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Social Network amid social differentiation in the Adoption of Improved Technologies: A Case Study of Mustard Hybrids in Rajasthan, India

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Abstract

This paper evaluates the role of social networks in the adoption of mustard hybrids. Our analysis employs comprehensive data combining information on the adoption of varieties, social network, village characteristics, and the census listing of farmers comprising demographic characteristics, and the adoption data for social network members. The first objective of the paper is to examine how the farmer's adoption decision relates to the adoption choices of their network members particularly in case of hybrids. The second objective is to test whether the lower-caste (Scheduled Caste/Scheduled Tribe [SC/ST]) farmers relied more on social networks for information as compared to the higher-caste (non-SC/ST) farmers. The final objective is to explore whether social network effects are more pronounced when farmers interact within their caste as compared to outside the caste. The paper follows the model of social learning in Bandiera and Rasul (2006) extended by introducing the individual level covariates of network members. Further, we try to address endogeneity concerns by including village fixed effects and by analyzing the social network effects in a dynamic adoption framework. We establish evidence of endogenous effects in the adoption choices of hybrids i.e. more pronounced for the lower caste (schedule caste/tribe) vis-a-vis the higher caste. Further, network effects are stronger with homophily within the same caste.

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1 Introduction

Adoption of modern technologies in the agriculture sector boosts agricultural productivity and farmers' incomes (Duflo et al., 2011). Diffusion of modern technologies in the agriculture sector is challenging for policymakers for many reasons, including problems with farmers' access to credit, the risks involved in agriculture, lack of farmer proficiency in new technology, and difficulties with information dissemination (Feder et al., 1985). A significant body of literature examines farmers' constraints in adopting modern technologies (Morris et al., 2007; Duflo et al., 2011). Diffusion of technologies through extension agents, and other interventions such as field level demonstrations is well documented in the literature for both developed and developing nations.[2] Another growing literature that studies the role of social networks for the information diffusion is comparatively limited, owing inter-alia to the comprehensive data requirements (Foster and Rosenzweig, 1995; Munshi, 2004; Bandiera and Rasul 2006; Conley and Udry, 2010; Maertens and Barrett, 2012). In particular, the studies on the role of social networks in the adoption of new agricultural technologies in India is rare.[3]

In the context of social learning, the topic that is not well understood in the literature is the heterogeneity in social network effects. We attempt to explore the heterogeneity in the social network effects by caste in the context of India. This analysis is warranted for several reasons. First, India has a long history of caste discrimination. Despite several policy initiatives, the studies show that lower castes have higher poverty rates, less access to credit facilities, and face other disadvantages. They also are less connected to extension workers, and soto information about modern technologies.Bandiera and Rasul (2006) show that farmers with better information are less sensitive to the adoption choice of their social networks.[4] Therefore, it is interesting to explore whether lower-caste farmers will rely more on their social networks for the information.This analysis is particularly useful to gain insights to identify thosegroups who rely more on their networks for the accessto information for agricultural technologies.

Another aspect that needs attention is to study the homophily in the context of caste, and examine whether social network effects are more pronounced when farmers interact within the same caste compared with those who interact outside the caste. This analysis is particularly important to explore the role of caste in the context of information diffusion.Currarini et al. (2008) study homophily through a theoretical model in

[2] Glendenning et al., 2010; Birkhaeuser et al., 1991
[3] Exceptions include, Matuschke and Qaim, 2009.

[4] They have conducted the study in the Northern Mozambique on the adoption of sunflower. They found an inverse U relationship between choices of the social network and adoption decision of the individual farmer, a pattern that can be shown to emerge only when endogenous effects are effective.

the context of friendship formation of high school students of United States of America (USA), and finds that friendship formation in similar groups resulted in similar preferences. Bandiera and Rasul's (2006) study shows that there is more correlation in adoption choices of individuals of the same religion. Therefore, we hypothesize that network effects are more pronounced when interacted within same caste, and provide empirical evidence on the homophily in the context of caste.

Our paper first investigates how farmers' adoption decisions relate to the adoption choices of their social network. Our second objective is to test whether the lower-caste (Scheduled Caste/Scheduled Tribe [SC/ST]) farmers relied more on social networks for information as compared to the higher-caste (non-SC/ST) farmers. Our final objective is to explore whether social network effects are more pronounced when farmers interact within their caste as compared to outside the caste.

