Friends or traders? Do social networks explain the use of market mechanisms by farmers in India*

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Abstract

A farmer's long-term relationship with a trader can improve access to market information, but removes the farmers' option to sell to other traders in a specific year. Social networks could act either as substitutes to traders, helping disseminate market information and fostering economies of scale, or as complements, where farmers help build relationships between their trader and their peers. Using a household survey from India, we investigate whether and how social networks are associated with a farmer's choice to enter into a long-term relationship with a trader. We find that peers directly affect such choice. Further, we find that network characteristics and the household's position within that network influence the decision to have a long-term relationship. Specifically, the more central position of the household and the smaller number of connections with other households, the higher the likelihood a household has a long-term relationship with at least one trader. We rule out that these effects are driven by proximity.

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1 Introduction and Motivation

Why do some farmers sell their crops to the same trader over a long period of time while others do not? There are at least two possible reasons for these long-term, informal contracts. In the contract farming literature, small-scale farmers who sell to the same buyer are guaranteed a steady level of income through more stable prices and constant demand (Key and Runsten, 1999; Miyata et al., 2009). Conversely, the rural indebtedness literature suggests that farmers are forced, either financially or socially, to sell their cash crops to the same trader (Mitra et al., 1986). Being forced to sell to only one channel prevents farmers from taking advantage of outside options including occasional price spikes due to seasonal variation, extreme weather, or exogenous supply shocks. This study tests whether farmers' social network characteristics and the decisions of their peers are correlated with a farmer's decision to have a long-term relationship with a trader. The study location is Thaltukhod Valley, located in Himachal Pradesh, India. In our setting, a long-term relationship between a farmer and a trader is commonly a verbally agreed informal contract that a farmer will sell cash crops to a specific trader for multiple periods. The relationships we observe in our setting last for at least 10 years.

Market intermediaries such as traders can help reduce transaction costs by disseminating market information and guaranteeing constant demand for crops throughout the growing season (Spulber, 1999; Banerji and Meenakshi, 2004). Personal relationships can also help reduce transaction costs by fostering information exchange, sharing risk, and taking advantage of economies of scale (Fafchamps and Minten, 1999). Although a number of studies have analyzed the importance of both social interactions and traders in economic outcomes in developing countries (Fafchamps, 1998; Fafchamps and Minten, 1999; Fafchamps and Minten., 2002; Narayan and Pritchett, 1999; Lyon, 2000; Conley and Udry, 2010), very little quantitative research explores the relationship between social networks and traders among farmers.

In Thaltukhod Valley, we observe that some farmers sell their cash crops to a specific trader continuously while others do not. Of those farmers who do not have a relationship with a trader, we see substantial differences in cash crop revenues between those whose peers use a trader versus those whose peers do not, particularly within a certain range of cash crop revenue (between approximately 5,000 to 15,000 Rupees during the past 12 months preceding our survey). Farmers with access to a trader through their peers earn more than those who neither use a trader themselves nor have access to one through their friends.[1]

This study attempts to link social network characteristics of farmers to their decision to have a long-term relationship with a trader. In particular, we investigate whether the variation in number of connections, diversity, and position in the social network are associated with the decision to have a long-term relationship with a trader, and look at whether social networks act as compliments or as substitutes for the more formal market mechanism of having a long-term relationship with a trader. We use social network analysis to derive characteristics of social networks, which encompass several attributes including the size, density, structure, and location within the network. Thus, we explore whether the nature of the social network and the position within the network are correlated with the decision to have a long-term relationship with a trader.

Further, we test whether farmers' decisions to have a long-term relationship with a trader are dependent on the decisions of their peers. Using spatial econometric methods, we test whether a household's peers significantly affect a household's decision to have a long-term relationship with a trader. One might be concerned that the peer effects are largely picking up unobserved effects of geography. To account for this concern, we show that our estimates are not largely driven by the effects of geographical proximity.

We find that farmers with a greater number of connections are less likely to establish a long-term trader-specific relationship. We also observe a strong effect of peers' outcomes on one's decision to have a long-term relationship: if a farmer's peers adopt a long-term relationship, the farmer is also much more likely to do so. Household char-

[1] See Figure 1 for illustration of this statistical evidence.

acteristics including livestock ownership (which may suggest evidence of greater time constraints and endowment) and caste (which may suggest evidence of sorting among social groups) are important determinants of a household's decision to have a long-term relationship with a trader. We instrument for peers' outcomes using observed attributes of peers of peers to account for peers' outcomes being jointly determined and endogenous. Then, we conduct a number of robustness checks to verify the validity of our results. However, we are aware that we might not be able to completely account for biases resulting from possible endogeneity of farmers' social relationships and other unobserved characteristics that may influence our results.

We see three main contributions of this study. First, to our knowledge, this is one of the first studies to analyze how a household's position within a social network relates to the decision to have a long-term crop-specific relationship with a trader. Our measures are not restricted to whether a tie exists between two households, but also include the nature, closeness, density, and degree of contact among the households in each village. In particular, we extend the literature by confirming peers may influence an individual's marketing decisions in agriculture (Fafchamps, 1998; Fafchamps and Minten, 1999). We focus on how social network characteristics affect economic outcomes similar to the work by Banerjee et al. (2013). Second, we take advantage of a dataset that includes information from all households across the 17 villages in Thaltukhod Valley containing detailed information about personal relationships at the individual level. The third contribution of this study is that this is one of the first studies to apply novel spatial econometric methods to the study of social networks in the context of agricultural context of a developing country. The empirical findings in this study might motivate subsequent theoretical developments of a relationship between social relationships and agricultural contracts.

2 Literature Review

In India, agricultural traders are important actors for farmers in their production and marketing strategies. Traders usually reside within the villages, and have sufficient financial resources to become sources of informal lending, especially for farmers who do not have access to credit from financial institutions like banks. Therefore, farmers may have long-term relationships with traders to borrow for their cultivation activities, input purchases, harvest costs, and any other random events such as crop losses, illnesses, weddings, and funerals.

On the other hand, the dependence on traders may not always be beneficial for farmers. Farmers who borrow from traders often incur high interest rates, which may come in the form of a penalty on their crop prices. Moreover, farmers are expected to back their loans to the traders right at harvest, necessitating immediate sale of their crops. And before they can borrow again for the next cropping season, they are required to pay back their loans first, which also means selling crops immediately crop sales after harvest. Due to the frequent absence of outside options for farmers to borrow, farmers have little bargaining power with their traders. This type relationship not only prevents farmers from taking advantage of arbitrage after harvest, they may also receive lower returns to their crops.

2.1 Contract Farming

Contract farming is one medium that can facilitate the sale of cash crops for small-scale farmers in many developing countries (Morrissy, 1974). Farmers who participate in this type of contract usually receive seed, fertilizer, technical assistance, market information and guaranteed price after harvest (Miyata et al., 2009). Therefore, contract farming is an attractive marketing channel that can help farmers solve insurance and production constraints (Grosh, 1994; Key and Runsten, 1999). In contrast, the participation in contract farming may limit farmers' outside options to sell via other marketing channels during occasional price spikes.

A number of studies note the benefits of participating in contract farming. From early studies including Morrissy (1974), Glover (1984), and Minot (1986), a considerable amount of evidence illustrates that participation in contract farming can improve farm income, and thus household welfare (Key and Runsten, 1999; Minten et al., 2009; Miyata et al., 2009; Neven et al., 2009; Bellemare, 2012; Michelson, 2013). However, very little quantitative work has taken into account the potential effects of social relationships in the context of contract farming. As identified in earlier studies, personal relationships are important for economic outcomes (Fafchamps, 1998; Woolcock, 1998). We note that in the context of our study, even though we do not observe an official, binding contract between a trader and a farmer, we can view the long-term relationship with a trader as a form of unofficial contract farming.

Previous studies on the relationship between a farmer and a trader in developing countries have been concentrated in Africa. Several studies find that these relationships help to improve economic conditions and productivity outcomes (Barrett, 1997; Fafchamps, 1998; Fafchamps and Minten, 1999, 2001). These more favorable outcomes result from a reduction in the time needed to transport goods and explore market opportunities, better information about the market, more stable demand and supply, and reduced loss from crop spoilage. The help of traders greatly enhances income opportunities for these small-scale farmers, reducing uncertainties in the quality and the buyer's willingness to pay, and in return, traders with well-connected networks enjoy higher revenues due to higher sales volume (Fafchamps, 1998; Fafchamps and Minten, 1999, 2001). There could be several other reasons that motivate a farmer to commit to a long-term relationship with a particular trader. One possible explanation is provided in the sociology literature on rural indebtedness in India.

