Effects of Peers on Agricultural Productivity in Rural Northern India

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Abstract

Using a unique dataset from a household survey containing explicit social relationships among individual farmers, this study estimate the effect of peers on the revenue from cash crop sales among small-scale farmers in Northern India. We explore the learning mechanism through which peer effect occurs through improved input use and higher degree of commercialization. The significant and positive peer effects support the evidence of social learning. We control for the *reflection problem* using the technique proposed by Bramoullé, Djebbari, and Fortin (2009). Additionally, the positive evidence of peer effects do not disappear when we alter the definition of peers.

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1 Introduction and Motivation

Personal interactions play an important role in shaping daily activities of people in many developing countries. Information transmitted through these interactions can be essential in determining economic outcomes. Even if we observe improved economic outcomes through social interactions, it is equally important to investigate the channel through which the learning mechanism takes place, whether it be technological adoption, input use or marketing. This study investigates the effects of peers through social networks on agricultural production of small-scale farmers in rural Northern India. Specifically, we focus on how the learning mechanisms among peer farmers might help them earn higher revenue from selling their cash crops. Note that throughout this paper, we refer to peers or friends as those households with whom a particular household reports to have a close relationship.[1]

Oster and Thornton (2012) describe three possible mechanisms of information transmission through peers. First, one might simply want to behave like peers. This could be a case of a farmer adopting a new type of seed because peers in the same group also use the new type of seed. Another mechanism is that one could also learn about improved benefits from peers who experienced positive results. The realization of an improved benefit could be a case of a farmer selling crops to the middle man who offer high prices because a friend who previously sold the crop to his middle man recommended the farmer to do so. Finally, one could learn how to use a technology from peers. The learning of technology from peers could be a case of a farmer learning from peers about how to apply pesticides most efficiently to the agricultural plots. It is necessary to note that certain agricultural practices are easier to learn than others.[2]

Several studies attempt to empirically estimate peer effects, that is, whether the average outcome of other individuals in a social network affects an individual's outcome in the same network. A critical issue facing empirical researchers in the peer

[1]In the context of this study, peers or friends could also be members of extended families, relatives and in-laws.

[2]For instance, cultivating a new crop is not as complicated a process as learning how to take care of livestock. See Abdulai and Huffman (2005) for more details about this argument.

effect literature is the *reflection problem* (Manski, 1993), which they seek to investigate whether the average outcome of other individuals in some social group affects an individual's outcome in the same group.[3] In other words, if one observes that a farmer and his peers are successful, it is difficult to disentangle whether a farmer influences his peers to become successful, or the opposite is true.

Manski (1993) argues that the *reflection problem* poses a challenge to researchers when attempting to disentangle the effects of peers through social interactions. Three possible hypotheses could explain such observation in which individuals who belong to the same peer group having similar outcomes. The first hypothesis is an individual's outcome varies depending on outcomes of other individuals in the same peer group. This peer effect is referred to as *endogenous effect*. For instance, a farmer who has good market information might inform his peers about when to market their crops to receive high prices. Second, an individual's outcome could also depend on the observed attributes of peers within the same group. This peer effect is referred to as *exogenous effect*. For example, a farmer could benefit from having peers with large family sizes, so that farmer could benefit from greater labor sharing opportunities. Finally, an individual could also experience similar outcomes with peers in the same group because they share similar observed attributes with their peers, which is referred to as *correlated effects*.[4]

Using data from a household survey conducted in Thaltukhod Valley, Himachal Pradesh, India, we test whether a household's farm revenue is dependent on the outcome of their peers within the same social network. Taking advantage of complete social network data, we follow the framework developed by Manski (1993), Brock and Durlauf (2001) and Moffitt (2001), and subsequently adopted by Bramoullé, Djebbari, and Fortin (2009) to estimate exogenous and endogenous effects of peers. The information that forms the basis of identification of peer effects comes from the information

[3] To quote Manski (1993), "The term reflection is appropriate because the problem is similar to that of interpreting the almost simultaneous movements of a person and his reflection in a mirror. Does the mirror image cause the person's movements or reflect them?"

[4] Sacerdote (2001) and Zimmerman (2003) address the problem of correlated effects by identifying through random assignments to individuals.

about interactions between each individual and peers in the same group. Specifically, each household was asked to list up to five closest peers in the same village with whom they share information on a regular basis.[5] We also include several factors including households' observed attributes (individual characteristics), geographical indicators, off-farm income opportunities and exposure to local agricultural extension agency in my estimation procedures. Within the scope of this paper, although we might not observe attributes of correlated effects specific to each network, we control for a number of factors that are common to each peer group including distance to market and village fixed effects.[6]

This study contributes to the existing literature in a number of ways. First, this study complements a small but growing number of studies analyzing the effects of peers through social networks on productivity in a small-scale agricultural community in a developing country setting (Conley and Udry, 2010; van Rijn, Bulte, and Adekunle, 2012). In particular, this study extends the analysis of peer effects to investigate the channel through which the social learning mechanism happens. Second, we control for the potential endogeneity of peer effects in the *reflection problem*. We adopt a generalized 2SLS approach similar to Bramoullé, Djebbari, and Fortin (2009) to capture unobserved characteristics common to an individual and their peers. Third, we note the potential problem of weak instruments in small sample according to the specification of the linear-in-means model proposed by Bramoullé, Djebbari, and Fortin (2009). Finally, the survey data contains all households across the 17 villages in the Thaltukhod Valley in Himachal Pradesh, India. Thus, we estimate the effect of peer networks without the potential problem of sampling bias.

[5] A similar survey question is used in Bramoullé, Djebbari, and Fortin (2009). Specifically, the authors use the information about peer relationships (up to five male and five female friends) to derive the demand for consumption of recreational activities among high school students in the USA using the In-school Add Health data.

[6] Since my study focuses on farmers' cash crop revenue in India, we expect to find evidence of positive peer effects. This is because the social structure in which social interactions are essentially driven by geography and social norms Ostrom (2000).

2 Literature Review

2.1 Peer Effects and Economic Outcomes

Several studies investigate the role of social interactions on various economic outcomes including technological adoption (Besley and Case, 1994; Foster and Rosenzweig, 1995; Munshi, 2004; Conley and Udry, 2010), diffusion of information (den Broeck and Dercon, 2011; Banerjee, Chandrasekhar, Duflo, and Jackson, 2012) and risk sharing (De Weerdt and Dercon, 2006; Fafchamps and Gubert, 2007; Weerdt and Fafchamps, 2011). My research poses a similar question: Do social interactions affect economic outcome? In particular, we investigate how peer effects though social networks have an impact on agricultural profitability of small-scale agricultural households in rural Northern India.

Several studies in economics show that personal relationships play an influential role in shaping economic outcomes in many fields of economics. However, research focusing on agricultural production has found mixed results on the relationship between peer effects and economic outcomes. While many studies of the literature find evidence of positive peer effects (Foster and Rosenzweig, 1995; Munshi, 2003, 2004; Bandiera and Rasul, 2006; Conley and Udry, 2010; Duflo, Dupas, and Kremer, 2011; Oster and Thornton, 2012), recent randomized controlled trials attempting to investigate the effect of peers' experience on agricultural production find either no significant impact (Duflo, Kremer, and Robinson, 2008) or negative impact (Kremer and Miguel, 2007) of peer effects.

A seminal paper by Conley and Udry (2010) is one of the first to study the effects of social learning on the use of input among pineapple farmers in Southern Ghana using explicit information about personal relationships. They find significant evidence that farmers adjust the amount of fertilizer applied onto their pineapple plots based on positive productivity outcome of their peers. Further, Bramoullé, Djebbari, and Fortin (2009) adopt the approach developed by Moffitt (2001) and Lee (2007) to disentangle peer effects in a social network framework. They use Monte Carlo simulations to demonstrate the procedure to estimate peer effects on the use of recreational services among secondary school students. They find that exogenous and endogenous effects can be separated using information about social networks, and their results correspond to those of other studies which use social networks to estimate peer effects (Giorgi, Pellizzari, and Redaelli, 2010; Lin, 2010).

2.2 Agricultural Productivity

Agricultural productivity plays a pivotal role in determining the livelihood status of the majority of small-scale farmers of many developing countries around the world. One option that could lead to greater productivity level among agricultural households is agricultural commercialization. Maxwell and Fernando (1989) emphasize the crucial role of cash crop cultivation in developing countries in promoting economic growth and guaranteeing food security of agricultural farmers. A seminal article by Johnston and Mellor (1961) analyzes the comparative advantage of labor-intensive cash crop cultivation among farmers in developing countries. Even non-food cash crop production can improve farm income. As an example, the authors reference silkworm cultivation in Japan as a means to ensure food security (Wood, Nelson, Kilic, and Murray, 2013).