We follow the model of social learning laid down in Bandiera and Rasul (2006) and extend their empirical specification by introducing the individual characteristics of network members in estimating the effect of social networks. We also conduct robustness tests to address concerns related to the endogeneity and simultaneity. Our paper is based on the primary survey conducted in 2016-2017 in Rajasthan of India. We constructed the data set by combining a farmers' module (information on the adoption of varieties and about social network members), a key informant survey (village characteristics), and a census listing of farmers (demographic characteristics and adoption data for social network members).

The paper finds a strong social network effect on the adoption of hybrids. In particular, the effect is more pronounced for the lower caste (SC/ST) than for the higher caste (non-SC/ST) which confirms the hypothesis that lower castes rely more on social networks for decisions related to adoption choices. Further, network effects are higher when farmers interact within their caste as compared to their interaction outside their caste.

This paper contributes to the literature in several ways. First, it contributes to the limited literature on the role of social network for the adoption of agricultural technologies for India. Second, it is one of the first papers to present the network effect disaggregated by caste, and contributes to the literature on heterogeneous network effects. Finally, the paper provides evidence on network effects for farmers who interact within their caste versus those who interact outside their caste.

The paper is organized as follows. The second section provides the details on the primary survey of farmers (social, economic, and agricultural profile of the mustard farmers), key informant survey, and survey of network members. This section compares the demographic characteristics of farmers with their network members as well. The third section discusses the empirical framework. The fourth section presents the results and discussion. The final (fifth) section concludes.

2 Data Set

The primary survey was conducted in Rajasthan by the International Food Policy Research Institute (IFPRI), New Delhi, as part of a nationwide study supported by the Indian Council of Agricultural Research (ICAR). It compiled representative data on the adoption of major crop varieties. The selected crops were wheat, mustard, pearl millet, and gram. It collected information pertaining to reference year 2015–2016, and was carried out from November 2016 to February 2017. This paper focuses on the adoption of hybrids for mustard farmers. The paper is based on the data collected from the following three different modules: farmers, village, and listing (based on census data).

Farmers' Module: This module collects information on adoption of varieties pertaining to reference year 2015–2016 and 2012–2013. It also gathers information on the time dimension in the adoption of varieties, such as, information on a variety's first adoption year. Further, it collects information on the variety dis-adopted before adopting the present variety. We incorporated a specific module to collect information on farmers' social networks. This module collects detailed information for three other farmers with whom the surveyed farmers spent most of their time in the week before the survey.Foster and Rosenzweig (1995), and Bandiera and Rasul (2006) in their framework to identify the social learnings from other farmers does not account for individual characteristics of network members. Banerjee et al. (2014) also highlights a huge role of central individuals for the information dissemination. Matuschke and Qaim (2009) further shows a significant exogenous effects of membersindividual characteristics in identifying the social network effects.Our module thus includes : individual characteristics such as caste, religion, age, source of income, land holding, and education level, in addition to the length of time that farmers spent together, and whether they seek mutual advice on agricultural topics (e.g., input use, agricultural management).

Village Module: This module collects information on village-level characteristics such as social group, employment, and land size, and on the distance of village from major institutions such as block headquarters, district headquarters, Krishi Vigyan Kendra (KVK) agricultural extension services, banks, and input dealers.

Listing Module: This module reviews the village census to gather information on demographic characteristics, name of the crop, and the variety planted in highest area, for 2015–2016. To assess issues in dynamic adoption, we also asked the name of the variety planted by farmer in 2012–2013.[5]

The information from the social network module finds that more than 90% of the farmers have their social networks from the village itself. This forms a basis for combining both the farmers and the listing modules. We get more than 70% inputs on varietal data for network members of each surveyed farmer from the listing module.[6]

2.1 Sample Design and Sample Size

The survey was carried out in 13 of Rajasthan's 29 districts.[7] The districts, which were spread across all agro-ecological zones (AEZs) of Rajasthan, were selected randomly from each zone.[8] The number of districts per zone was decided based on the total cropped area of major crops. The selected crops in Rajasthan were wheat, mustard, and gram in the rabi season, and pearl millet in the kharif season. Three blocks from each district and two villages from each block were selected randomly. To select households, a complete household listing was developed for each selected village, with four quintiles based on total cultivable land and five households selected randomly from each quintile.[9] This paper considers the sample of 470 mustard farmers.