2.2 Rural Indebtedness

Since farmers are often credit constrained agricultural traders are those with enough financial resources to become potential lenders, they use loans as a channel to extract profits from farmers who borrow from them (Goyal, 2010). One of the consequences of rural indebtedness is that farmers find themselves stuck with a particular trader because they have to pay back their debt. Added to other marketing constraints such as the lack of market information, inability to verify the quantity of cash crops, indebtedness may enshrine a farmer's dependence on a trader, reducing their bargaining power and resulting in lower crop returns (Bardhan, 1991; Clay, 2004).

Rural indebtedness is among the most significant causes of economic and social obstacles to greater farm investments and income growth in agricultural communities, especially in India (Mitra et al., 1986). The cause of indebtedness from extensive borrowing can originate from various sources including family, illness, financial, production, consumption, and investment shocks (Tandon, 1988). This vicious cycle of debt obstructs farmers from achieving higher economic gains. Also, due to improvements in rural infrastructure and production technology, the desire to ensure potential productivity gains through extensive and costly investments could result in substantial debt for many small-scale farmers.

2.3 Personal Relationships and Economic Outcomes

Personal relationships are important for daily economic activities. These social networks are viewed as a form of capital that can foster cooperation and coordination, and generate economic returns (Putnam et al., 1993; Fafchamps, 1998; Woolcock, 1998; Jackson, 2010; De Giorgi et al., 2010; Oster and Thornton, 2012). As a result, social networks may substitute for market intermediaries, and reduce the transaction costs of marketing. Conversely, social networks may enhance the benefit of using a trader, since market knowledge provided by the trader can now spread further, and the pooling potential of the social network may generate economies of scale for the trader themselves. Thus, we wish to determine whether social networks and long-term relationships with a trader are complements or substitutes in the sale of cash crops in India.

Fafchamps and Minten (1999) highlight how familiarity and trust in a social network can help facilitate economic exchange in several regards. The social network can foster better economic outcomes of the small-scale farmers through improved access to information, especially about technology adoption and market opportunities (Kranton, 1996). The broader is the network, the greater are the sources of information. The adoption of a new production technology or market mechanism by an individual with a large network is more likely to result in a significant dispersion of similar adoptions throughout his social networks (Bandiera and Rasul, 2006). Due to this crucial role of the social network, we examine how social network characteristics, such as type, diversity, and location of the househodl within the network are associated with the household's long-term relationship with a trader.

Despite the various functionalities, social networks likely cannot fully replicate some of the roles performed by a trader. Several studies have carefully analyzed the role of trust between traders and farmers, and argue that it greatly fosters cooperation (Fafchamps and Minten., 2002). The adoption of a trader can signal quality of agricultural products to the final buyer because the trader wants to uphold their reputation with the consumers (Kherallah and Kirsten, 2002). Thus, through reputation, a trader can help reduce uncertainties about product quality and delivery facing the buyer. A social network, on the other hand, is a non-market mechanism that relies heavily on personal interactions among small-scale farmers. As a result it may not be able to create trust and reputation between farmer and consumer.

3 Data and Setting

3.1 Study Area

The study area is Thaltukhod Valley, an area of 17 villages and 522 households located in the Indian Himalayas.[2] Due to missing data, we use information from only 510 households.[3] Villages vary in size ranging from 11 up to 66 households, and are

[2]See Figure 2 for map of Thaltukhod Valley, with cash crop production locations, road access, agricultural fields and forest area.

[3]We omit households who did not report any social relationships with other households in the same village.

located at between 1,748 and 2,489 meters of elevation above the mean sea level.

[Figure 1 around here]

Like elsewhere in India, Thaltukhod farmers' main activities include subsistence agriculture, commercial crop cultivation, and livestock rearing. The forest areas adjoining each village is source of fuel wood, fodder, timber, fencing, and medicinal herbs. Households in each village own between two and seven plots varying in size, elevation, and slope. Some plots are shared among households in the same village. Within each plot, each household owns a specific parcel. These parcels vary in size within and across villages.

In 2008, a comprehensive survey was administered to households in these villages. Households were asked detailed questions about their livelihood activities for the previous four years (2004-2007), and ten years ago (1998). The survey also collected detailed information about social ties from all households, and whether the household has a long-term relationship with a trader and for which crop. Households were also asked about cropping rotation, land allocation decisions, input expenditures, and revenue from sales of cash crops.

Based on survey data, Thaltukhod farmers mainly grow three cash crops: kidney beans, potatoes, and green peas, and three types of food crops: maize, wheat, and barley.[4] Kidney beans and potatoes are traditional cash crops in Thaltukhod. However, peas were introduced recently, first appearing five years before the survey was conducted. According to the data from the survey, all households grow at least one of the three cash crops annually. They sell their cash crops to traders at the local market multiple times in a growing season. In this study, we focus on whether a household sells each of their cash crop to the same trader over a long-term period (at least ten years). Specifically, approximately 10% of the households growing kidney beans, 60% of those growing potatoes, and 37% of those growing peas report having long-term relationship with a trader.

[4]The revenue from the three main cash crops account for approximately 97% of total crop revenue among Thaltukhod farmers.

3.2 Social Network Information

Using detailed information about interpersonal relationships from all villages in our sample, we construct a matrix that identifies the links between households within a social network. All social ties considered in this study are directed but unweighted.[5]

We ask two questions about social interactions with peers.[6] Each household is asked to name three households from whom they frequently seek advice about general livelihood matters, and two households from whom they seek advice specifically about agriculture.[7] We use the union of these two groups as our basis of a peer group for each household in our study. Thus, each household can list up to a maximum of five different households as links within the same social network.[8]

Using information about social ties among households in each village, we create a map of social networks for each village in our sample. Then, we use social network analysis to generate social network characteristics for each household in a network. We analyze three social networks characteristics of the households in Thaltukhod Valley. The variables of interest are degree, k-step reach, and eigenvector. We provide formal definitions of these social network variables in Appendix A. We also give an illustrative example of the social network characteristics used in this study in Appendix B. The degree, k-step reach, and average reciprocal distance variable can help explain how much information can flow within a network due to its size, spread, and closeness but they do not fully capture a household's influence on other households within the same network. The eigenvector variable captures the influence of a household with respect to all other households within the same network since it is a measure of network centrality.

[5]A *directed* connection exists from household i to j only if household i reports a connection with household j but not vice versa. The social ties between households i and j are *unweighted* because they do not contain the information on strength of such relationship.

[6]In the context of this study, peers or friends could also be members of extended families, relatives and in-laws. We assume a closed network at the village level only. Therefore, we assume that cross-village relationships are relatively weak. This assumption is supported by anecdotal evidence from the initial field work in the area.

[7]Approximately 45% of the households listed only two in the former category as peers while the remaining named three.

[8]About 30% of the households listed five distinct other households as their peers while 25% of the households reported that their general peers are also their agricultural peers.

3.3 Summary Statistics

[Table 1 around here]

The summary statistics of the individual characteristics of the households who commit to a long-run relationship with a trader and those who do not are presented in Table 1. Farmers who have long-term relationship with a trader earn slightly higher aggregate household income than those who do not, but the difference is not statistically significant. Further, farmers with long-term relationships earn more cash crop revenue than those without such relationships, and the different is statistically significant. Only two other characteristics significantly differ between those households who have and do not have long-term trader relationships: caste and purchased energy. Specifically, households who have a long-run relationship are more likely to belong to a higher of the two main castes in the setting, and also use more purchased energy as part of their total energy use. This finding on caste is not surprising because all traders working in the area are of higher caste.

[Table 2 around here]

Table 2 illustrates the summary statistics by types of cash crop cultivated. Most of the individual and social networks characteristics are similar across households that grow each type of crops with a few notable differences. Of the three main cash crops, farmers make the highest cash crop revenue from selling potatoes in a growing season. Pea farmers on average own more land than those who also grow kidney beans and potatoes. Moreover, households that grow potatoes and peas on average own slightly more stall-fed cattle, purchase more energy (LPG and kerosene), and consume more food from their own production. Finally, the ratio of farmers who are high caste relative to low caste is largest for those who grow peas.

4 Conceptual Framework

To explore how social networks associate with the relationship between a seller (farmer) and a buyer (trader), we model the long-term relationship as a relational contract following the framework by Gibbons (1997).[9] Then, we discuss the association between social networks and long-term relationships. To our knowledge, no existing theoretical model in the literature is directly applicable to the context of this study. However, there are at least two existing theoretical considerations that might help explain whether social networks act as complements or substitutes with observed economic outcomes (Bramoullé et al., 2014; Belhaj et al., 2014).