The agricultural productivity level of small-scale farmers in developing countries could greatly benefit from improved market information (Jensen, 2007; Aker, 2010; Goyal, 2010) and social learning (Conley and Udry, 2010; van Rijn, Bulte, and Adekunle, 2012). However, farmers do not always have equal access to market information. One possible option that could help farmers overcome this market information barrier is through the communication with their peers. The interaction between peers could help reduce transactions cost in marketing through fostering information exchange, sharing of risk and enabling economies of scale (Fafchamps and Minten, 1999; Durlauf and Fafchamps, 2005).

2.3 Spatial Dependence in Agricultural Production

Economic studies on agricultural production benefit greatly from the growing number of spatially explicit data available. The availability of such data permits economists to apply spatial econometric models to tackle various problems in applied economics including environmental, resources and agricultural problems. The richness of spatially explicit data allows researchers to focus their studies on multiple scales ranging from plot, household, village or regional levels.[7]

Following two seminal works by Anselin (1988, 2002), a growing number of studies account for spatial dependence in various fields of applied economics. With regards to agricultural production, one of the first studies to use spatial econometric model to study agricultural production is Holloway, Shankar, and Rahman (2002). The authors investigate the diffusion of high-yielding variety (HYV) rice among individual farmers in Bangladesh. They find significant and positive neighborhood effects of adoption among Bangladeshi rice farmers. Similarly, Langyintuo and Mekuria (2008) find strong neighborhood effects on land allocation decisions of maize farmers in Mozambique. More recent applications of spatial dependence in technological adoption in an agricultural production setting include Liverpool-Tasie and Winter-Nelson (2012), Maertens and Barrett (2013) and Genius, Koundouri, Nauges, and Tzouvelekas (2014).

Several subsequent studies which use spatial econometric models to study agricultural production also take advantage of the increasingly available GIS generated variables to account for effects of geographical distance. Other studies on agricultural production also highlight the importance of controlling spatially related attributes.[8] These studies find that taking spatial dependence into account produces very different estimation results compared to estimating the models without controlling for spatial dependence.

[7] A detailed review of economic studies with spatially explicit data can be found in Bell and Dalton (2007).

[8] See Pattanayak and Butry (2005) and Sarmiento and Wilson (2008), among others.

3 Theoretical Framework

This section outlines a theoretical model we use to study the agricultural productivity of cash crop cultivation among small-scale farmers in Thaltukhod Valley. We modify the production function outlined in Conley and Udry (2010) to make it more relevant to the context analyzed. The production function employed builds on a common and convenient specification which accounts for the stochastic nature of agricultural production (Just and Pope, 1978). Further, we also account for spatial correlation across farmers, which represent channels through which peer effects could be transmitted. Suppose each farmer i is a risk-neutral agent who seeks to maximize expected profits.

Let w_i account for spatial correlation across farmers.[9] This spatial correlation among farmers w_i can be either exogenous (observed attributes of peers) or endogenous (outcome of peers) effects of peers, which are channels through which peers learn from each other.

A farmer's production function of each cash crop j can be specified as follows:

$$R_{ij} = P_{ij}(F(K_{ij}) + \epsilon_{ij}) \tag{1}$$

where the error term $\epsilon_{ij} = w_i e_{ij}$ represents unobserved i.i.d. productivity shock with zero mean across different farmers. $K_{ij} = w_i k_{ij}$ is aggregate cash input used by farmer i for crop j.[10] The production function (technology) is denoted by $F(K_{ij}) = w_i f(K_{ij})$. The price of crop j farmer i receives from total sales is $P_{ij} = w_i p_{ij}$. Last, R_{ij} is the revenue from total sales of cash crop j grown by farmer i.

From the production function in Equation (1) there are a number of ways peer effects could be communicated in the context of small-scale farming community in Thaltukhod Valley. First, farmers can learn from each other through price information. Farmers can benefit from the information from their friends about the time to harvest

[9]This model specification assumes that this spatial correlation w_i is known to the farmers, but not to the researcher.

[10]The aggregate input is the value of inputs used by each farmer which includes fertilizer, seeds, pesticides, herbicides, saplings and human labor. The problem of excess input purchases can be reconciled by the fact farmers in the area of study have limited storage space and resources.

or sell their cash crops in order to receive the best prices. Farmers can also learn from each other about agricultural production or technology. For example, the introduction of mechanization or improved seed can impose challenges many farmers on how to most effectively use the new technology. To overcome the learning curve, farmers can learn from their friends about how to use the new technology to improve productivity. Finally, farmers could also learn from each other through making similar decisions about input use. Farmers might only start applying a new type of fertilizer or pesticide onto their plots if they observe that their friends also start applying the same fertilizer or pesticide.

4 Identification Strategy

4.1 Identification of Peer Effects

The formulation of the empirical model to investigate peer effects and agricultural revenue closely follows the standard linear-in-means model.[11] The standard assumptions of the linear-in-means model can be found in detail in Moffitt (2001). We closely follow the model specification outlined in Lee (2007) and Bramoullé, Djebbari, and Fortin (2009) of the linear-in-means model to identify peer effects through social networks.

Given a population of size L, suppose that each household $i, (i = 1, ..., n)$ belongs to a specific social network S_i of size n_i containing peers j. Each individual household does not belong to his social network, $i \notin S_i$. Let y_i be the agricultural productivity of each household i, which is measured the profit per land unit allocated to grow cash crops. Let x_i denote observed individual characteristics of household i and there are $k, (k = 1, ..., K)$ characteristics. Specifically, the model can be expressed as follows:

[11] In a linear-in-means model, each individual's outcome has a linear relationship with own individual characteristics, the average outcome of peers in a reference group and their individual characteristics, as explained in detail in Lee (2007) and Bramoullé, Djebbari, and Fortin (2009).

$$y_i = \alpha + \beta \frac{\sum_{j \in S_i} y_j}{n_i} + \gamma x_i + \delta \frac{\sum_{j \in S_i} x_j}{n_i} + \epsilon_i \tag{2}$$

where the parameters β and δ capture endogenous and exogenous effects.

Similar to the constraint imposed by Bramoullé, Djebbari, and Fortin (2009), we require that $|\beta| < 1$.[12] The error term ϵ_i captures each household's unobserved individual characteristics. These unobserved characteristics are assumed to be strictly exogenous, which implies $E[\epsilon_i|x_i] = 0$. This specification assumes that i.i.d. samples are drawn from a population of size L with a fixed and known network structure and strict exogeneity Bramoullé, Djebbari, and Fortin (2009). Alternatively, this structural model can be illustrated in matrix form given below:

$$\boldsymbol{y} = \boldsymbol{l}^{'}\alpha + \boldsymbol{G}\boldsymbol{y}^{'}\beta + \boldsymbol{x}^{'}\gamma + \boldsymbol{G}\boldsymbol{x}^{'}\delta + \boldsymbol{\epsilon} \tag{3}$$

where $\boldsymbol{y}$ represents an $n \times 1$ vector of agricultural productivity for the entire population, $\boldsymbol{l}$ is an $n \times 1$ vector of ones, $\boldsymbol{x}$ is an nxk vector of observed individual characteristics, $\boldsymbol{G}$ is a $n \times n$ weights matrix indicating relationships between two households where $G_{ij} = \frac{1}{n_i}$ if household i is a friend of household j and 0 otherwise.[13]

All social ties considered are directed but unweighted.[14] Under this specification, the parameter β resembles the spatial auto-regressive coefficient in a typical spatial lag model. Lee (2007) notes that there exists identification in this structural model if groups are of different sizes. This requirement also holds in my dataset. Therefore, the identification of peer effects through social networks we adopt uses the variation in agricultural productivity levels of peers (endogenous effects) and individual characteristics of peers (exogenous effects) to explain a household's productivity.

[12]This condition restricts that one's own outcome cannot be dominated by the marginal effects of peers.

[13]The row-normalization of the interaction matrix $\boldsymbol{G}$ assumes that peers have similar weights for one's outcome. This can address the potential bias of top-coding.

[14]Household i is linked to household j with a *directed* only if household i reported household j as one of their peers, but not vice versa. The link between households i and j is *unweighted* because it does not take into account the strength of tie.

