitate successful collective action. For example, women's groups also known as the self-help groups found in rural areas are one of the important networks found in rural areas of developing countries. These groups have a much higher chances of obtaining financial services, training programs and initial physical capital to start a new initiative from government and non-government organizations. With the help of social network analysis we can analyze the structure of these networks and identify its chances of being successful at collective action. For instance, if collective action requires a high level of trust and cooperation then the degree to which everyone knows and interacts with everyone else in a network is particularly important. It indicates the level of group solidarity, and is a condition for enhancing trust. On the other hand, in some of these networks when there is perfect flow of information, convergent expectation between two or three individuals can arise resulting in isolated or disconnected individuals within the network. This can in turn act as a hindrance to successful collective action. Social network analysis could provide insights into such as aspects of a network. Future studies can provide empirical evidence on the importance of network structure for successful collective action

b) Understanding the different types of interaction patters among individuals in tribal communities is essential for contributing to their development. Social network analysis on different types of tribes could be used to gain a deeper understanding of their interaction patterns.

c) Further studies can be done by taking into account social networks outside the village. Analysis on the combined effect of social networks within and outside the villages as well as the differences in effects created by networks within and outside the villages can provide insights into the bridging and bonding aspects of social networks.

d) Further studies can also be done to identify and examine the extent of ripple effects created by government initiatives or policies (eg: MGNREGA, ICDS). Further, activities initiated by development projects such as the APM could result in multiplier within and outside the project areas. This can also be examined by modeling social networks.

e) Studies can also be done on the relevance and importance of social network effects on other development phenomena such as non-farm job opportunities, use of improved farming techniques and use of new and improved fertilizers.

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APPENDIX A

a.1 ***Social Network Survey***

Background Information

Date of the survey (DD/MM/YYYY) :	
Enumerator Name:	
Have the Consent from been read and singed by the respondent/ head of the household	**Response:**

If NO, please ask the respondent to read and sign the consent form. If respondent cannot understand the form, please read it to him / her, and ask the respondent to sign or indicate with an 'X'.

Starting time of module (00:00) - Hour: Minute:

End time of the module (00:00)- Hour: Minute:

	NAME	**CODE**
State:		
District:		
Taluk/Block:		
Panchayat:		
Village/Ward:		

Hamlet:		
HH Serial No		
Name of the head of HH:		
Tribal group:		

To be completed after the interview

Name of the field Supervisor	
Survey checked by field supervisor	
Date:	**Signature:**

1.	**General Information**	
1.1	Who is being interviewed?	Name:
1.2	Gender	Male: Female:
1.3	Status	a) Head of the Household b) Spouse of head of the Household c) Other…………………………………….(Specify)
1.4	What is your religion?	a) Hinduism b) Islam c) Christianity d) Other…………………………………….(Specify)

1.5	What is your caste? (*specify if they refuse to say or they don't know*)	a) Scheduled Tribe b) Scheduled Caste c) OBC d) General
1.6	What is your sub-caste?	a) Paniya b) Kurichiyas c) Mullu Kuruma d) Urali Kuruma e) Kattunaickans f) Other……………………………………………(specify)
1.7	What is your mother tongue?	a) Malayalam b) Tamil c) Kannada d) Other…………………………………….(specify)
1.8	Do you speak any other languages?	Yes: No:
1.9	Which ones? (*name all*)	a) Malayalam b) Tamil c) Kannada d) Other…………………………………….(specify)
1.10	Is this village your native home?	Yes No

Social Network questions

2	**Close relatives**	
2.1	Who are your relatives that you maintain good relations with?	
	Name: Spouse/Father: Place of residence: HH No:	Name: Spouse/Father: Place of residence: HH No:
	Name: Spouse/Father: Place of residence: HH No:	Name: Spouse/Father: Place of residence: HH No:
	Name: Spouse/Father: Place of residence: HH No:	Name: Spouse/Father: Place of residence: HH No:
	Name: Spouse/Father: Place of residence: HH No:	Name: Spouse/Father: Place of residence: HH No:

Note: Following questions are about people's networks within the village.