To formalize the long-term relationship between a farmer and a trader, we begin with the assumption that a farmer plays an infinitely repeated game with a trader, and then can decide whether to defect or not during each time period t associated with an interest rate r. According to Gibbons' formalization, the interest rate r can reflect the likelihood of the parties trading again after each period.[10]

In the context of our setting, farmers choose whether to continue in the long-term relationship with a trader or not. For each time period t, farmer i decides between the returns from selling crop j to the same trade in this period or *continuation*, (C_{ijt}), versus the potential gain from selling to a different trader in this period or *defection*, (D_{ijt}), plus the long-run benefits from selling to different traders who offer the highest prices or *independence*, (I_{ijt+1}) minus the *search cost* for the best offer in each time period t, (S_{ijt+1}). In our setting, each payoff component could depend on a farmer's network characteristics namely $C_{ijt}(N)$, $D_{ijt}(N)$, $I_{ijt+1}(N)$, and $S_{ijt+1}(N)$.

[9] In its simplest form, a long-term trading relationship between a farmer and a trader can be viewed as one form a *relational contract*. Due to the nature of such long-term relationship that does not posses formal enforcement mechanisms, there must be self-enforcing agreements between the two parties. An example of a formal enforcement mechanism is an enforcement mechanism by a third party such as a legal court (Gibbons, 1997). Therefore, in a contract of this nature, agents might decide to continue or stop a relationship as more information arises. This new information could take the form of trust or reputation.

[10] In our context, the interest rate r could reflect the time value for money and the value of trust and reputation that could grow over time. For the trader, a farmer might tell other farmers in his network connection to sell to a particular trader because of his reputation. On the other hand, a trader might decide to provide the farmers with additional help such as financial assistance for wedding ceremonies or free seeds as the relationship continues.

Different network characteristics might affect each component of the payoffs in different directions.[11] For example, farmers who have peers with long-term trader relationships may have lower search costs (S_{ijt+1}) because of the information shared by their peers. For each period, t, the farmer faces the following decision:

$$(1+\frac{1}{r})C_{ijt}(N) > D_{ijt}(N) + (\frac{1}{r})[I_{ijt+1}(N) - S_{ijt+1}(N)]. \tag{1}$$

In each period t, farmer i has two options: continue with the long-term relationship selling crops to the same trader, or defect and sell to different traders offering higher prices from then on. Farmer i chooses to continue the long-term trader relationship in period t only if the expected payoff from continuing $(1+\frac{1}{r})C_{ijt}(N)$ is greater than the payoff from defection in period t, $D_{ijt}(N)$, plus the net present value of the payoffs from becoming independent starting from period $t+1$ onwards minus the search costs for the best prices offered $(\frac{1}{r})[I_{ijt+1}(N) - S_{ijt+1}(N)]$.

It is useful to consider how the decision of whether to establish a long-term relationship is associated with the decisions made by two connected agents. On the one hand, farmers in the same social network might decide to coordinate and establish long-term relationships with a trader in favor of information exchange, risk pooling, and economies of scale. Such coordination could increase the payoffs from staying in a long-term relationship $C_{ijt}(N)$ among farmers who share the same traders. In this case, coordination among social connections and long-term relationships are complements. On the other hand, certain farmers might decide to refrain from committing to selling to a particular trader if they believe they could obtain information from their peers who have long-term relationships with traders. Some farmers might think that they have access to information from their peers which allows them to sell to traders that would offer them the best price in each season, which is to increase the long-run

[11] This means that when taking the underlying effects from network connections into account, the values of each payoff for each farmer could change significantly. In our study, we observe empirical evidence of both complementarity and substitution between network connections and long-term relationships. However, such correlation could arise from any unobserved correlated attributes of the network formation process by itself. Manski (1993) refers to this scenario as *correlated effects*, which we cannot capture in this study and is a limitation.

payoff from selling to different traders in each period $I_{ijt+1}(N)$; $\frac{dI_{ijt+1}}{dN} > 0$. Also, these farmers might realize that their network connections could provide them with sufficient market information to make marketing decisions, which helps them reduce search cost $S_{ijt+1}(N)$; $\frac{dS_{ijt+1}}{dN} < 0$. This scenario suggests that social networks can substitute for having long-term relationships.

5 Estimation Strategy

5.1 Identification

5.1.1 Selection among Farmers

Manski (1993) describes that in the analysis of social interactions, one must distinguish among exogenous, endogenous and correlated effects. Without controlling for these three effects, empirical analysis of social networks might suffer from biased and incorrect interpretations (Matuschke, 2008). *Endogenous effects* arise because the decision of one's peers might influence one's decision to commit to a long-term relationship with a trader. This simultaneity problem is referred to as the *reflection problem*, where peer outcomes maybe jointly determined and endogenous (Manski, 1993). *Exogenous effects* account for the fact that individuals might belong to the same peer group because they share similar observed attributes. For example, farmers who receive higher education might join the same social network to share information they receive from their training classes. *Correlated effects* explain the scenario of peers having similar outcomes because they are exposed to similar local, environmental or cultural contexts. For instance, farmers who live in the same village might be exposed to similar agro-climatic factors, geographical constraints, and crop prices, resulting in similar productivity outcomes.

To account for correlated effects specific to each network, we include network-level fixed effects to account for unobserved variation across different social networks. If the correlated effect has a similar impact of all individuals within a network, it may influence the results in this study. But if the correlated effect has differential impacts on individuals within a network, and that impact also varies according to the network structure and leads to individuals having differential outcomes, we cannot account for such correlated effect in our study. Similarly, correlated effects might be present among farmers who grow the same type of crop. To control for this concern, we also include crop-specific fixed effects in our models that will remove any variation specific to each cash crop. We control for exogenous effects by including individual observed attributes and also observed characteristics of peers that might be associated with the decision to engage in a long-term relationship with a trader.

5.1.2 Selection from Traders

One might be concerned that traders might target specific farmers contingent on village or type of cash crop to commit to long-term relationships. To establish a claim against this concern, we explore the statistical evidence from our data. We ask whether we observe multiple traders operating within a single village and we find that there are at least three traders buying crops from farmers within each village. The proportion of the households having long-term relationship with at least one trader for one of their cash crops ranges from 47% to 77% among all villages in Thaltukhod. Thus, it is clear that traders do not have a geographic monopoly, and that all villages have both farmers who have crop-specific long-term relationships with traders and those who do not.

In terms of traders' activities in Thaltukhod villages, we observe that there are between three to six traders working with the farmers in each village. Among the six traders working in the area, traders work with farmers in as few as three villages, and as many as eight in the entire 17 villages, suggesting that traders do not target which villages they would like to work with. Moreover, we observe that all six traders buy all of the main cash crops (kidney beans, potatoes, and peas) from at least one farmer in each village. Therefore, this statistical evidence argues that traders do not select which villages and which cash crops to buy from Thaltukhod farmers.

5.1.3 Social Network Formation

One might be worried that the social connections in each village are formed endogenously due to common unobservable characteristics between peers. For example, all pea farmers join the same network to gain information about growing peas.

To test for this concern, we test the likelihood of two households being friends by using exogenous characteristics namely caste status and geographical proximity. We find significant evidence that caste status and geographical proximity are good indicators of peers. Therefore, we argue that the social connections in Thalthukod are largely formed exogenously.

5.2 Econometric Specifications

We test the likelihood that a household commits to a long-term relationship with a trader using a logistic regression model. Specifically, the estimation model is of the form:

$$Pr\{\boldsymbol{y} = 1\} = \frac{1}{1 - \alpha\boldsymbol{l} - \beta\boldsymbol{x} - \gamma\boldsymbol{x} - \boldsymbol{c} - \boldsymbol{v} - \boldsymbol{\epsilon}} \tag{2}$$

where $\boldsymbol{y}$ represents an $n \times 1$ vector of the binary choice to remain in long-run relationship with a trader, $\boldsymbol{l}$ is an $n \times 1$ vector of ones, $\boldsymbol{x}$ is an $n \times k$ matrix of observed household individual characteristics and social network characteristics, $\boldsymbol{c}$ is a matrix of crop-specific fixed effects, and $\boldsymbol{v}$ is a network-level fixed effects.