4.2 Instrumentation for Endogenous Peers Effects

The identification strategy adopted from the standard linear-in-means model as proposed by Moffitt (2001) allows us to estimate the exogenous and endogenous effects of peers separately. However, the effect of the average outcome of peers in a social network is endogenous. The endogeneity arises from the fact that a farmer's outcome and the average outcome of peers can be correlated with common unobserved characteristics. This correlation can lead to omitted variable bias in the estimation of peer effects and needs to be corrected for endogeneity (Wooldridge, 2010). Since it is likely that peers who belong to the same social network will have similar outcomes, the failure to correct for the endogeneity of average outcome of peers will lead to biased estimates of peer effects through social networks among these Indian farmers.

We employ a generalized two-stage least squares (2SLS) method as suggested by Kelejian and Prucha (1998), with modifications by Lee (2007).[15] This approach uses the average of friends of friends' observed attributes to form the instrument set for the average outcome of friends in one's social network to correct for endogeneity. This is achieved by multiplying the interaction matrix between an individual and his peers by itself to form the average of exogenous individual effects of friends of friends. In other words, $\boldsymbol{G}^2\boldsymbol{x}$ is the instrument set for $\boldsymbol{G}\boldsymbol{y}$, which contains all the observed attributes of friends of friends. This validity of this instrument is discussed extensively in Manski (1993), Moffitt (2001) and Lee (2007). Since the average of individual characteristics of friends of friends' are exogenous[16] and are correlated with the average profitability level of friends, it satisfies the exclusion restriction to be a valid instrument for the average profitability level of friends. In other words, the observed attributes of friends of friends can only affect one's outcome level through the average outcome of friends.

Bramoullé, Djebbari, and Fortin (2009) explain how this set of instruments is able to identify peer effects through social networks as discussed in Moffitt (2001) and Lee (2007). First, consider Equation (1), since generally $|\beta| < 1$ and the matrix $\boldsymbol{I} - \beta\boldsymbol{G}$ is

[15] Bramoullé, Djebbari, and Fortin (2009) note that since this approach does not assume homoskedasticity, parameters estimates are only consistent, but not asymptotically normal.

[16] See Equation (4).

invertible, the reduced form of Equation (1) can be written as follows:

$$\boldsymbol{y} = \alpha(\boldsymbol{I} - \beta\boldsymbol{G})^{-1}\boldsymbol{l} + (\boldsymbol{I} - \beta\boldsymbol{G})^{-1}(\gamma\boldsymbol{I} + \delta\boldsymbol{G})\boldsymbol{x} + (\boldsymbol{I} - \beta\boldsymbol{G})^{-1}\boldsymbol{\epsilon}. \tag{4}$$

Due to the fact that $(\boldsymbol{I} - \beta\boldsymbol{G})^{-1} = \sum_{k=0}^{\infty} \beta^k \boldsymbol{G}^k$ and there is no household with no peers, we can rewrite Equation (6) as follows:

$$\boldsymbol{y} = \frac{\alpha}{(1-\beta)}\boldsymbol{l} + \gamma\boldsymbol{x} + (\gamma\beta + \delta)\sum_{k=0}^{\infty} \beta^k \boldsymbol{G}^{k+1}\boldsymbol{x} + \sum_{k=0}^{\infty} \beta^k \boldsymbol{G}^k \boldsymbol{\epsilon}. \tag{5}$$

Thus, we can rewrite Equation (7) in terms of conditional expectation of the average profitability level in the cultivation of cash crop of peers in one's social network on $\boldsymbol{x}$ as follows:

$$E[\boldsymbol{G}\boldsymbol{y}|\boldsymbol{x}] = \frac{\alpha}{(1-\beta)}\boldsymbol{l} + \gamma\boldsymbol{G}\boldsymbol{x} + (\gamma\beta + \delta)\sum_{k=0}^{\infty} \beta^k \boldsymbol{G}^{k+2}\boldsymbol{x}. \tag{6}$$

Moffitt (2001) makes note of a scenario where identification is not possible when social networks are of the same size and there are isolated individuals. Supposed that all social networks are of the same size m. Let $\boldsymbol{W}_m$ be the matrix that represents the interaction between a household and his peers in a social network. The elements of interaction matrix take the value $\boldsymbol{W}_{m,ij} = \frac{1}{m-1}$ if $i \neq j$ and 0 otherwise. This means that the interaction matrix $\boldsymbol{G}$ has $\boldsymbol{W}_m$ as their diagonal blocks. In this instance, then $\boldsymbol{G}^2 = \frac{1}{m-1}\boldsymbol{I} + \frac{m-2}{m-1}\boldsymbol{G}$ for $m \geq 2$. In other words, if $\boldsymbol{G}^2$ can be written as a linear combination of $\boldsymbol{I}$ and $\boldsymbol{G}$, then peer effects cannot be identified in this linear-in-means model. This linear combination leads to the problem of multicollinearity, which poses an obstacle to achieve identification of peer effects.

Lee (2007) notes how to identify peer effects through social network when individuals interact with their peers. Consider an example with two groups of peers that interact with one another. These two groups are of sizes m_1 and m_2, where $m_1, m_2 \geq 2$. Then, the block diagonal matrix of interaction $\boldsymbol{G}$ is as follows:

$$\beta = \begin{bmatrix} \boldsymbol{W}_{m_1} & 0 \\ 0 & \boldsymbol{W}_{m_2} \end{bmatrix}.$$

The expression for the block diagonal matrix that forms the individual characteristics of friends of friends is given by $\boldsymbol{G}^2 = \lambda_0 \boldsymbol{I} + \lambda_1 \boldsymbol{G}$. The diagonal elements of this matrix $\boldsymbol{G}$ is $\lambda_0 = \frac{1}{m_1 - 1} = \frac{1}{m_2 - 1}$. so in this case if $m_1 = m_2$, the matrices $\boldsymbol{I}, \boldsymbol{G}$ and $\boldsymbol{G}^2$ will not be linearly independent. So, if $m_1 \neq m_2$, the matrices $\boldsymbol{I}, \boldsymbol{G}$ and $\boldsymbol{G}^2$, and identification of peer effects will be possible.

From Equation (8), the conditional expectation of the average profitability level in the cultivation of cash crop of peers in one's social network on $\boldsymbol{x}$ can be expressed further as:

$$E[\boldsymbol{Gy}|\boldsymbol{x}] = \frac{\alpha}{(1-\beta)}\boldsymbol{l} + b_0\boldsymbol{x} + b_1\boldsymbol{Gx} + b_2\boldsymbol{G}^2\boldsymbol{x} \tag{7}$$

where $b_2 \neq 0$ if $\beta \neq 0$ and $\gamma\beta + \delta \neq 0$.[17] Thus, Lee (2007) successfully shows that one can use $\boldsymbol{G}^2\boldsymbol{x}$ as a valid instrumental variable for $\boldsymbol{Gy}$. Under this model specification, effects of peers through social network of small-scale farmers in Thaltukhod Valley can be identified.[18]

4.3 Challenges to the Identification Strategy

One might question whether the above identification strategy adopted is able to fully capture the effects of peers through social networks on agricultural profitability among the Indian farmers. The potential challenges that we may face when attempting to identify peer effects through social networks are related to factors including selection of peers among farmers, geography, off-farm income opportunities and access to agricultural extension. Given the significant roles of these factors on the agricultural productivity level of farmers in many developing countries, the failure to address the potential impact of these factors could lead to biased results.

4.3.1 Selection among Farmers

One might worry if social networks are formed because productive farmers choose to seek advice from farmers of similar level of productivity. To account for this potential

[17] Detailed derivations of Equation (9) can be found in Bramoullé, Djebbari, and Fortin (2009).
[18] Lee (2007) also assumes in this model specification that there is no specific group fixed effects.

issue, we add village-level fixed effects into the regression model. The village fixed effects will remove any variation within the different villages because the social networks in this study are defined only to exist within the village level. The village fixed effects, however, do not capture any variation between the social networks of different villages.

In the context of this study, the variations within and between each village could be thought of as *correlated effects* as mentioned in Manski (1993). Since we cannot control explicitly for the variation across village, we have to proceed with the assumption that there are no *correlated effects* arising from the variation across different villages. This assumption is a limitation of the identification strategy in this study.

4.3.2 Geography

The geographical landscape plays an important role in determining agricultural profitability. This is because that it affects both agronomic factors including rainfall, temperature and soil quality, and physical factors such as transportation cost. Farmers who grow their cash crops at a higher elevation might receive very different profit levels from farmers have plots at a much lower elevation due to variation in factors including temperature and rainfall. In the case of Thaltukhod Valley, elevation is particularly important for farmers who grow peas. Peas that are grown at a higher elevation take longer to mature and farmers who grow them tend to receive lower prices. Similarly, farmers who grow cash crops on a plot with a higher slope cannot grow as many units of crop of the same amount of land as farmers who grow their crops on the same amount of land but with a lower slope.