3.	**Meeting to watch television**	
3.1	Does your household have a television?	Yes ……………….3.1 No ……………….3.4 Broken ………………3.4
3.2	Does anyone come to your house to	Yes

	watch television?	No
3.3	Names of the people who come:	
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:
3.4	Do you go to anyone's house to watch Television?	Yes No
	Names of the people:	
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:

4.0	**Help with medical emergency**	
4.1	If you had a medical emergency and were alone at home, what do you have to do to get to the hospital?	
4.2	Who would you ask for help in getting to a hospital?	
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:
	Name: Spouse/Father:	Name: Spouse/Father:

	HH No:	HH No:
4.3	Who would ask you for help in getting to a hospital if he/she had a medical emergency and were alone at home?	
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:

5.0	**Borrowing Kerosene, Rice, Wheat, Sugar, Oil**	
5.1	If you needed to borrow Kerosene, rice, wheat, sugar or some other necessary good, to whom would you go to?	
	Names of the people:	
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:
5.2	Who would come to you if they need to borrow any of the above?	
	Names of the people:	
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:

6.0	**Visiting places of worship**	
6.1	Do you visit temple/mosque/ church?	Yes No
6.2	Do you go with anyone else?	Yes No
6.3	Names of the people:	
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:

7.0	**Borrowing Rs.100**	
7.1	IF you suddenly needed to borrow Rs.100 for a day, who would you ask?	
	Name: Spouse/Father: Place of residence: Relation: HH No:	Name: Spouse/Father: Place of residence: Relation: HH No:
	Name: Spouse/Father: Place of residence: Relation: HH No:	Name: Spouse/Father: Place of residence: Relation: HH No:
7.2	Have you borrowed from this person in this past?	Yes No
7.3	Is this person a moneylender?	Yes

		No
7.4	Who would you trust enough, that if he/she needed to borrow Rs.100 for a day you would lend it to him/her?	
	Name: Spouse/Father: Place of residence: Relation: HH No:	Name: Spouse/Father: Place of residence: Relation: HH No:
	Name: Spouse/Father: Place of residence: Relation: HH No:	Name: Spouse/Father: Place of residence: Relation: HH No:
7.5	Has this person borrowed from you in the past?	Yes No
7.6	If you need to borrow a bigger amount (Rs 3000 – Rs 5000), who would you go to?	
	Name: Spouse/Father: Place of residence: Relation: HH No:	Name: Spouse/Father: Place of residence: Relation: HH No:
	Name: Spouse/Father: Place of residence: Relation: HH No:	Name: Spouse/Father: Place of residence: Relation: HH No:
7.7	Have you borrowed money from any financial institutions?	
	Yes	If Yes, list

	No	
7.8	Did anyone in the village help you with that?	
	Name: Spouse/Father: Place of residence: Relation: HH No:	Name: Spouse/Father: Place of residence: Relation: HH No:
	Name: Spouse/Father: Place of residence: Relation: HH No:	Name: Spouse/Father: Place of residence: Relation: HH No:
7.9	Do you think knowing any influential person would help you to get better access to financial services? If yes, who are they?	
	Name: Spouse/Father: Place of residence: Relation: HH No:	Name: Spouse/Father: Place of residence: Relation: HH No:
	Name: Spouse/Father: Place of residence: Relation: HH No:	Name: Spouse/Father: Place of residence: Relation: HH No:

8.	**Help with personal decision**	
8.1	If you had to make a difficult personal decision, whom would you ask for advice?	
	Name: Spouse/Father:	Name: Spouse/Father:

	HH No:	HH No:
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:
8.2	Who would come to you for advice about a difficult personal decision?	
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:

9.0	**Participating in SHGs/ other savings groups and farmer's clubs**	
9.1	Name all informal/formal groups that you are part of?	
9.2	Who do you go to for advice?	
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:
9.3	Who comes to you for advice?	
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:
	Name: Spouse/Father:	Name: Spouse/Father:

	HH No:	HH No:

10.	**Identifying local leaders**	
10.1	In this village, who are the people that you consider to be influential and respected by everyone? How frequently do you speak to him/her?	
	Name: Spouse/Father: Place of Residence: Position: HH No:	Often Sometimes Rarely Never
	Name: Spouse/Father: Place of Residence: Position: HH No:	Often Sometimes Rarely Never
	Name: Spouse/Father: Place of Residence: Position: HH No:	Often Sometimes Rarely Never
	Name: Spouse/Father: Place of Residence: Position: HH No:	Often Sometimes Rarely Never

11.	**Home gardens**		
11.1	Do you have a home garden?		
11.2	In the past 12 months, what did you do with the foods produced in your home garden?		
	• household consumed it alone • household sold all of it alone • used for home consumption and sold excess quantity	Yes Yes Yes	No No No
11.2.1	Did you share it with your relatives, friends or neighbors?	Yes No	
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:	
11.2.2	Did you trade it for other products consumed by the household	Yes No	
11.2.3	Other (specify)		
11.2.4	Did anyone share their produce with you?	Yes No	
	Name: Spouse/Father: HH No:	Name: Spouse/Father: HH No:	

12	**Agricultural Products for sale**
12.	Do you produce any agricultural food products for sale?
12.1	What are the steps involved in marketing? Who do you contact first?
12.2	Who are your main customers?