Next, we test the hypothesis that a household's decision to commit to a long-term relationship depends on the decisions of their peers within the same social network. To investigate this hypothesis, we follow the standard specification of the spatial lag model (Anselin, 1988, 2002), but with some modifications to accommodate the binary nature of the dependent variable. The basic spatial probit model with a binary response dependent variable is given as follows:

$$\boldsymbol{y} = \rho\boldsymbol{G}\boldsymbol{y} + \beta\boldsymbol{x} + \boldsymbol{c} + \boldsymbol{v} + \epsilon \tag{3}$$

where ρ represents the autoregressive parameter and $\boldsymbol{G}$ is the weights matrix of social interactions between households.[12]

Under this specification, the marginal effect of the spatial autoregressive term ρ captures the social interaction effects among peer farmers and the $\boldsymbol{G}$ matrix can also be referred to as the 'contiguity' matrix. A positive autoregressive market effect estimate ρ implies complementarities among peers' decisions. This means the probability of farmers' committing to long-term relationships with traders increases when their peers also have long-term relationships with traders. On the other hand, a negative autoregressive marginal effect estimate ρ implies that farmers' and their peers' decisions are substitutes, which means the likelihood of committing to long-term relationships decreases when their peers also have long-term relationships with traders.

Equation (3) allows us to estimate the relationship between a farmer's decision to have a long-term relationship with traders and the decisions made by peers. However, it is likely that a farmer's decision and the decisions made by a farmer's peers are exposed to common unobserved characteristics, resulting in similar outcomes for $\boldsymbol{y}$ and $\boldsymbol{Gy}$. This correlation could lead to an endogeneity problem. To account for this problem, we follow the approach by Kelejian and Prucha (1998) to instrument for peers' decisions $\boldsymbol{Gy}$ with a set of instruments $\boldsymbol{z}$ as in the Klier-McMillen linearized GMM spatial binary response model (Klier and McMillen, 2008).[13]

The instrument set $\boldsymbol{z}$ we use to account for the endogeneity problem consists of observed attributes of friends, $\boldsymbol{Gx}$, of friends of friends, $\boldsymbol{G}^2\boldsymbol{x}$, and of friends of friends of friends $\boldsymbol{G}^3\boldsymbol{x}$ similar to the instrument set used in Bramoullé et al. (2009). That is, $\boldsymbol{Gx}$, $\boldsymbol{G}^2\boldsymbol{x}$, and $\boldsymbol{G}^3\boldsymbol{x}$ form the instrument set $\boldsymbol{z}$ for $\boldsymbol{Gy}$. We argue that friends of friends' observed attributes can be used as valid instruments for one's outcome because they may exogenous affect friends' outcome. Thus, the only channel through which friends

[12]Note that this autoregressive parameter is different from an ordinary spatial autoregressive parameter. With this specification, it captures the interaction effect among peers based on stated social relationships and not the interaction effect among peers due to geographical proximity.

[13]Klier and McMillen (2008) use the linearized GMM spatial logit model to study the agglomeration of auto supplier locations in the United States. In an earlier study by Holloway et al. (2002), the authors use the spatial probit model to study the adoption of high-yielding variety (HYV) rice among farmers in Bangladesh.

of friends' characteristics can affect a farmer's outcome is through the outcomes of a farmer's peers.

6 Results and Discussions

6.1 Empirical Results

Our analysis focuses on three characteristics of social networks: degree, two-step reach, and eigenvector. In Tables 3 to 4, we report the marginal effects of the three characteristics from the logit regressions. All marginal effects reported are evaluated at the mean of the data. In Table 3, we first consider the degree variable, which measures the number of connections a household has within a network. Its marginal effect estimates suggest that the greater number of connections a household has within a network, the less likely they are to have a long-term relationship with a trader for selling their crops, controlling for both network and crop fixed effects (Table 3, Column (4)).

Next, because different crops might exhibit different effects on trader choice, we split the sample by crop type (Table 4). While not consistently statistically significant in all specifications, we find evidence that the household's eigenvector is significant for farmers who grow beans and potatoes (Table 4, Columns (1) - (4)), and degree is weakly significant (at the 0.15 level) among farmers who grow peas (Table 4, Column (6)). These results indicate that the greater influence a household has within a social network, the higher likelihood of that household having a long-term trader relationship among farmers who grow beans and potatoes. Also, we find evidence that the number of connections a farmer has within a network may substitute for the farmer's decision to have a long-term relationship with a trader, particularly for those who grow peas.

To provide the magnitude of marginal effect estimates for the social network characteristics, we consider the estimates in Table 3 and Table 4. The statistical significance of the degree variable is more obvious when we run regressions by pooling all the crops together. Thus, we provide the interpretations of the magnitude of each variable based on the focus on the specifications in which they have the most obvious significance, and we include crop-specific fixed effects in order remove any unobserved characteristics specific to any crop. In Column (4), the marginal effect of the degree variable indicates that a one unit increase in the degree variable decreases the likelihood of the farmer's having a long-term trader relationship by 0.71 unit, holding all else constant. In Table 4 Columns (2) and (4), we find that a one unit change in the eigenvector variable is associated with a 0.788 unit increase in the likelihood of farmers having a long-term trader relationship among those who grow kidney beans, and a 0.430 unit increase for those who grow potatoes.

In all specifications, we control for several household characteristics that might be associated with the household's decision to enter a long-term relationship with a trader. The control variables include landholding size, livestock ownership, number of stall-fed cattle, family size, caste, amount of purchased fuel, and the number of months with own-food consumption. In Table 3, we report the marginal effects for the control variables. We find that households who own more livestock are more likely to have a long-term relationship with a trader. Also, households that that have a greater quantity of stall-fed cattle are less likely to have a long-term relationship with a trader. The caste variable is also significant, which means that households who belong to the higher of the two main castes in the sample are more likely to have a long-term relationship with a trader. This result is not surprising since all six traders working in the area belong to the higher of the two castes in the area.

Next, I investigate whether the decision of one's peers to have a long-term relationship with a trader affects one's decision to sell to the same trader for an extended period of time. I instrument peers' outcomes by using an instrument set containing peers' observed characteristics and peers of peers' observed characteristics as used in Bramoullé et al. (2009). The parameter of interest for this test is the spatial autoregressive paper, ρ, in a typical spatial probit model. In Table 5 Panel A, I report the estimates of how the decisions of one's peers to have a long-term relationship with a trader may affect one's own decision. I find that on average if one's peers have a long-term relationship with a trader, the marginal effect of one's having a long-term relationship with a trader increases by approximately 43% when controlling for both network and crop fixed effects (Table 4, Column (4)). I find that even after when controlling for the decisions of friends, we still find negative and significant marginal effects estimates for the degree variable after controlling for network and crop fixed effects (Table 5, Columns (2) and (4)). This suggests that peers' decisions to establish establish a long-term relationship with a trader does not entirely dominate the effects of the degree variable, the number of connections a household has within the network.

We consider the decision to enter a long-term relationship with a trader contingent on peers' decisions separately by each crop. In Table 6 Panel A, we observe a strong and significant relationship between farmers' and their peers' decisions to enter in a long-term relationship with a trader only for the sales of peas and potatoes, both when controlling for network fixed effects and we do not. When controlling for network fixed effects, we find that a one unit increase in the decision of peers on average to have a long-term trader relationship leads to a 0.487 and a 0.032 unit increase in the marginal effects of farmers also have a long-term trader relationship. This result makes intuitive sense because from the fieldwork, we learned that the cultivation and marketing processes of potatoes are associated to higher uncertainties than those of peas, which may necessitate greater information from peers.

Potatoes are subject to idiosyncratic production shocks and storage uncertainties.[14] Therefore, having a long-term relationship may be necessary and beneficial for the marketing of potatoes. Our results are consistent with those of another study about the marketing of potatoes in India by Mitra et al. (2013), the authors find that supplying potato farmers in West Bengal with information from nearby potato wholesale markets

[14]The uncertainty associated with potatoes is mainly due to disease shocks and storage life. Potato blight largely affects all producers in a region at the same time, resulting in substantial shocks to supply, causing the price of potatoes sold to fluctuate greatly over time. The long storage life of the potatoes allows them to be stored up to two years, allowing retailers to mitigate against these potential supply shocks. A farmer will neither necessarily know about blight in a neighboring production area, nor how many potatoes are currently in storage in the primary retail markets. Thus, potato producers do not observe these key components of expected market price unless informed by a trader.

does not help them reduce the middleman margins when they try to sell their potatoes after harvest.

For the marketing of peas, we find that both the decisions of peers to have a long-term relationship and farmers' social network characteristics are important for a farmer's decision to have a relationship with a trader. The results are not surprising given that peas were introduced to local farmers in the Thaltukhod Valley recently, and farmers might not have sufficient knowledge and market information about the production of peas. As for kidney beans, being a traditional crop that has been cultivated in the area for a long time, farmers are very familiar its production practices and marketing strategies. Moreover, the marketing of kidneys is subject to relatively low uncertainty compared to potatoes and peas because kidney beans can be stored for extended periods after harvest.