To capture the possible effects of geographic indicators on farm profitability, we include three variables; distance to the main trading location, elevation and slope. Distance to the main trading location stop is measured by the Euclidean distance to the main market in Thaltukhod Valley. Elevation is measured in meters above average sea level and slope is measured in degrees.

4.3.3 Off-farm Income Opportunities

In any growing season, information about uncertainty in the market of cash crops could discourage farmers from investing significant amount of time, effort and resources into their cash crop production. The incomplete nature of the cash crop market in a rural economy leads to a greater need to search for off-farm income sources among small-scale agricultural households. These off-farm income opportunities serve as a means to help small-scale farmers stabilize household income in order to help support food security and alleviate poverty. A review article by De Janvry and Sadoulet (2006) provide a detailed explanation of potential off-farm income opportunities due to market imperfections.[19] Since the information about off-farm income opportunities could also be transmitted through interactions among households within the same social network, it is important that we control for this factor as well.

To control for off-farm income opportunities of farmers in the Thaltukhod Valley, we include determinants of income that households could earn off their farms. Specifically, we control for household labor income, forest income and distance to the closest bus stop. Labor income is labor wage that members of a household earn from working outside their farms. Forest income mainly comes from the collection of firewood or timber around their neighborhood which are sold in the market for cash. As noted by Bell and Dalton (2007), distance to the closest paved road indicates the access to formal markets, which could determine the degree of market participation (Abdulai and Huffman, 2005) and off-farm labor supply (Fafchamps and Shilpi, 2003).

4.3.4 Access to Agricultural Extension Agency

Of all public investments in the agricultural sector, agricultural extension is among the most accessible to small-scale farmers. Agricultural extension helps bridge the gap between research laboratories and agricultural fields in communicating new in-

[19] For more formal and more detailed discussion about this literature on agricultural household model, please refer to the seminal work by Singh, Squire, Strauss, and Bank (1986). Benjamin (1992) and Jacoby (1993) are two popular empirical applications of agricultural household models in a developing country setting.

formation, better farm practices and more efficient managerial skills to the farmers (Birkhaeuser, Evenson, and Feder, 1991). Despite the considerable government spending injected into agricultural extension services, returns to investments in agricultural extension services can vary depending on the context (Anderson and Feder, 2007). However, recent attempts to evaluate the role of agricultural extension services on agricultural productivity in developing countries find significant positive impact of agricultural extension services on agricultural productivity (Evenson and Mwabu, 2001; Owens, Hoddinott, and Kinsey, 2003; Godtland, Sadoulet, de Janvry, Murgai, and Ortiz, 2004). Since the knowledge about cash crop cultivation obtained from agricultural extension can also be shared among peers in the same social network, it is necessary that we also control for this potential knowledge spillover.

To account for the potential impact of access to agricultural extension on the profitability level of small-scale farmers, we use two measures of exposure to the services provided by the agricultural extension; whether a household visited the local extension office (=1 if ever visited) and frequency of visits (number of days in a year).

5 Data and Summary Statistics

The dataset used is from a household survey of small-scale farmers in Thaltukhod Valley, Himachal Pradesh, India. A map of the study area is in Figure 1. There exists a considerable difference in the livelihood activities of the small-scale agricultural households in the Thaltukhod Valley. The majority of the population in Thaltukhod live on subsistence farming, cash crop cultivation, livestock rearing, and civil service jobs. These farmers also rely on the forest areas neighboring each village. Such dependence on the forest include fuel wood gathering, livestock grazing, collection of fodder, timber and medicinal herbs. There is a clear distinction in agricultural areas that belong to each village. Each village owns between two and seven plots varying in size, elevation, slope and aspect. Within each agricultural plot, each household owns a specific parcel, which varies in size.

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 social networks of the all households and whether the household has a long-term relationship with a trader and for which crop. The survey also contains detailed crop information for each household. Each household grows three types of cash crops (and some for own consumption): kidney beans, potatoes and green peas. They also grow three types of food crops (not for commercial purpose): maize, wheat and barley. According to the data from the survey, all households grow one or more cash crops of kidney beans, potatoes and green peas.

To estimate the effects of peers on agricultural productivity among rural Indian farmers. We first calculate the total revenue from all cash crop sales (in rupees) in a growing season for each farm household.[20] We use this variable as the dependent variable to test the extent to which peers have an impact on a household's agricultural profitability. To estimate peer effects, we construct spatial weights matrix based on stated relationships between households in a given social network. Then, we incorporate weights matrix of social interactions to the regressions. This approach allows us to separate exogenous and endogenous effects of peers on productivity of small-scale agricultural households in India.

The summary statistics of the households in our dataset are shown in Table 1. The original survey contains information of all 522 households in the Valley. However, due to missing data, the total number of observations used in this paper is 510. An average household in the sample has 5.71 members, of which 1.76 persons are between the age of 0-14, 3.61 persons are between the ages of 15-60, and 0.35 persons are above 60 years old. Eighty-five percent of the households belong to the higher caste. In each household, 40% of all members receive at least 8 years of education, which is the compulsory education level in India. Each household owns 8.18 bhigas[21] of land

[20] The total revenue variable is the sum of total sales in rupees of farm households of their kidney beans, potatoes and peas.

[21] 1 bhiga = 0.2 acre = 0.0809 hectare

and 6.204 of which is allocated to grow cash crops. The average livestock holding of households is 0.57 unit. The agricultural plots that households in Thaltukhod Valley own are situated 2,006 meters above the sea level and have 26.18 degrees of slope. They are 0.017 and 0.032 Euclidean units away from the main trading location in Thaltukhod Valley and the closest public bus stop. Each household earns on average 3,106 rupees [22] from off-farm activities and 139 rupees from forest resources in a growing season. 98% of the households report that they have been in contact with the local agricultural extension (from the Indian Ministry of Agriculture) and each household talks with the extension about 5 times in a calendar year.

This study focuses on the outcome of cash crop cultivation across different households: total revenue from all cash crop sales in a growing season. On average, a household earns 9,392 rupees from cash crop sales in a growing season (kindney beans, potatoes and peas combined).

There is a considerable level of variation in all three variables that measure cash crop outcome across households and across villages, which can be illustrated using kernel density plots. The kernel density estimations of total cash crop sales revenue can be found in Figures 2. We have also included kernel density estimations of the the total revenue from cash crop sales across 4 randomly selected villages from the dataset, which can be found in Figure 3.

6 Empirical Results

6.1 Validity of Instruments

The validity of instruments is essential to any estimation results involving instrumental variable approach. As Bramoullé, Djebbari, and Fortin (2009) note, friends of friends' (who are not my friends) exogenous characteristics can be used to instrument for the average outcome of my peers. Therefore, we use all observed attributes of friends of friends as potential potential candidates for instruments: proportion land for

[22] 1 Indian rupee is approximately equal to $0.02.

cash crop, livestock ownership, family members between 15-60 years, caste and total land holding. To construct convincing arguments to support the validity of such instruments, we first argue that observed attributes of friends of friends can help influence the average outcome of friends. For example, caste also plays in an important in daily lives of throughout India and Pakistan Ostrom (2000).

In the context of Thaltukhod Valley, one's caste status could indicate greater access to credit sources and leadership in local governing institutions. These types of access could be a good source of market information. Therefore, if friends of friends with greater access to such information sources, one's friends could also benefit of such information in order to earn greater revenue, and so does that person himself. This effect might be particularly strong for a household which belongs to the lower caste and has friends belonging to the higher caste. Livestock ownership is another component that could also affect revenue of one's friends. Since livestock can be a very useful input in agricultural production in Thaltukohd Valley. Farmers with close relationships might could bring their livestock to plow and work on their plots together or farmers could also borrow livestock from their friends to work on their land, resulting in information exchange. So, one could receive advice and information from one's friends through the livestock activities they do with their friends of friends.

To further confirm the validity of such instruments in this paper, we carry out a test for robust pairwise correlation between each instrument (friends of friends' exogenous characteristics) and cash crop outcomes (revenue). The results can be found in Table 2. All excluded instruments exhibit significant coefficients. These results yield additional evidence of the validity of instruments that the observed attributes of friends of friends are highly correlated with the average of friends' cash crop revenue.