2.2. Social, Economic, and Agro-Ecological Profile of Mustard Farmers

This subsection discusses the social, economic, and agro-ecological profile of the mustard farmers, in the context of adoption of hybrids. Table 1 presents the social, economic, and agro-ecological profile of the sample farmers. The overall sample suggests that cultivation in Rajasthan is male dominated; 98% of surveyed households were headed by men. Education measured in terms of years of schooling suggests that the head of the household in mustard farming has an average six years of education. Feder et al. (1985)

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[5] Initially, we have decided to ask the name of the variety farmers planted in 2010-11, but in the pre-testing survey, we are getting less responses for the same, therefore, we have decided to shorten the recall period to get better responses.

[6] After cleaning, and matching data to census listing we were able to match data on 70% of the surveyed farmers.

[7] The selected districts are Bharatpur, Bikaner, Bundi, Chittorgarh, Churu, Dausa, Hanumangarh, Jhunjhunu, Jodhpur, Karauli, Shri Ganganagar, Sikar, and Sirohi.

[8] Irrigated North Western Plain, Hyper Arid Partial Irrigated Zone, Internal Drainage Dry Zone, Transitional Plain of Luni Basin, Semi-Arid Eastern Plain, Flood Prone Eastern Plain, Sub-Humid Southern Plains &Aravalli Hills, Humid Southern Plains, and Humid South-Eastern Plains.

[9]The listing module queried the land owned and the total cultivable land. Households with zero cultivable land did not occur in the sample frame.

argue that education can be used as proxy for the ability to decipher information for the adoption of modern technology. In this context, there are many studies that find a positive association of education with modern technology adoption. In our context, we are modeling the adoption of hybrids; a technology that would need relevant information and its processing which could be correlated with education. The average age of the household head is 45 years. Age can be used as a proxy for experience, and we expect that it is positively associated with the adoption of hybrids. The number of family members involved in cultivation activity on average is three out of six members. This variable is particularly important for labor-intensive hybrids.

Table 1: Sample profile of mustard farmers

Variables	Mean	Standard deviation
Mustard hybrid (Yes=1)	0.60	0.49
Male (Yes=1)	0.98	0.16
Education (Year)	6.16	4.94
Age (Year)	44.76	14.74
Age square (Year)	2220	1376
Kisan Credit Card (KCC) (Yes=1)	0.52	0.50
Scheduled caste/scheduled tribe (SC/ST) (Yes=1)	0.23	0.42
Below poverty line (BPL) (Yes=1)	0.15	0.36
Source of income (Agriculture=1)	0.90	0.30
Member of farmer group (Yes=1)	0.04	0.18
Members involved in farming (#)	2.83	1.65
Smartphone (Yes=1)	0.13	0.34
Asset index (estimated value)	0.69	2.52
Land quintiles		
First land quintile	0.15	
Second land quintile	0.15	0.35
Third land quintile	0.33	0.47
Fourth land quintile	0.38	0.49
Agro-ecological zone (AEZ)		
Arid region	0.18	–
Rainfed region	0.40	0.49
Irrigated region	0.42	0.49
Source of Information		
Farmers (neighbor) (Yes=1)	0.78	0.41
Progressive farmer (Yes=1)	0.57	0.50
Friends/relatives (Yes=1)	0.86	0.34
Extension officer (Yes=1)	0.07	0.25
Krishi Vigyan Kendra (KVK) (Yes=1)	0.01	0.12
Radio/television/newspaper (Yes=1)	0.18	0.38
Input dealer (Yes=1)	0.42	0.49
Distance from the village for the key places		
Input dealer (in kilometers [km])	8.13	6.77
Block headquarters (in km)	14.35	8.42
KVK (in km)	11.98	8.22
Bank (in km)	6.32	3.74

Source: IFPRI-ICAR survey, 2017

Distribution by social group shows that 23% belong to SC/STs, i.e. the lowest caste. A priori, we expect them to have a negative association with the adoption of hybrids. Out of the total sample, about 15% possess

Below Poverty Line (BPL) and *antyodaya* (government food subsidy for the poorest) cards, while 85% have Above Poverty Line (APL) cards. It is hypothesized that poorer farmers are less likely to adopt hybrids. Out of the total sample, 90% report cultivation as their main source of livelihood, and the remaining 10% report income from non-agricultural activity.With regard to farmer access to credit, the government of India has provided Kisan Credit Cards (KCCs) to supply farmers with credit facilities.[10] Only 52% mustard farmers surveyed have these cards. Farmers with credit facilities are more likely to adopt hybrids.