6.2 Robustness Checks

6.2.1 Proximity Effects

One might be concerned that our results are largely driven by geographical proximity, which might be correlated with unobservable characteristics such as distance to paved roads or other factors that might affect the decision to adopt a long-term trader relationship. A number of other studies define one's peers as those who are the households who are geographically proximate peers including Liverpool-Tasie and Winter-Nelson (2012) and Helmers and Patnam (2014). To investigate this concern, we test whether the decision to enter in a long-term relationship with a trader of the farmers who live in close proximity have a significant impact on a household's long-term relationship with a trader.

In Panel B of Tables 4 and 6, we replace the weights matrix based on self-reported relationships between farmers in our sample with the weights matrix based on geography. In particular, we define geographic neighbors as four closest neighbors based on Euclidean distance from GPS coordinates. Our results show that the spatial autoregressive parameter based on geographic neighbors are not significant, suggesting that the results are not largely driven by unobserved location-specific characteristics.

6.2.2 Top Coding

One might worry about the issue of top-coding, that by the construction of the survey questions about social ties, we leave out a number of links that households did not get to report. Two studies involving peer network information by de Weerdt (2002), and Fafchamps and Gubert (2007) report considerable missing information, which could lead to biased estimates due to loss of information of social ties (Chandrasekhar and Lewis, 2011).

To account for this concern, we row-normalize the social interaction matrix between households in each social network. By row-normalizing the interaction matrix, we assume that all peers that each farmers report to have close relationships with have equal effects for one's outcome. Moreover, in our dataset, 45% of the households reported only a two links per category in the pre-survey qualitative interviews conducted before the survey was administered.

6.2.3 Individual Heterogeneity

One may be concerned that our results are driven by unobserved individual heterogeneity across farmers in our sample. Specifically, high earning farmers may not require a long-term relationship with a trader due to greater outside options. On the other hand, low-earning farmers may similarly require to establish long-term relationships with a trader because they due to their high marketing and management constraints. Low-earning farmers may also be clustered together together in networks, which could also drive the results. These two scenarios together may generate spurious effects across the sample which may imitate social effects between peers and drive the results.

To test for this possibility, we eliminate farmers whose cash crop revenues are in the highest and lowest deciles for each village in our sample. In Table 7, Panel A, we still find positive and significant effects of friends' on farmers' decision to establish a long-term relationship with a trader in all but one of our specifications. When controlling for both network and crop fixed effects, the effect is weakly significant (p-value = 0.012). Therefore, we verify that unobserved individual heterogeneity which may mimic social effects from peers' decisions do not largely drive our findings.

6.2.4 Peer Effects Model

Another model specification in the literature that investigates the association between social networks and outcome is the peer effects framework, which assumes that both peers' outcome and peers' characteristics may explain one's outcome. Building on the theoretical works by Manski (1993), Moffitt (2001) and Lee (2007), Bramoullé et al. (2009), and Helmers and Patnam (2014) provide empirical evidence that the outcome of peers and some of peers' observed attributes are important determinants of one's outcome.

To control for the possibility that peers' observed attributes could also related to one's decision to establish long-term relationships with a trader, we provide another specification under the peer effects framework. The peer effects framework specifies an individual's outcome may be explained by his peers' outcomes, his own observed attributes and his peers' observed attributes (Manski, 1993; Moffitt, 2001). We regress a farmers' decision to enter a long-term relationship with a trader as a function of their own characteristics and the average characteristics of their peers and present the results in Table 7, Panel B. Similar to our earlier findings, we find strong and significant effects of peers' decisions on a farmer's decision to commit to a long-term relationship. Therefore, peers' observed attributes (including their social network characteristics) may also help explain a farmers' decision to establish a long-term relationship in addition to his own observed characteristics and social network characteristics.

6.2.5 Linear Probability Model

Finally, in Table 8, we run a set of alternative specifications similar to the ones in Table 5 except that we use a linear probability model instead. The results indicate that the coefficient estimates reported in Table 8 are smaller than the marginal effects reported in Table 5. However, the significance levels of the variables of interests remain largely unchanged.

7 Conclusion

This paper investigates the decision made by small-scale farmers in India to invest in a long-term relationship with a trader. The data come from a survey conducted of 522 households in 17 villages in Thaltukhod Valley in Himachal Pradesh, India. We put together a dataset containing the household level individual characteristics that captures economic conditions, social status, education level, and geographical details. I also construct social network variables that indicate the type, diversity, and position of each household within the social networks of each village from the weights matrix that determine the links between the households. Then, we perform econometric analyses of the likelihood that each household decides to establish a long-term relationship with a trader to help them sell their agricultural produce based on the individual household's demographic, economic, and social network characteristics.

The main findings from this study can be summarized as follows. First, we find that if a farmer's peers commit to a trader long-term relationship, the farmer is more likely to do so as well. Specifically, we find significant effects among farmers who grow potatoes and peas, but not among those who grow kidney beans, which might be subject to lower uncertainties in their cultivation and marketing processes. Second, different characteristics of a household's village social network can either perform as complements (position) or substitutes (number of connections) with a long-term relationship with a trader as these network characteristics reflect different levels of exposure to market information for each agricultural household in each village of Thaltukhod Valley. Third, households observed characteristics such as caste, opportunity cost of agricultural labor, and the dependence on the market consumption are positively correlated with the investment in a long-run relationship with a trader. And most importantly, farmers make the decision to commit to a trader given their crop choice. Potatoes are more likely to be commercialized through a long-term relationship with a trader due to its high level of uncertainty, while kidney beans are least likely to be marketed through a trader since they contain the lowest level of hidden information.

The results presented in this paper highlight the importance of social networks in reducing transaction costs facing small-scale farmers in India when they sell their crops. Although certain household and network characteristics are likely to be more important in determining the decision to have a crop-specific, long-run relationship with at least one trader, we would like to further evaluate to what extent these factors matter. Moreover, the regression results from the spatial econometric specifications indicate that farmers' decision to make a specific investment depends on the decisions of their peers, rather than geographic distance. In other words, peer effects dominate geographical effects for a small-scale farmer in deciding to invest in a long-term relationship with a trader.

Our results may help highlight the importance of market access for small-scale farmers in a developing country setting, specially in India. A study by Mallory and Baylis (2013) points out that agricultural markets do not usually stay open long after harvest, which may limit opportunities for farmers to access them later in the season. One channel that may help farmers mitigate the limited access to markets is through the use of traders, who can help provide them with market information, guarantee constant demand for their crops, and become the source for lending. As noted earlier in the paper, for a given range of cash crop revenues earned by farmers , farmers who have long-term trader relationships earn higher revenues than those who do not, and also greater than those who do not have trader relationships and whose friends also do not. This evidence suggests that relying on peers for information and other uses, while important, may not be able to fully imitate the functionality of a trader.

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Table 1: Summary Statistics (By Long-term Relationship with Trader)

	Long-term Relationship		No Relationship	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Income (1000 rupees)	25.203	50.884	21.981	22.367
Cash crop revenue (1000 rupees)	9.800	7.530	8.775	7.309
Grow kidney beans (1=yes)	0.593	0.492	0.567	0.497
Grow potatoes (1=yes)	1.000	0.000	1.000	0.000
Grow peas (1=yes)	0.550	0.498	0.498	0.501
Degree	0.217	0.142	0.208	0.146
Two-step reach	0.603	0.263	0.565	0.276
Eigenvectors	0.222	0.142	0.195	0.155
Elevation (meters)	2049.28	197.83	2040.73	192.23
Land (bhigas)	8.441	5.755	8.190	9.863
Livestock (units)	0.632	1.105	0.488	0.852
Stall-fed cattle (number)	0.550	0.816	0.463	0.816
Purchased energy (% of total use)	0.612	9.979	0.069	0.755
Own-food consumption (m./y.r)	2.956	1.203	2.971	1.159
Family size (head count)	5.756	2.301	5.655	2.419
Caste (1=higher)	0.886	0.318	0.798	0.402
Observations	307		203	

Table 2: Summary statistics (By Type of Crop Grown)

	Kidney Beans		Potatoes		Peas	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Long-term relationship (1=yes)	0.094	0.292	0.601	0.489	0.374	0.484
Cash crop revenue (1000 rupees)	1.015	1.114	5.545	4.437	2.832	5.552
Degree	0.265	0.145	0.214	0.258	0.261	0.153
Two-step reach	0.695	0.242	0.588	0.268	0.683	0.253
Eigenvector	0.241	0.140	0.211	0.148	0.238	0.139
Elevation (meters)	2158.61	152.14	2045.87	195.47	2171.97	153.16
Land (bhigas)	9.175	8.896	8.341	7.651	10.046	9.145
Livestock (units)	0.515	1.066	0.575	1.013	0.578	1.127
Stall-fed cattle (number)	0.438	0.751	0.516	0.817	0.507	0.812
Purchased energy (%)	0.290	3.644	0.396	3.133	0.489	4.081
Own-food consumption (m./yr.)	2.751	0.956	2.962	1.185	2.944	1.026
Family size (head count)	5.774	2.322	5.716	2.347	5.748	2.308
Caste (1=higher)	0.879	0.327	0.851	0.356	0.959	0.198
Observations	297		510		270	

Appendices

A Definitions of Network Characteristics

This section provides formal definitions of social network characteristic variables in this paper. Jackson (2010) provides a comprehensive review on other measures of social networks.