6.2 Regression Results

The estimation results in Table 3 show that although own observed attributes match exactly to average exogenous effects of peers, the linear-in-means model according to the specification in Bramoullé, Djebbari, and Fortin (2009) can be estimated with significant results. Specifically, we estimate spatial OLS and generalized 2SLS models with robust standard errors in the presence of heteroskedasticity and find point estimates of endogenous effects to be 0.164 and 0.654, which are both statistically significant. Similarly, we also estimate both models with village-specific dummy variables. This control at the village level removes all the variation across the village, which is the level that each network in the dataset is defined. The point estimates for endogenous effect for OLS and 2SLS models when controlling for village fixed effects are -0.109, which is not significant, and 0.563, which is significant. The increase in coefficient estimates for endogenous effects suggests an evidence of negative omitted variable bias. In other words, the average cash crop revenue of peers underestimates a farmer's cash crop revenue if it is not instrumented. This omitted variable bias can lead to other biased coefficient estimates of other explanatory variables in the same regression. The point estimates of the endogenous social effects indicate that a 1% increase in average revenue of peers increases a household's revenue from selling cash crops by 0.654% and 0.563% according to the 2SLS models without and with controlling for village-level charactertistics (Table 3, Columns 2 and 4).

A possible explanation for this negative omitted variable bias could be due to limited resources. Labor supply is an important element in agricultural productivity in Thaltukhod Valley. However, individual household labor supply is limited. To mitigate this labor supply constraint, peers share labor actively in all stages of agricultural production. To receive the best possible prices for cash crops, farmers have to harvest their crops at a particular time. However, if a group of peers share labor work on one farm, other farms that are owned by other peers receive less labor supply to work on that farm and might not be able to harvest their crops in time to receive the best possible prices.

A farmer's own characteristics and the mean of peers' observed attributes appear to significantly a household's effect cash crop revenue. The larger a household's allocated land to grow cash crop is, the more livestock a household owns, and the larger the total land holding is, the higher likelihood a household will earn greater revenue from selling cash crops. On the other hand, if peers on average allocate more land to grow cash crop and own larger land in total, a farmer's cash crop revenue is likely to be lower. These results are consistent with the story of labor pooling among farmers in Thaltukhod Valley. However, this cannot be observed directly by an econometrician.

One might worry that the inclusion of both a farmer's and his peers' characteristics in the same regressions might lead to multicollinearity. To check this, we test for variation within factor (VIF) for all specifications and detect that no variable has VIF over 15. This verifies that multicollinearity is not a major problem. For a farmer's own characteristics, significant determinants that lead to greater cash crop revenue include area cultivated, livestock holding, elevation and slope. Farmers who allocate more land area to grow cash crop and own more livestock tend to earn higher revenue from their cash crops. Plots that are located at a higher elevation tend to be larger in size, and plots of higher slope are less favorable to grow crops.

One important issue that arises from the estimation of peer effects of agricultural revenue among Thaltukhod households is the test statistics associated with generalized 2SLS estimation. When estimating peer effects without controlling for village-specific characteristics (Table 3, Column 2), the Kleibergen-Paap Wald F statistic is 9.255. This is associated with a 10% - 20% maximal instrumental variable relative bias according to the Stock-Yogo critical values. An implication of this regression is that the construction of the linear-in-means model can lead to biased estimates due to weak instruments with a small sample size.[23] However, such biased due to weak instruments in small sample size could be mitigated by estimating 2SLS model and controlling for village-specific characteristics (Table 3, Column4). This specification improves the explanatory power of the instrument set significantly. The Kleibergen-Paap Wald F statistic is 16.308, and the relative bias is lower to only between 5%-10%. In both models, the p-values of the Hansen J statistic are 0.525 and 0.251, which indicate that the set of instruments

[23] This is an issue that does not get discussed in Bramoullé, Djebbari, and Fortin (2009), so it remains to be seen whether there estimation results would also suffer from this issue.Note that the sample size in Bramoullé, Djebbari, and Fortin (2009) from the Add-Health data is 55,208, while there are only 510 households from Thaltukhod Valley in this study.

does not overidentify the endogenous social effects.

Table 4 reports the first-stage predicted average revenue of peers. The regression results show that almost all instruments except family members aged 15-60 when not controlling for village-specific characteristics and total land ownership have statistically strong explanatory power for the average revenue of peers, which is the endogenous social effects. The statistical significance of the instruments helps guarantee that the first-stage regressions predict the endogenous social effects rather accurately.

6.3 Robustness Checks

We test for a number of possible confounding factors that could affect a farmer's cash crop revenue; geography, off-farm income opportunities and access to agricultural extension. The results for these tests for confounding factors are reported in Tables 5 and 6. For geography, we account for distance to the main market in Thaltukhod Valley, elevation, and slope. These factors are all statistically insignificant. With regards to off-farm income opportunities, we control for distance to the nearest bus stop, labor income and forest income and also found no significant effects of these factors. Finally, the exposure to agricultural extension, we test for contact with extension (dummy variable) and frequency of visits, and find significant effect of frequency of visits from extension on a farmer's cash crop revenue. Since the frequency of visits from extension has a significant impact on a household's cash crop revenue, it is essential that we test whether this significance of extension visits impact is correlated with the average cash crop revenue of peers. We test for the joint significance of parameters estimates for the regression in Table 6 Column 4 and the p-value of the test is 0.0154, meaning there is not sufficient evidence to claim that peer effects and extension visits are not jointly significant at the 0.05 level. Moreover, we use correlation test for peer effects and visits from extension and its associated p-value is 0.0348, rejecting the null hypothesis that peer effects and extension visits are correlated at the 0.05 level.

There are a number of qualifications which are the limit factors of this study. A potential variable I would like to include is soil quality. However, this information is not available in the dataset. Also, this study does not remove common background variables that could be eliminated by the $(\boldsymbol{I}-\boldsymbol{G})$ transformation of the group interaction matrix. Finally, this study uses a cross-sectional dataset. Thus, we cannot capture the dissipation of information over time or other time-varying effects in this study.

6.4 Possible Learning Mechanisms

In section 6.2, we found the positive effects of peers on a household's agricultural revenue. In this section, we explore the possible learning channels through which peer effects operate and result in an improvement in one's farm income. One mechanism we expect to see evidence of social learning through peers is the use of cash inputs. The existence of positive peer effects in farm income take into account potential peer effects on price discovery, marketing strategies and technology use of farmers.[24] To investigate whether the positive peer effects observed in farm income arise mainly from technology use or from marketing channel, we test for the effects of social learning on the use of cash inputs, and two modern inputs: fertilizer and pesticide.[25]

Table 7 presents regression results by using total household expenditures on cash inputs, fertilizer and pesticide as dependent variables. We observe significant and positive effects of peers on total household expenditures on cash inputs and pesticide, but not on inorganic fertilizer. The absence of significant peer effects on fertilizer use might be due to its cost, high degree of substitution with organic fertilizer such as manure and lack of availability in the local market. The use of pesticide can be dependent on exogenous production shocks such as pests or blight, which can lead to substantial crop losses for many farmers. Therefore, the collective use of pesticide among peer farmers might be beneficial due to reasons including cost sharing, learning by doing and positive spillovers. Similarly, the use of aggregate cash inputs also significantly depends on the influence of peers due to similar reasons. Overall, we observe that the

[24] Ideally, we also would like to test the effects of peers of price information of Thaltukhod farmers. However, we do not have reliable data about on prices of cash crops farmers received.

[25] Cash inputs include fertilizer, seeds, pesticides, herbicides, saplings and other inputs. One might be concerned that the input purchases we observe are not all for use in the same crop year. Given farmers have limited storage space and financial resources, we believe excess input purchases to be minimal.

effects of peers in input use are stronger (0.803 for cash inputs and 0.799 for pesticide)[26] than the effects of peers in farm income (0.563).[27] Therefore, the learning mechanism among peers in input use translates into positive peer effects in farm income.

We also investigate the effects of peers on the degree of commercialization among farmers. Peas were recently introduced into Thaltukhod Valley around 5 years before the survey was conducted, so we suspect that its cultivation practices might not be completely familiar to all farmers yet. Such unfamiliarity with the production process requires learning by doing, which can also be facilitated by learning from peers. Additionally, peas are highly perishable, and need to be delivered to the market at the right time in order to receive a good price. So, farmers might require strategic coordination among peers in order to make sure they can guarantee high price for their peas.

In Table 8 we use the proportion of land area allocated to growing cash crops by each farmer as the dependent variable. We notice significant positive peer effects on the proportion of land allocated to growing cash crops, especially to peas. However, we do not observe similar effects on the proportion of land allocated to kidney beans and potatoes. This result is not surprising because kidney beans and potatoes are established crops in the area, which might not require much information from peers.[28]

6.5 Alternative Definitions of Social Networks

One might wonder that our construction of the peer interaction matrix to estimate the effects of peers on farm income might be contingent due to the definition of peers. Since our prior construction of the interaction matrix $\boldsymbol{G}$ takes the combination of both peers that a household consult for general and agricultural matters, we split the two groups of peers and estimate their effects separately.