We constructed an asset index for the farmer as a proxy for farmers' wealth. Feder et al. (1985) show that wealthier farmers are more likely to bear risks involved in the adoption of a new technology. We hypothesized a positive association between the asset index and the adoption of hybrids. This study also uses four land quintiles based on farm size.[11] This was done to understand the distribution of farmers engaged in mustard cultivation. Only 15% farmers from both the first and second land quintiles were engaged in mustard cultivation. By contrast, 33% and 38% of farmers from the third and fourth quintiles engaged in mustard cultivation, which indicates that marginal and small farmers are less involved in mustard cultivation than medium and large farmers.

We also capture the sources of information used for adoption in 2015–2016. The breakdown is as follows: neighbors (78%), progressive farmers (57%),[12] friends/relatives (86%), extension officers (75), KVK (1%), radio/television/newspaper (18%), and input dealers (42%). Further, 13% of surveyed farmers have smartphones. The government of India has implemented a range of smartphone applications to disseminate information on modern agricultural practices. It is important to know whether this is associated with modern technology adoption. We also include variables that capture the connectivity of villages to block headquarters, banks, the nearest KVK, and input dealers. Our village module examined the distance of a village from these centers. The data show that usually the input dealer is about 8 kilometers (km) from the village, block headquarters is 14 km away, KVK 12 km away, and a bank is about 6 km away. It is hypothesized that greater distances will result in higher transportation costs including greater time and are expected to be negatively associated with adoption.

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[10] KCC holders are covered under personal accident insurance up to ₹50,000 for death and permanent disability, and up to ₹25,000 for other types of risk. The premium is borne by both the bank and borrower in a 2:1 ratio. KCC offers two types of credit: cash credit and term credit (for activities such as pump sets, land development, and modern technologies).

[11] The total sample size of the survey is about 1,500 farmers including wheat, mustard, pearl millet, and gram farmers. The land quintiles are based on this sample.

[12] Progressive farmers are defined as those farmers who adopt modern agricultural technologies in the agriculture, and are the source of information for other farmers.

2.3. Social Network Members

Our survey asked for information about the three persons with whom the farmers interact the most. From 470 mustard farmers, we collated information for 1,410 network members, asking about their relationship with the farmers, their demographic characteristics, and their adoption patterns. We found that about 90% of them are friends (64%) and relatives (26%), and the rest were neighbor farmers (8%), and 2% were others (*panchayat* [village council] workers or local leaders). To better understand them, we compared their characteristics with the farmers—for example, whether farmers have a network within or outside their caste, as well as if they have a network with persons of the same age, education, and land profile.

Table 2 presents the number of network members of the same caste (out of three) as reported by mustard farmers. For general category farmers, 62% farmers reported all the three members of the same general caste in their social network, 15% reported two members of the same caste, 10% reported one member of the same caste, and 13% reported all three members in the other than general category. For other backward classes (a separate category of lower-caste farmers), 91% farmers reported all the three members of the same caste, 6% reported two members of the same caste, 1% reported one member of the same caste, and 2% reported all the three members of other castes. For SC/STs, 75% farmers reported all the three members of the same caste, 12% reported two members of the same caste, 8% reported one member of the same caste, and 5% reported all three members of non-SC/STs.

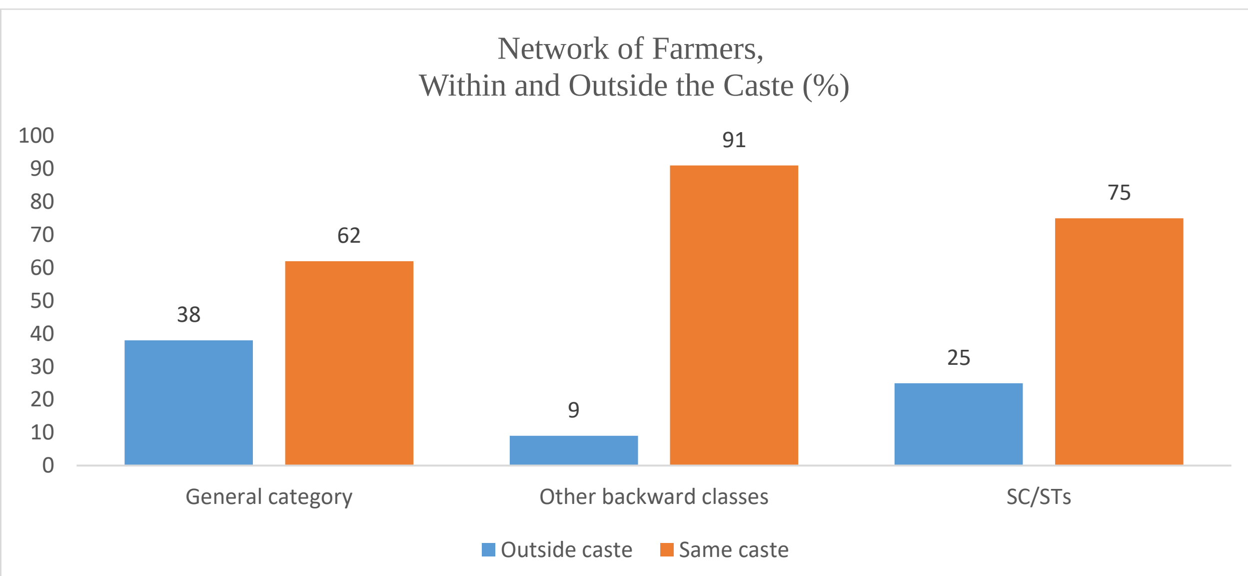
Table 2: Number of network members of the same caste (out of three members) as reported by mustard farmers