A map of social network (N, G) consists of nodes (i.e. farm households), $N = \{1, ..., n\}$, and a binary social interaction matrix $\boldsymbol{G}$ of dimension nxn. g_{ij} represents elements of matrix $\boldsymbol{G}$ where $g_{ij} = 1$ if two farm households i and j are connected and 0 otherwise.

- **Degree Centrality**
  Degree centrality $d_i(g)$ refers to the proportion of of links connected to a node i to the total number of nodes. A node with degree $n-1$ would be directly linked to all other nodes in a graph and is quite central in the network.

  $$d_i(g) = \sum_j g_{ij}/(n-1)$$

- **Eigenvector Centrality**
  The eigenvector centrality e_i represents the eigenvector centrality for a social network $\boldsymbol{G}$ (Bonacich, 1972). The centrality of node i is proportional to the sum of eigenvector centrality of all its connected nodes. Let λ be the propotionality factor.

  $$\lambda e_i = g_{i1}e_1 + ... + g_{in}e_n = \sum_j g_{ij}e_j$$

- **Average Reciprocal Distance (ARD)**
  The average reciprocal distance (ARD) is a measure of closeness centrality. In other words, it indicates how short the paths between nodes are. A greater value of ARD indicates that the node is more connected to other nodes in a network. Let p_j be the length of path between node i and node j and C_i is the closeness parameter.

  $$C_i = 1/\sum_j p_j g_{ij}$$

  ARD is usually normalized with respect to the maximum value of closedness, so in percentage terms, ARD is defined as follows.

  $$ARD_i = C_i/(C_{max} - C_{min})$$

- **K-Neighborhood and K-step Reach**
  A neighborhood of node i is a set of all nodes that node i is directly linked to.

  $$N_i(g) = \{j : g_{ij} = 1\}$$

  The neighborhood of set of nodes S is the union of the neighborhoods of its members.

  $$N_S(g) = \cup_{i\in S} = \{j : \exists i \in S, g_{ij} = 1\}$$

  The k-neighborhood of a node i is the set of all nodes that can be reached by k steps from node i.

$$N_i^k(g) = N_i(g) \cup (\cup_{j \in N_i(g)} N_j^{k-1}(g))$$

The k-step reach is the proportion of all nodes in a map that can be reached within k steps from node i.

$$RN_i^k(g) = (n-1)/N_i^k(g)$$

B Illustration of Social Network Characteristics

To provide a better understanding of the network measurements discussed earlier, consider the two maps of social networks in village 6, Tegar and village 14, Bhumchayan, presented in Figures 3 and 4.

As a comparison, compare household number 5 in village 6 (labeled as HH5 in Figure 2) and household number 16 in village 14 (labeled as HH16 in Figure 3). Both households are circled in red in the village network maps. Although both households appear to be centrally located within each network, they have very different values of eigenvector and two-step reach variables. For the eigenvector variable, the eigenvector value of household 5 in village 6 is 0.411 whereas that of household 16 in village 14 is 0.226. The explanation of such difference in eigenvector values is that as the network of village 14 is much larger than the network of village 6 (because there are more households in village 14 than in village 6), the degree of influence a central household has on all the other households in a bigger network is less than that of a central household that belongs to a smaller network. The two-step reach of these two households is also different. The two-step reach of household 5 in village 6 is 0.371. This figure indicates that within two steps, this household can reach 37.1% of all the households in this network. On the other hand, in a much denser network as in village 14, the two-step reach variable of household 16 is 0.969. This means that almost all of the households within this network can be reached from this household within two steps. To summarize the difference between the two network variables, we can think of the two-step reach variable as a measure of pure information flow within a social network. However, the eigenvector variable mainly captures the influential effects of a node on the other nodes within the same network.

The summary statistics of the social network variables (presented in Table 1) clearly indicate that households with higher network eigenvectors are more likely to establish a long-term relationship a trader for a long-term relationship to help them sell their cash crops. The degree variable, which measures the average number of links, or network contacts, a household has, is slightly higher among households dealing with a trader. The k-step reach variable, which in this study uses k=2, measures the number of nodes within the network reachable within 2 steps, has a mean of 0.55 among the households that dont use a trader and 0.60 among those that do. This statistic means that 55 or 60 percent of the network are friends of friends.

The average reciprocal distance variable is a measure of closeness of centrality. It indicates the average shortest possible path length between a node in network and any other nodes is in the network. We observe almost no difference in this category between those that do not use a trader and those who use a trader (0.49 to 0.51). The last network variable of interest is the eigenvector variable. The eigenvector defines centrality by indicating how connected one household is to all the other households within the same network. Put differently, the eigenvector is an indicator of how important a node is in the entire network. Due to this feature, this measurement can help describe the degree of influence a node has on its neighboring nodes. Households that are in contact with at least one trader have an average eigenvector of 0.22, which is only slightly higher than those who do not (0.19). Therefore, given the statistics of these network variables, there is some evidence that the structure of the social networks has an impact on the household's decision to have a long-term relationship to help commercialize their agricultural produce.

Table 3: Marginal effects of the likelihood of long-term relationship (LR) by crop

	(1) LR	(2) LR	(3) LR	(4) LR
Social network measures				
Degree	-0.368	-0.635*	-0.306	-0.710**
	(0.206)	(0.329)	(0.220)	(0.349)
Two-step reach	0.107	0.192	0.138	0.231
	(0.111)	(0.157)	(0.118)	(0.167)
Eigenvector	0.238	0.242	0.133	0.207
	(0.168)	(0.199)	(0.178)	(0.206)
Household Controls				
Land	0.011	0.040	0.049	0.044
	(0.038)	(0.044)	(0.040)	(0.046)
Livestock	0.182**	0.202**	0.273***	0.243**
	(0.084)	(0.087)	(0.092)	(0.095)
Stall-fed cattle	-0.067	-0.085*	-0.106**	-0.103*
	(0.048)	(0.049)	(0.052)	(0.053)
Family size	0.004	0.004	0.003	0.006
	(0.007)	(0.007)	(0.007)	(0.008)
Caste	0.169***	0.156**	0.130***	0.177**
	(0.047)	(0.071)	(0.050)	(0.065)
Purchased fuel	0.003	0.003	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.005)
Own-food consumption	-0.005	-0.021	-0.025	-0.020
	(0.018)	(0.020)	(0.017)	(0.021)
Network FE	-	Yes	-	Yes
Crop FE	-	-	Yes	Yes
Observations	1,077	1,077	1,077	1,077

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Marginal effects are evaluated at the mean of data.