We estimate Equation (2) again using both alternative definitions of social networks among peers (for general and agricultural matters) and still find significant effects of

[26] Table 7, Columns (1) and (3).

[27] Table 3, Column (4).

[28] Conley and Udry (2010) also observe similar outcome where significant peer effects are evident only in a new crop, but not in other established crops.

peers on a household's cash crop revenue, as shown in Table 9. Specifically, the point estimate for the average effects of peers for agricultural matters (0.851) is higher than that of peers for general matters (0.647). Thus, when we consider only those peers listed as sources of agricultural information, we observe a higher point estimate of peer effects. This estimate indicates that peer effects are likely transmitted more strongly through agricultural peers, not just any peers.

7 Conclusion

In this paper, we use complete social interaction information among small-scale farmers in Thaltukhod Valley, Himachal Pradesh, India to estimate the effects of peers on agricultural revenue from cash crops. Our estimation approach closely follows the method developed by Moffitt (2001), Lee (2007) and empirically illustrated by Bramoullé, Djebbari, and Fortin (2009), which could solve the *reflection problem* Manski (1993). In particular, this approach could explicitly estimate exogenous and endogenous social effects separately.

The estimation results find evidence of positive and significant effects of peers on cash crop revenue. In other words, farmers are more likely to earn higher revenue from selling cash crops if their peers on average earn more from cash crops. Moreover, a farmer's certain observed attributes and those of peers also have significant effects on cash crop revenue. We also test for a number of confounding factors that could potentially post a challenge to the identification strategy used in this paper and found that geography, off-farm income opportunities and access to agricultural extension do not have causal effects on agricultural revenue of the households in my dataset. The results in this paper also show that the specification of the linear-in-means model according to Bramoullé, Djebbari, and Fortin (2009) can lead to biased results from weak instruments in small sample sizes. However, such problem could be compromised by removing common unobserved characteristics that individuals in the same network face.

We also conduct a number of robustness checks for confounding effects and mechanism tests to uncover potential learning channels among farmers. The results indicate the presence of positive peer effects for input use, especially for pesticides, but not for fertilizer. There is evidence of peer effects is prevalent the cultivation of a recently introduced crops to the region namely peas but not for established crops like kidney beans and potatoes. Also, we also alter the definitions of social networks and still observe persistent effects of social learning from peers.

This study adds to a growing number of studies that use explicit social network data to estimate economic outcomes (Conley and Udry, 2010; Giorgi, Pellizzari, and Redaelli, 2010; Lin, 2010). Within a context of small-scale farmers in developing countries, where agricultural productivity is essential to household welfare, having greater access to information and technological improvements can significantly improve their livelihoods. However, a number of studies on technological adoption have shown that take-up rates are usually slow and sub-optimal (Munshi, 2004; Abdulai and Huffman, 2005; Bandiera and Rasul, 2006).

Our results indicate that peer effects could influence farmers' behavior, which affects productivity. This finding has an important policy implication for agricultural productivity. For instance, if the government or the local agricultural extension is to introduce new information or technology to a group of farmers in a village, it can cost-effectively train only a few individuals to become trainers for other farmers. These trainers can subsequently transmit information or share knowledge about a new technology to their peers. The results from our robustness checks also show that there are positive effects of learning from peers in the use of technology (cash input use) and in the cultivation of a new crop (peas). However, we cannot claim that social learning through peers would be the only and most efficient way of learning about new information on agriculture in a context of rural farm community.

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Table 1: Summary statistics

Variable	N	Mean	Std. Dev.	Min.	Max.
Family size (persons)	510	5.716	2.347	1	17
Family members 0-14 years (persons)	510	1.765	1.538	0	8
Family members 15-60 years (persons)	510	3.608	1.8	0	10
Family members above 60 years (persons)	510	0.349	0.633	0	3
Education at least 8 years (% of family members)	510	0.402	0.252	0	1
Caste (=1 if high caste)	510	0.851	0.356	0	1
Land holding (bhiga)	510	8.184	6.128	0.5	50
Cash crop land (bhiga)	510	6.204	4.997	0.25	45
Livestock ownership (units)	510	0.575	1.013	0	13
Distance to main trading location (Euclidean unit)	510	0.017	0.012	0.001	0.447
Elevation (meters above mean sea level)	510	2007.00	219.86	1323.67	2518.39
Slope (degrees)	510	26.184	5.215	12	39.833
Distance to the nearest bus stop (Euclidean unit)	510	0.032	0.015	0.010	0.068
Labor income (rupees)	510	3105.65	3266.78	0	25000
Forest income (rupees)	510	139.80	1366.66	0	26000
Contact with extension agent (=1 if yes)	510	0.984	0.124	0	1
Frequency of talks with extension agent (times/year)	510	5.076	2.448	0	24
Cash crop revenue (rupees)	510	9391.96	7452.17	500	95400
Fertilizer expenditure (rupees)	510	2633.99	2191.12	300	31200
Pesticide expenditure (rupees)	510	684.31	729.53	0	15000

Table 2: Instrument Robustness Support

Instruments	Test statistics
Robust pairwise correlation	
Proportion of cash crop land	0.260***
Livestock	0.279***
Family members 15-60 years	-0.076**
Caste	0.260***
Total land holding	0.055***

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

Table 3: Estimates of Cash Crop Revenue (rupees)

	(1) Revenue Spatial OLS	(2) Revenue 2SLS	(3) Revenue Spatial OLS	(4) Revenue 2SLS
Endogenous social effects				
Endogenous effect	0.164**	0.654**	-0.109	0.563**
	(0.079)	(0.292)	(0.093)	(0.275)
Own characteristics				
Proportion of cash crop land	0.592***	0.678***	0.623***	0.695***
	(0.083)	(0.103)	(0.081)	(0.086)
Livestock	0.0921***	0.0839**	0.0881*	0.0813**
	(0.036)	(0.033)	(0.046)	(0.037)
Family members 15-60 years	0.0186	0.0186	0.0222*	0.0212*
	(0.012)	(0.012)	(0.013)	(0.013)
Caste	0.0501	0.0505	0.0936	0.0913
	(0.197)	(0.224)	(0.189)	(0.217)
Total land holding	0.0427***	0.0423***	0.0418***	0.0412***
	(0.011)	(0.011)	(0.011)	(0.011)
Exogenous social effects				
Proportion of cash crop land	-0.185	-0.499**	0.0881	-0.413
	(0.122)	(0.206)	(0.220)	(0.277)
Livestock	0.0728*	-0.0565	0.126***	-0.0463
	(0.037)	(0.088)	(0.042)	(0.081)
Family members 15-60 years	-0.0134	-0.0191	-0.0149	-0.0173
	(0.019)	(0.021)	(0.021)	(0.024)
Caste	0.549***	0.265	0.700***	0.372
	(0.202)	(0.298)	(0.197)	(0.279)
Total land holding	-0.0125***	-0.0359**	0.00116	-0.0334**
	(0.005)	(0.015)	(0.006)	(0.016)
Village dummy	-	-	Yes	Yes
Test statistics				
Kleibergen-Paap Wald F statistic	-	9.255	-	16.308
Hansen J statistic	-	3.200	-	5.373
Hansen p-value	-	0.525	-	0.251
Observations	510	510	510	510

Standard errors in parentheses

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

Table 4: 2SLS First-stage Estimates of Endogenous Social Effects

	(1) Endog. Effects OLS	(2) Endog. Effects OLS
Own characteristics		
Proportion of cash crop land	-0.110*	-0.0883**
	(0.057)	(0.035)
Caste	-0.0933	-0.0960
	(0.234)	(0.181)
Livestock	-0.00651	-0.00943
	(0.013)	(0.012)
Family members 15-60 years	0.00241	0.00488
	(0.008)	(0.006)
Total land holding	0.00150	0.000667
	(0.002)	(0.001)
Included instruments		
Proportion of cash crop land	1.039***	0.993***
	(0.156)	(0.131)
Caste	-0.177	-0.215
	(0.438)	(0.293)
Livestock	0.204***	0.221***
	(0.027)	(0.029)
Family members 15-60 years	0.0183	0.0113
	(0.018)	(0.016)
Total land holding	0.0534***	0.0555***
	(0.006)	(0.005)
Excluded instruments		
Proportion of cash crop land	-0.454**	-0.828***
	(0.161)	(0.200)
Caste	0.907**	0.772***
	(0.374)	(0.258)
Livestock	0.124**	0.183***
	(0.038)	(0.040)
Family members 15-60 years	-0.00435	-0.0478**
	(0.025)	(0.024)
Total land holding	-0.0113**	-0.00966
	(0.005)	(0.007)
Village dummy	-	Yes
Test statistics		
R-square	0.7212	0.8131
Observations	510	510