	Within the village	
	Name: Spouse/Father: Place of Residence: HH No:	Name: Spouse/Father: Place of Residence: HH No:
	Name: Spouse/Father: Place of Residence: HH No:	Name: Spouse/Father: Place of Residence: HH No:
	Outside the village:	
	Name: Spouse/Father: Place of Residence: HH No:	Name: Spouse/Father: Place of Residence: HH No:
	Name: Spouse/Father: Place of Residence: HH No:	Name: Spouse/Father: Place of Residence: HH No:
12.3	Did anyone help you to make these connections?	
	Name: Spouse/Father: Place of Residence: HH No:	Name: Spouse/Father: Place of Residence: HH No:

13	**Non-Agricultural Products for sale**
13.1	Do you produce any other products for sale?
13.2	What are the steps involved in marketing? Who do you contact first?

13.3	Who are your main customers?	
	Within the village	
	Name: Spouse/Father: Place of Residence: HH No:	Name: Spouse/Father: Place of Residence: HH No:
	Name: Spouse/Father: Place of Residence: HH No:	Name: Spouse/Father: Place of Residence: HH No:
	Outside the village:	
	Name: Spouse/Father: Place of Residence: HH No:	Name: Spouse/Father: Place of Residence: HH No:
	Name: Spouse/Father: Place of Residence: HH No:	Name: Spouse/Father: Place of Residence: HH No:
13.4	Did anyone help you to make these connections?	
	Name: Spouse/Father: Place of Residence: HH No:	Name: Spouse/Father: Place of Residence: HH No:

14	**Public Services/Programs**	
14.1	Where do you get information about government programs/policies?	
	Name: Spouse/Father:	Name: Spouse/Father:

	Place of Residence: HH No:	Place of Residence: HH No:
	Name: Spouse/Father: Place of Residence: HH No:	Name: Spouse/Father: Place of Residence: HH No:
14.2	Do you think that knowing people who are influential and have good contacts will help you to get faster and better access to these services?	
	Yes	No
14.3	If yes, who are they?	
	Name: Spouse/Father: Place of Residence: HH No:	Name: Spouse/Father: Place of Residence: HH No:

To be filled by the enumerator:

For questions 1 & 2, indicate the appropriate response using a scale which varies from [poor, fair, good, very good, excellent]

1.	Comprehension level of the respondent	
2.	Cooperation level of the respondent	
3.	Was anyone else present during the interview?	
	Name: Spouse/Father:	Name: Spouse/Father:
4.	Did this person assist the respondent with answers?	

Table a.2: OLS estimates of explanatory variables on Income diversification

Explanatory Variables	All households
Average diversification of the network	0.360 (0.259)
Agriculture Income (change in every Rs. 10000)	-0.002 (0.002)
Non- Agriculture Income (change in every Rs.10000)	0.014** (0.006)
Age of household head	-0.002 (0.002)
Gender of household head(male=1)	-0.037 (0.083)
Education level of household head	-0.028 (0.020)
Size of the household	-0.024 (0.024)
Social category (Scheduled tribe=1)	0.021 (0.066)
Access to information	-0.020 (0.057)
Access to credit	0.004 (0.063)
Crop failure	-0.073 (0.075)
Constant	0.650** (0.234)

Table a.3: Regression estimates of instruments used on diversification and income variables.

	Diversification	Agricultural Income	Non - agricultural Income
Irrigation pump	0.150	32.849***	-17.366**
	(0.164)	(5.046)	(6.667)
Computer	-0.081	-0.878	11.137***
	(0.062)	(1.910)	(2.524)
Fridge	-0.018	2.226**	6.206**
	(0.049)	(1.521)	(2.010)
Gas	0.018	2.033	3.151**
	(0.030)	(0.929)	(1.227)