Table 4: Marginal effects of the likelihood of long-term relationship (LR)

	(1) LR Beans	(2) LR Beans	(3) LR Potato	(4) LR Potato	(5) LR Peas	(6) LR Peas
Social network measures						
Degree	-0.153	0.142	-0.551	0.621	-0.234	-1.15^{+}
	(0.196)	(0.531)	(0.451)	(0.495)	(0.397)	(0.754)
Two-step reach	0.036	0.306	0.169	0.132	0.131	0.456
	(0.113)	(0.208)	(0.339)	(0.231)	(0.232)	(0.335)
Eigenvector	0.368*	0.788*	0.402*	0.430^{+}	0.119	0.158
	(0.203)	(0.394)	(0.560)	(0.270)	(0.408)	(0.642)
Household Controls						
Elevation	-0.0001	0.0003	-0.0001	-0.0001	-0.0002	-0.0003
	(0.0002)	(0.003)	(0.0002)	(0.001)	(0.0003)	(0.003)
Land	0.072	0.049	0.066	-0.058	0.003	-0.049
	(0.078)	(0.094)	(0.055)	(0.064)	(0.076)	(0.092)
Livestock	0.526**	0.460*	0.296**	0.262*	0.454*	0.404
	(0.248)	(0.245)	(0.150)	(0.148)	0.254	(0.268)
Family size	0.013	0.017	-0.002	-0.0004	0.009	0.017
	(0.014)	(0.015)	(0.010)	(0.011)	(0.014)	(0.015)
Caste	0.117	-0.200	0.131*	0.214**	-0.170	-0.284**
	(0.122)	(0.215)	(0.074)	(0.109)	(0.145)	(0.129)
Purchased fuel	0.000	0.000	0.052*	0.050*	0.036	0.019
	(0.000)	(0.000)	(0.026)	(0.026)	(0.027)	(0.020)
Own-food consumption	-0.073*	-0.055	-0.035	-0.036	-0.035	-0.003
	(0.042)	(0.049)	(0.023)	(0.027)	(0.038)	(0.046)
Stall-fed cattle	-0.219	-0.187	-0.135	-0.128	-0.198	-0.178
	(0.014)	(0.133)	(0.083)	(0.082)	(0.139)	(0.144)
Network FE	-	Yes	-	Yes	-	Yes
Observations	294	293	510	510	270	270

Robust standard errors in parentheses

$^{+}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Marginal effects are evaluated at the mean of data.

Table 5: Marginal Effects of long-term relationship (LR) based on social network characteristics

	(1) LR	(2) LR	(3) LR	(4) LR
Panel A. Self-reported peers				
Spatial autoregressive parameter				
Rho	0.632***	0.359**	0.479***	0.430***
	(0.139)	(0.156)	(0.155)	(0.166)
Social network measures				
Degree	-0.762	-1.879**	-0.783	-2.15**
	(0.759)	(0.840)	(0.819)	(0.916)
Two-step reach	0.257	-0.482	0.326	-0.144
	(0.561)	(0.913)	(0.614)	(0.990)
Eigenvector	0.457	0.607	0.035	0.458
	(0.432)	(0.500)	(0.461)	(0.522)
Panel B. Geographic peers				
Spatial autoregressive parameter				
Rho	-0.108	0.076	0.040	0.098
	(0.080)	(0.088)	(0.086)	(0.098)
Social network measures				
Degree	-1.357	-1.588*	-1.050	-1.787**
	(0.745)	(0.833)	(0.801)	(0.906)
Two-step reach	-0.225	-0.645	0.031	-0.336
	(0.552)	(0.912)	(0.606)	(0.984)
Eigenvector	0.670	0.581	0.155	0.429
	(0.428)	(0.498)	(0.458)	(0.517)
HH Controls	Yes	Yes	Yes	Yes
Network FE	-	Yes	-	Yes
Crop FE	-	-	Yes	Yes
Observations	1,077	1,077	1,077	1,077

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: HH controls include landholding, livestock ownership, family size, caste, use of purchased fuel, own-food consumption (months/year) and stall-fed cattle. Geographical distance weights matrix uses 4-nearest neighbor specification. Rho represents spatial autoregressive parameter.

Table 6: Marginal Effects of long-term relationship (LR) based on social network characteristics

	(1) LR Beans	(2) LR Beans	(3) LR Potato	(4) LR Potato	(5) LR Peas	(6) LR Peas
Panel A. Self-reported peers						
Spatial autoregressive parameter						
Rho	-0.001	-0.003	0.328**	0.487**	-0.018	0.032*
	(0.052)	(0.051)	(0.192)	(0.026)	(0.075)	(0.026)
Social network measures						
Degree	-0.522	-0.759	-1.623	-1.813	-0.554	-0.734
	(0.419)	(0.424)	(1.118)	(2.272)	(0.427)	(0.480)
Two-step reach	0.195	0.007	0.339	0.449	0.630	0.453
	(0.312)	(0.424)	(0.846)	(1.296)	(0.427)	(0.480)
Eigenvector	0.415	0.362	0.947	1.189	0.222	0.485
	(0.227)	(0.269)	(0.610)	(0.703)	(0.405)	(0.466)
Panel B. Geographic peers						
Spatial autoregressive parameter						
Rho	-0.017	-0.128	-0.001	0.044	-0.039	-0.032
	(0.023)	(0.284)	(0.052)	(0.029)	(0.023)	(0.026)
Social network measures						
Degree	-0.475	-0.759	-0.522	-0.809	-0.469	-0.554
	(0.311)	(0.424)	(0.419)	(0.758)	(0.551)	(0.555)
Two-step reach	0.190	0.007	0.195	0.049	0.605	0.630
	(0.311)	(0.424)	(0.312)	(0.422)	(0.424)	(0.427)
Eigenvector	0.351	0.362	0.415	0.472	0.469	0.222
	(0.237)	(0.269)	(0.227)	(0.259)	(0.424)	(0.405)
Network FE	-	Yes	-	Yes	-	Yes
Observations	297	297	521	521	276	276

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: HH controls include landholding, livestock ownership, family size, caste, use of purchased fuel, own-food consumption (months/year) and stall-fed cattle. Geographical distance weights matrix uses 4-nearest neighbor specification. Rho represents spatial autoregressive parameter.

Table 7: Robustness Checks: Marginal Effects of long-term relationship (LR)

	(1)	(2)	(3)	(4)
	LR	LR	LR	LR
Panel A. Individual Heterogeneity				
Spatial autoregressive parameter				
Rho	0.535***	0.188	0.368**	0.266+
	(0.143)	(0.169)	(0.160)	(0.181)
Panel B. Peer Effects Model				
Spatial autoregressive parameter				
Rho	0.791***	0.484**	0.706***	0.579***
	(0.181)	(0.196)	(0.192)	(0.211)
Network FE	-	Yes	-	Yes
Crop FE	-	-	Yes	Yes
Observations	1,077	1,077	1,077	1,077

Standard errors in parentheses

$^{+}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: HH controls include landholding, livestock ownership, family size, caste, use of purchased fuel, own-food consumption (months/year) and stall-fed cattle. Geographical distance weights matrix uses 4-nearest neighbor specification. Rho represents spatial autoregressive parameter.

Table 8: Likelihood of long-term relationship (LR) based on social network characteristics

	(1) LR	(2) LR	(3) LR	(4) LR
Panel A. Self-reported peers				
Spatial autoregressive parameter				
Rho	0.241***	0.141**	0.163***	0.144***
	(0.052)	(0.058)	(0.049)	(0.056)
Social network measures				
Degree	-0.355*	-0.691**	-0.239	-0.708**
	(0.201)	(0.306)	(0.189)	(0.284)
Two-step reach	0.033	0.206	0.147	0.188
	(0.099)	(0.138)	(0.091)	(0.132)
Eigenvector	0.159	0.231	0.064	0.213
	(0.159)	(0.180)	(0.143)	(0.167)
Panel B. Geographic peers				
Spatial autoregressive parameter				
Rho	-0.039	0.033	0.011	0.341
	(0.029)	(0.032)	(0.027)	(0.031)
Social network measures				
Degree	-0.417**	-0.595*	-0.255	-0.610**
	(0.198)	(0.307)	(0.188)	(0.286)
Two-step reach	0.003	0.176	0.122	0.157
	(0.100)	(0.141)	(0.091)	(0.134)
Eigenvector	0.263	0.228	0.111	0.208
	(0.003)	(0.180)	(0.144)	(0.168)
HH Controls	Yes	Yes	Yes	Yes
Network FE	-	Yes	-	Yes
Crop FE	-	-	Yes	Yes
Observations	1,077	1,077	1,077	1,077

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: HH controls include landholding, livestock ownership, family size, caste, use of purchased fuel, own-food consumption (months/year) and stall-fed cattle. Geographical distance weights matrix uses 4-nearest neighbor specification. Rho represents spatial autoregressive parameter.