Standard errors in parentheses

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

Table 5: Tests of Confounding Effects: Estimates of Cash Crop Revenue (rupees)

	(1) Revenue 2SLS	(2) Revenue 2SLS	(3) Revenue 2SLS	(4) Revenue 2SLS
Endogenous social effects				
Endogenous effect	0.579**	0.565**	0.527**	0.622**
	(0.267)	(0.281)	(0.263)	(0.284)
Own characteristics				
Proportion of cash crop land	0.657***	0.658***	0.664***	0.657***
	(0.095)	(0.096)	(0.093)	(0.096)
Livestock	0.0852***	0.0851**	0.0840**	0.0827**
	(0.032)	(0.033)	(0.034)	(0.033)
Family members 15-60 years	0.0191	0.0174	0.0190	0.0188
	(0.012)	(0.012)	(0.012)	(0.013)
Caste	0.00667	0.0505	0.0724	0.00780
	(0.212)	(0.217)	(0.216)	(0.218)
Total land holding	0.0424***	0.0424***	0.0425***	0.0423***
	(0.011)	(0.011)	(0.011)	(0.011)
Distance to market	-32.49			
	(33.03)			
Elevation		0.000366		
		(0.0003)		
Slope			-0.0120	
			(0.00855)	
Distance to bus stop				21.55
				(32.01)
Exogenous social effects				
Proportion of cash crop land	-0.480**	-0.449*	-0.402**	-0.551***
	(0.188)	(0.237)	(0.185)	(0.178)
Livestock	-0.0386	-0.0337	-0.0283	-0.0583
	(0.081)	(0.083)	(0.081)	(0.081)
Family members 15-60 years	-0.0188	-0.0167	-0.0143	-0.0160
	(0.021)	(0.021)	(0.020)	(0.021)
Caste	0.351	0.315	0.322	0.295
	(0.278)	(0.285)	(0.275)	(0.286)
Total land holding	-0.0327**	-0.0322**	-0.0290**	-0.0346**
	(0.014)	(0.015)	(0.013)	(0.015)
Distance to market	33.92			
	(33.13)			
Elevation		-0.000344		
		(0.0003)		
Slope			0.00756	
			(0.010)	
Distance to bus stop				-18.76
				(32.33)
Test statistics				
Kleibergen-Paap Wald F statistic	8.710	8.510	9.363	7.885
Hansen J statistic	3.91	5.166	5.53	4.323
Hansen p-value	0.563	0.396	0.355	0.504
Observations	510	510	510	510

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Tests of Confounding Effects: Estimates of Cash Crop Revenue (rupees)

	(1) Revenue 2SLS	(2) Revenue 2SLS	(3) Revenue 2SLS	(4) Revenue 2SLS
Endogenous social effects				
Endogenous effect	0.596**	0.589**	0.679**	0.727**
	(0.276)	(0.287)	(0.294)	(0.322)
Own characteristics				
Proportion of cash crop land	0.670***	0.668***	0.683***	0.648***
	(0.010)	(0.010)	(0.105)	(0.106)
Livestock	0.0848**	0.0857***	0.0828**	0.0823**
	(0.033)	(0.033)	(0.033)	(0.033)
Family members 15-60 years	0.0185	0.0187	0.0186	0.0133
	(0.012)	(0.012)	(0.013)	(0.013)
Caste	0.0524	0.0520	0.0485	0.0978
	(0.219)	(0.217)	(0.227)	(0.238)
Total land holding	0.0424***	0.0424***	0.0423***	0.0420***
	(0.011)	(0.011)	(0.011)	(0.011)
Labor income	0.000000795			
	(0.000006)			
Forest income		-0.00000411		
		(0.00001)		
Contact with extension			0.0279	
			(0.102)	
Frequency of talks wth extension				0.0244**
				(0.010)
Exogenous social effects				
Proportion of cash crop land	-0.461**	-0.461**	-0.517**	-0.483**
	(0.201)	(0.202)	(0.207)	(0.219)
Livestock	-0.0420	-0.0382	-0.0637	-0.0807
	(0.083)	(0.086)	(0.088)	(0.094)
Family members 15-60 years	-0.0179	-0.0181	-0.0193	-0.0186
	(0.021)	(0.021)	(0.021)	(0.022)
Caste	0.298	0.296	0.254	0.173
	(0.286)	(0.289)	(0.302)	(0.329)
Total land holding	-0.0332**	-0.0327**	-0.0371**	-0.0382**
	(0.014)	(0.015)	(0.015)	(0.016)
Labor income	-0.00000290			
	(0.00001)			
Forest income		-0.0000148		
		(0.00002)		
Contact with extension			-0.203	
			(0.247)	
Frequency of talks with extension				-0.00999
				(0.014)
Test statistics				
Kleibergen-Paap Wald F statistic	7.978	8.041	7.796	7.005
Hansen J statistic	5.477	5.431	3.205	2.947
Hansen p-value	0.360	0.366	0.668	0.708
Observations	510	510	510	510

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Robustness Checks: Estimates of Input Expenditures (rupees)

	(1) Cash Inputs 2SLS	(2) Fertilizer 2SLS	(3) Pesticide 2SLS
Endogenous social effects			
Endogenous effect	0.803**	-0.430	0.799***
	(0.363)	(0.183)	(0.192)
Own characteristics			
Proportion of cash crop land	0.369*	0.255	3.220**
	(0.219)	(0.248)	(1.510)
Livestock	0.0470	-0.0320	0.335
	(0.030)	(0.80)	(0.246)
Family members 15-60 years	0.0323**	0.0572*	0.145
	(0.014)	(0.030)	(0.104)
Caste	0.870*	-0.244	-1.523
	(0.474)	(0.355)	(1.189)
Total land holding	0.0280***	0.0402***	0.0812***
	(0.005)	(0.007)	(0.025)
Exogenous social effects			
Proportion of cash crop land	-0.195	-0.0287	-5.010***
	(0.331)	(0.349)	(1.528)
Livestock	-0.0620	0.435**	-0.351
	(0.071)	(0.195)	(0.510)
Family members 15-60 years	-0.0109	0.0418	0.0300
	(0.036)	(0.095)	(0.152)
Caste	-0.821	0.705	0.547
	(0.56)	(0.587)	(1.116)
Total land holding	-0.0158*	0.00141	-0.115***
	(0.009)	(0.013)	(0.037)
Village dummy	Yes	Yes	Yes
Test statistics			
Kleibergen-Paap Wald F-statistic	4.465	6.728	14.045
Hansen J statistic	1.246	1.353	2.236
Hansen p-value	0.871	0.245	0.327
Observations	504	504	504

Standard errors in parentheses

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

Table 8: Robustness Estimates Proportion of Cash Crop Land

	(1) Crop Land 2SLS	(2) Kidney Bean Land 2SLS	(3) Potato Land 2SLS	(4) Pea Land 2SLS
Endogenous social effects				
Endogenous effect	0.809*	0.740	0.895	0.910*
	(0.475)	(0.484)	(0.734)	(0.287)
Own characteristics				
Livestock	0.00457	0.00232	0.00704	-0.00169
	(0.007)	(0.003)	(0.005)	(0.005)
Family members 15-60 years	-0.000982	-0.00113	-0.00117	0.00290
	(0.003)	(0.001)	(0.002)	(0.002)
Caste	0.0288	-0.00326	-0.0431*	0.0514
	(0.044)	(0.011)	(0.019)	(0.030)
Total land holding	-0.00441***	-0.00120**	-0.00170*	-0.000032
	(0.002)	(0.0004)	(0.0007)	(0.001)
Exogenous social effects				
Livestock	0.00387	-0.000845	-0.00192	0.00809
	(0.016)	(0.008)	(0.007)	(0.009)
Family members 15-60 years	0.00518	0.00633	0.000548	-0.00343
	(0.006)	(0.004)	(0.003)	(0.003)
Caste	-0.0793***	-0.00579	0.0283	-0.0512
	(0.030)	(0.016)	(0.068)	(0.033)
Total land holding	0.0107**	-0.000556	0.00124	0.00194
	(0.006)	(0.001)	(0.001)	(0.001)
Village dummy	Yes	Yes	Yes	Yes
Test statistics				
Kleibergen-Paap Wald F-statistic	3.665	4.196	1.073	22.799
Hansen J statistic	1.054	0.037	0.003	1.208
Hansen p-value	0.305	0.847	0.955	0.547
N	509	509	509	509