Social group	Members of the same caste	One member of the same caste	Two members of the same caste	Three members of the same caste
General category	12 (13%)	9 (10%)	14 (15%)	58 (62%)
Other backward classes	6 (2%)	3 (1%)	17 (6%)	248 (91%)
SC/STs	6 (5%)	9 (8%)	13 (12%)	85 (75%)

Source: IFPRI-ICAR survey, 2017

Figure 1 summarizes the above findings: 62% of the general category farmers have their network within their caste and 38% have their network outside their caste, 91% of other backward classes farmers have their social network within their caste and 9% outside their caste, and 75% of SC/ST farmers have their network within their caste and 25% outside their caste. Farmers in Rajasthan thus interact socially within their caste, consistent with the socially and culturally diverse nature of the state. The figure clearly indicates a big incidence of homophily within the caste. The highest among other backward classes followed by SC/ST and general category.

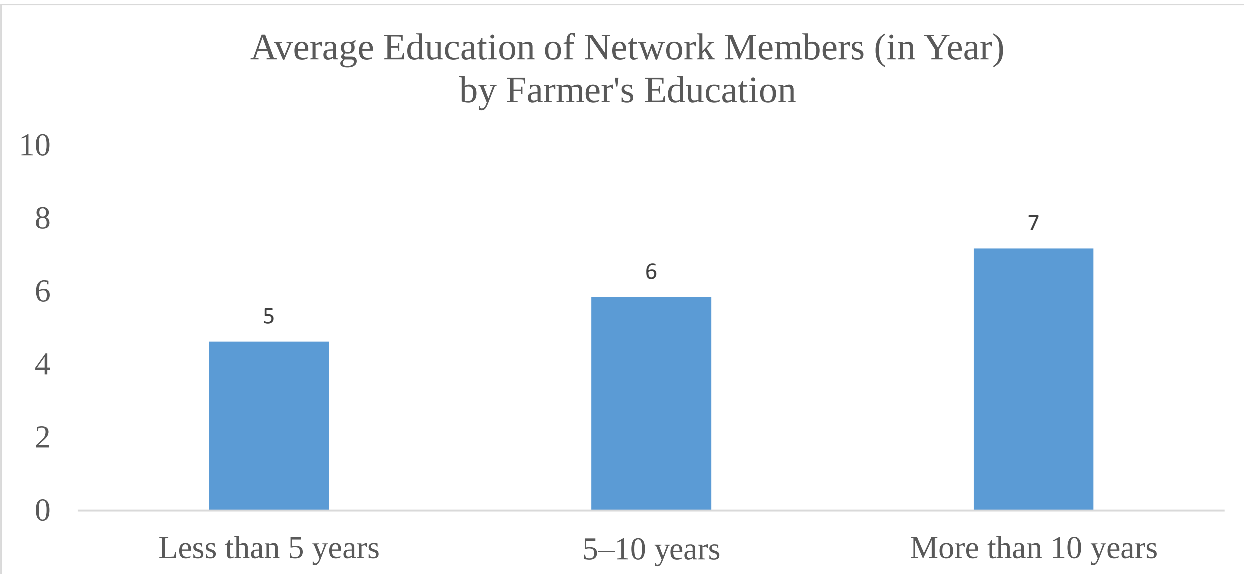
Figure 1: Network of farmers, within and outside the caste (%)



Source: IFPRI-ICAR survey, 2017

Figure 2 compares the education profile of the farmers and their network members. We define farmers' education levels in three categories: those with less than 5 years of schooling, those with 5 to 10 years of schooling, and those with 10 or more years of schooling. The result shows that the average education years for network members for the first, second, and third categories are five, six, and seven years, respectively. This result shows some deviation in social interaction; for example, the first and second categories interact with those in their same education profile, while third category interacts with less educated network members.