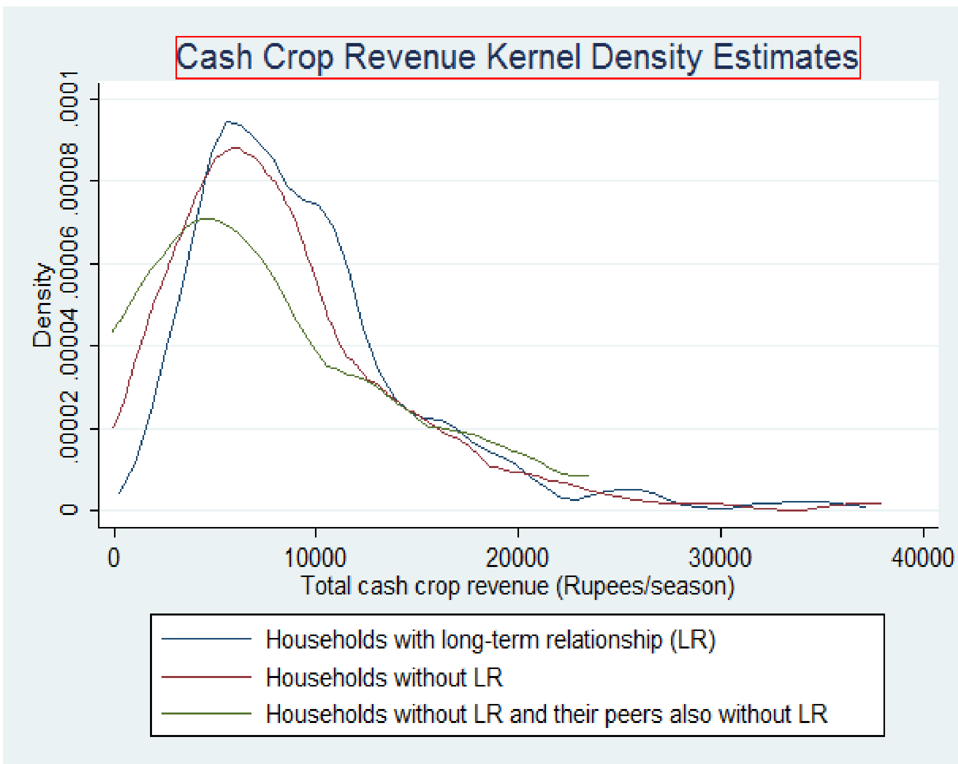

Figure 1: Cash Crop Revenue Kernel Density

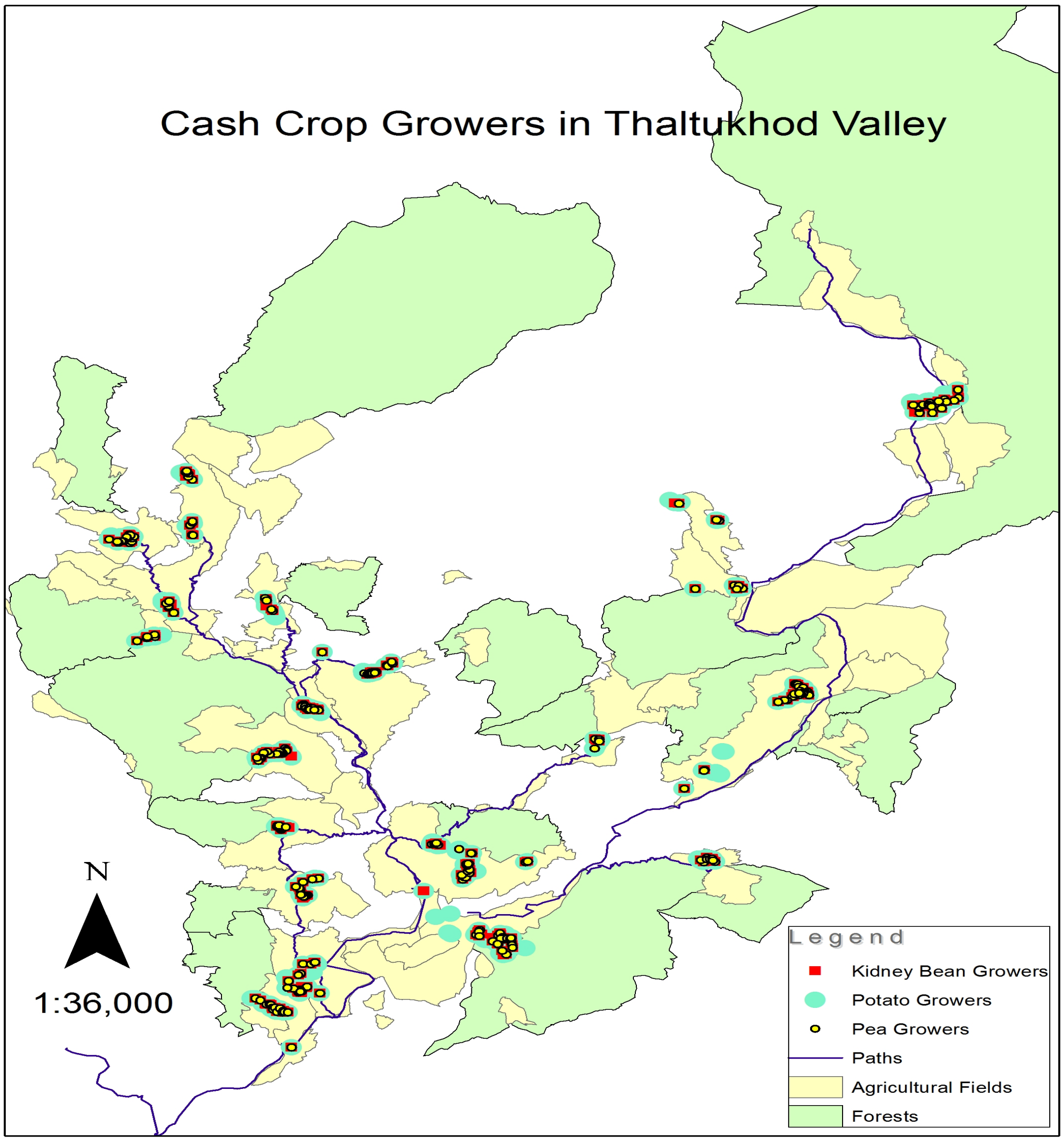

Figure 2: Production Locations of Cash Crops in Thaltukhod Valley.

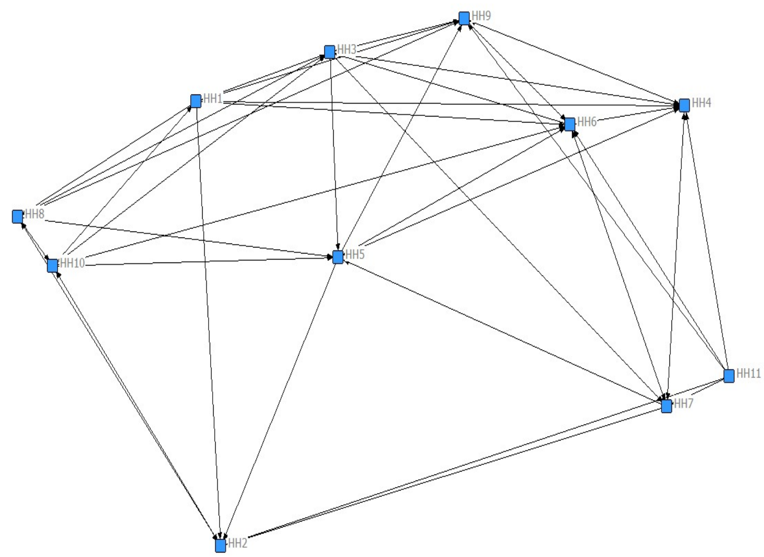

Figure 3: Village 6 - Tegar

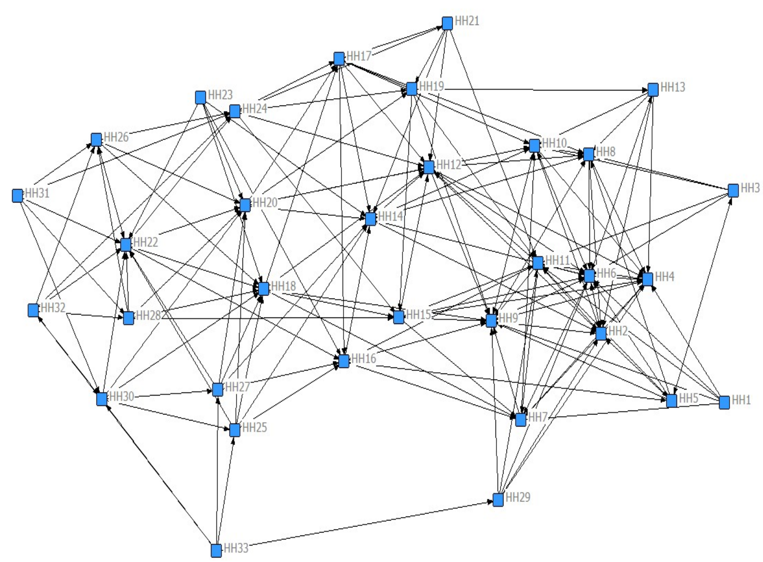

Figure 4: Village 14 - Bhumchayan