Standard errors in parentheses

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

Table 9: Robustbess Checks: Alternative Definitions of Social Networks

	(1)	(2)
	Revenue	Revenue
	2SLS	2SLS
Endogenous social effects		
Endogenous effect	0.647**	0.851*
	(0.310)	(0.441)
Own characteristics		
Proportion of cash crop land	0.775***	0.890***
	(0.258)	(0.286)
Livestock	0.0871**	0.0923***
	(0.036)	(0.035)
Family members 15-60 years	0.0186	0.0109
	(0.012)	(0.016)
Caste	0.337*	0.429**
	(0.177)	(0.188)
Total land holding	0.0421***	0.0417***
	(0.011)	(0.011)
Exogenous social effects		
Proportion of cash crop land	-0.295	-0.772**
	(0.279)	(0.369)
Livestock	-0.0640	-0.0538
	(0.068)	(0.088)
Family members 15-60 years	-0.0354**	-0.0251
	(0.017)	(0.020)
Caste	0.0297	-0.234
	(0.252)	(0.369)
Total land holding	-0.0180*	-0.0268**
	(0.010)	(0.014)
Village dummy	Yes	Yes
Test statistics		
Kleibergen-Paap Wald F statistic	3.679	4.867
Hansen J statistic	0.335	2.256
Hansen p-value	0.988	0.133
Observations	508	504

Standard errors in parentheses

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

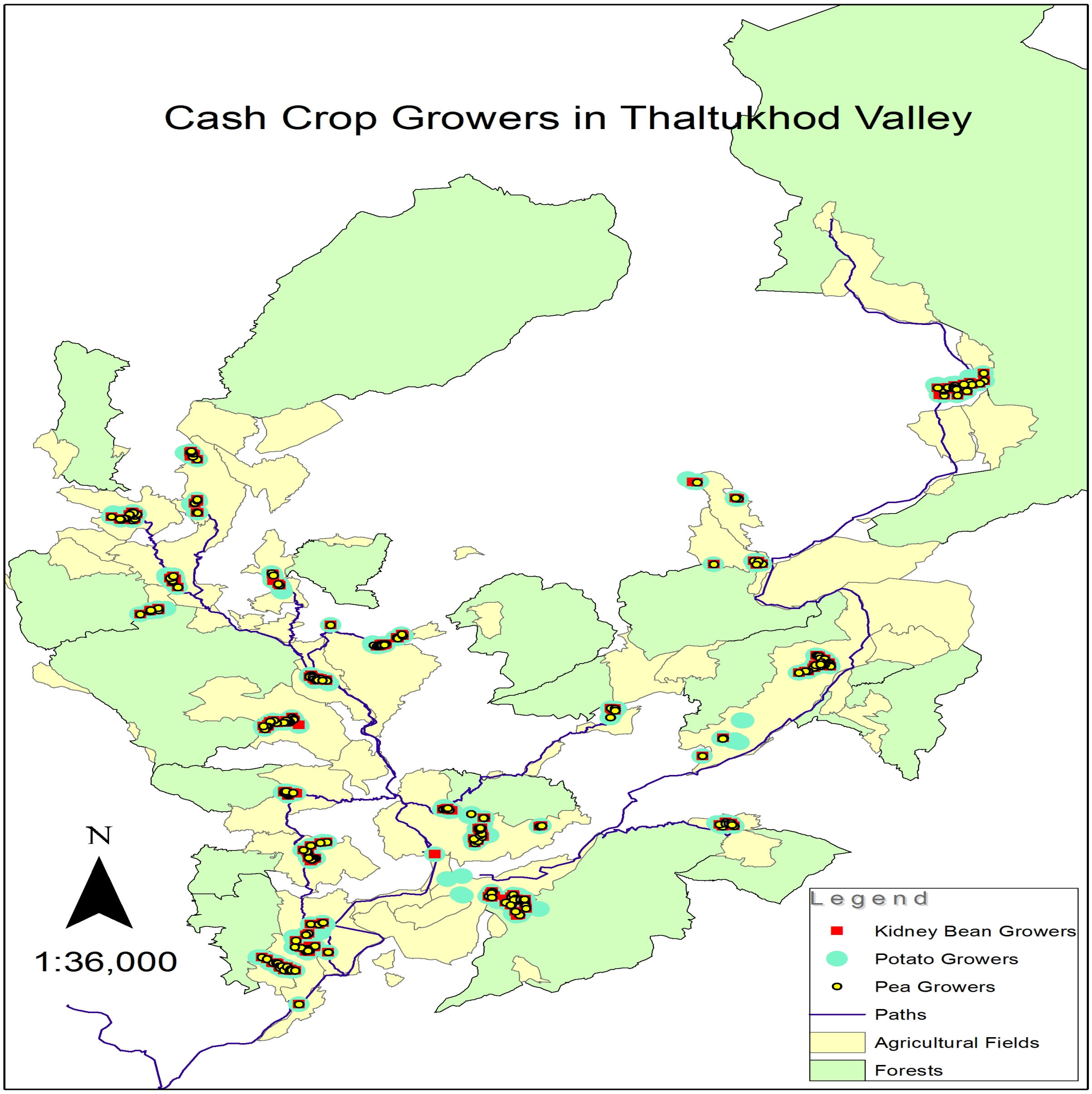

Figure 1: Production Locations of Cash Crops in Thaltukhod Valley.

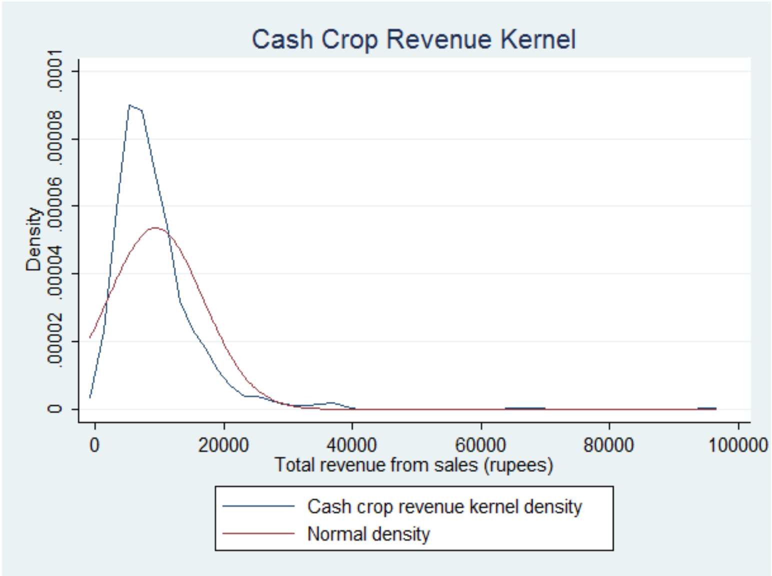

Figure 2: Cash Crop Revenue Kernel.

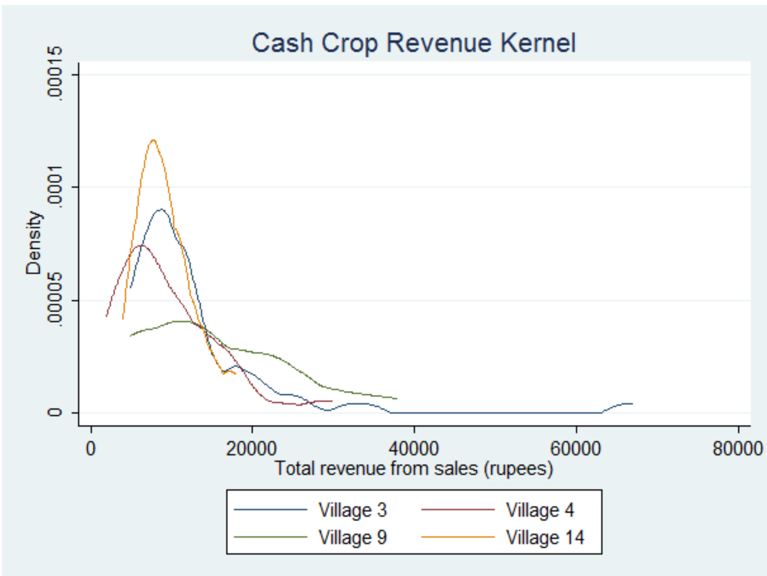

Figure 3: Cash Crop Revenue Kernel across Villages.