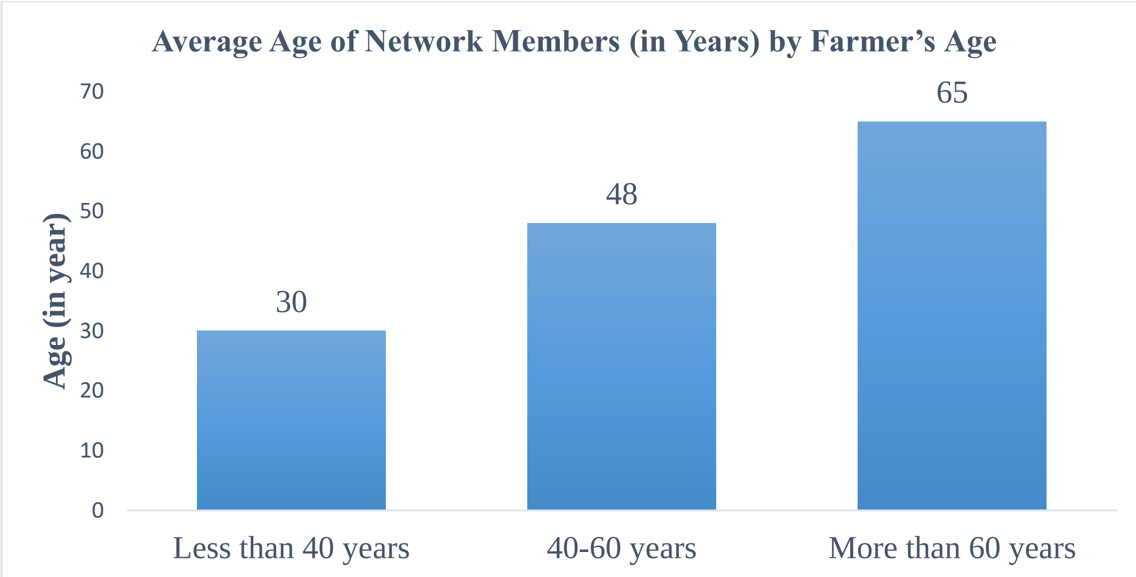
Figure 2: Average education of network members (in year) by farmer's education



Source: IFPRI-ICAR survey, 2017

Figure 3 compares the age profile of the farmers with their network members. We define farmers' age ranges in three categories: those less than 40 years of age, those between 40 to 60 years of age, and those over 60 years of age. The result for interaction among social network members shows 30, 48, and 65 years in first, second, and third categories. This suggests that farmers interact with network members of similar age.

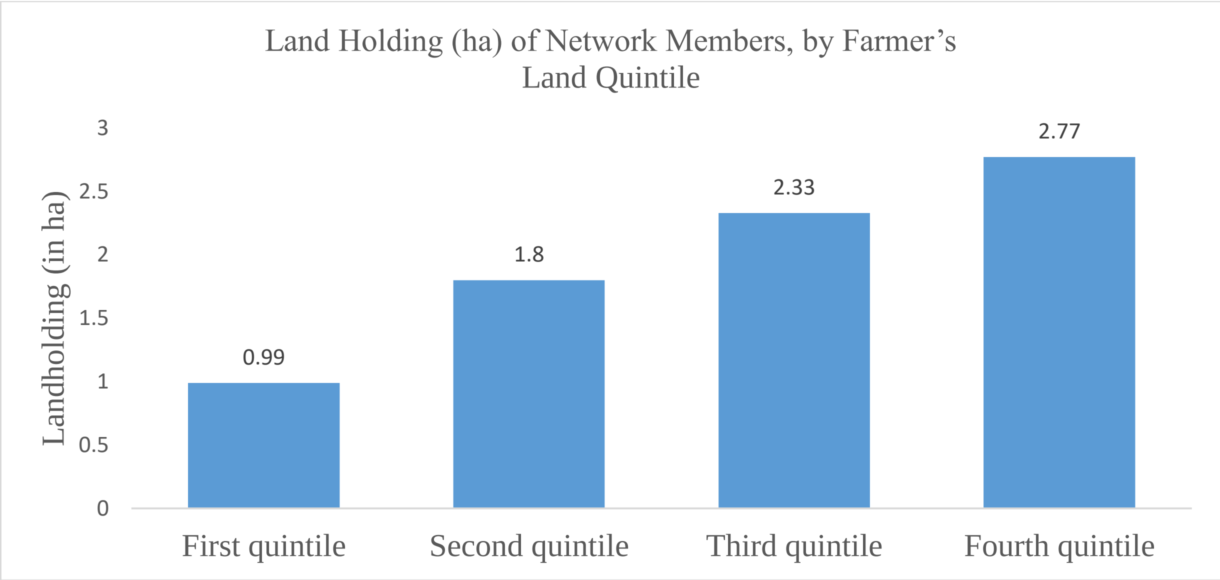
Figure 3: Average age of network members (in years) by farmer's age



Source: IFPRI-ICAR survey, 2017

Figure 4 compares the land profile of farmers with that of their network members. We made four land quintiles: the first quintile corresponds to marginal farmers, the second to small farmers, the third to medium farmers, and the fourth to large farmers. For social network members, land holdings are 0.99, 1.80, 2.33, and 2.77 hectares (ha) of land in first, second, third, and fourth quintiles, respectively. This indicates that in terms of land profile, farmers also are interacting within their land classes.

Figure 4: Average land holding (ha) of network members, by farmer's land quintile



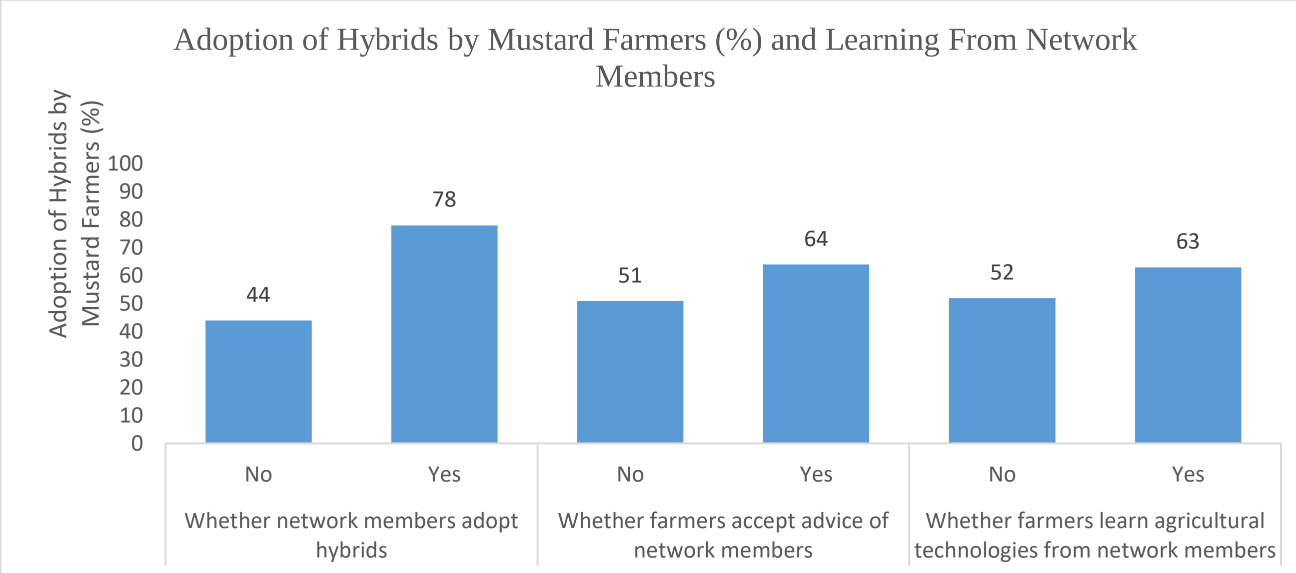
Source: IFPRI-ICAR survey, 2017

Note: The first land quintile corresponds to marginal farmers. The fourth land quintile corresponds to large farmers.

Figure 5 presents the adoption of hybrids (by percentage of farmers) for three different indicators. The first indicator is whether or not network members adopt hybrids. The results show that only 44% farmers adopt hybrids when their network members do not, whereas 78% of farmers adopt hybrids when their network members do. The second indicator is whether or not farmers accept advice from network members. The results show that when farmers do not accept the advice of network members, 51% adopt hybrids, yet when they do accept advice, 64% adopt hybrids. The third indicator is whether or not farmers learn agricultural technology from network members. The result shows that when farmers learn agricultural technology from the network members, 63% adopt hybrids, yet when they do not learn about technology, 52% adopt hybrids. All these results are statistically significant. They clearly indicate that network members' adoption choices are associated with farmers' adoption choices.

The next section formulates the empirical strategy to establish the relationship between farmers' adoption choices and network members' adoption choices.

Figure 5: Adoption of hybrids by mustard farmers (%) and learning from network members



Source: IFPRI-ICAR survey, 2017

3 Identifying Network Effects

Identifying the effect of social network is challenging for several reasons. The first challenge is to identify and measure social networks correctly which requires the complete mapping of each farmer's social networks. This requires significant amount of time and resources. We adopted the sociometric method to measure network links, and asked each farmer for a maximum of three people with whom he or she spent maximum time (Rogers, 2003). The second challenge is identification of the endogenous social effects.

Towards this, we follow the conceptual model of social learning as laid down in Bandiera and Rasul (2006), and assume that farmers do not know the optimal level of input for mustard production. Level of input is automatically changed by adopting a new technology (hybrid seed in our context). As hybrids have different traits than OPVs, and may have a different requirement in terms of machine, irrigation, labour, fertilizer, and pesticides. Farmers' can update their beliefs on these requirements based on their experience in previous years and/or the experiences of their social network members. Through these learnings, farmers seek to maximize the profitability of their cultivation activity by implementing the optimal level of inputs required in the adoption of hybrid seeds.

Further, farmer's initial decision to adopt new technology (hybrid seed) may depend on learning from several sources, for example, they may learn from own social network of friends/relatives/neighbors/others, learn from extension agents, and other channels (such as training or frontline demonstrations of frontier technologies). Here, we limit ourselves to focus on learning through the social networks in the adoption of new technologies.

Identifying endogenous social network effects as distinct from exogenous and correlated effects needs careful exploration. We begin the analysis with the following equation:

$$a_{ivb}=\beta X_{ivb}+\eta\ \overline{a_{vb,2014-15}}+\varepsilon_{ivb} \qquad (1)$$

Where i is farmer, v is the village, b is the block, and a is the adoption of mustard hybrid, and takes value 1 if farmer adopt mustard hybrid in $2015-16$ and 0 otherwise, X is the covariates related to farmers, $\overline{a_{vb,2014-15}}$ captures the average adoption rate at the village level. Estimating this specification suggests that the social network effect is no longer individual-specific, and therefore it is not possible to differentiate whether individuals behave similarly because of endogenous or exogenous effects or solely because of correlated effects at the village level. Through this specification, the social network effect cannot be clearly identified and estimation results may be inconclusive.

To identify individual-specific social network effect, we consider the specification that includes the adoption choice of network members in place of village adoption rates:

$$a_{ivb}=\beta X_{ivb}+\gamma a_{nvb(i)}+\varepsilon_{ivb} \qquad (2)$$

Where i is farmer, v is the village, b is the block, and n denotes the network members. X denotes the individual characteristic of farmers, a denotes the adoption of hybrids in 2015–2016, and ε is the error term. $a_{nvb(i)}$ is the adoption decision of social network member n corresponding to individual farmer i *in* 2015–2016, and it takes value 1 if at least one network member adopt hybrids and 0 otherwise. The coefficient γ measures endogenous effects.

To account for correlated effects, we include block fixed effects for controlling the characteristics at the block level that may lead to correlated adoption choices among farmers such as the availability of input and output markets, access to agricultural institutions, and access to information's related to agriculture. To address that, we should ideally include village fixed effects for controlling the characteristics at the village level but that lead to reduce the analysis sample significantly as the sample of mustard farmers per village is small. Therefore, we also include detailed village characteristics such as distance from input dealer, block headquarter, district headquarter, and agriculture institutions to account for correlated effects in addition to the block fixed effects. We extends the specification 2 as follows:

$$a_{ivb} = \beta X_{ivb} + \gamma a_{nvb(i)} + \Phi Z_{vb} + \lambda G_{vb} + \varepsilon_{ivb} \tag{3}$$

All other notations are same as specified for equation 1. Z is the village-level characteristics. G represent the block fixed effects. ε is the error term.

Banerjee et al. (2014) and Matushcke and Qaim (2009) highlights the importance of specific individuals in the information diffusion through social networks. They argue that, it is always possible that farmer's choices may also get influenced from the characteristics of network members. Further, the individual characteristics may also explain the process of selection into the social networks, therefore, the inclusion of individual characteristics in the specification is also important for taking care of endogeneous sorting of individuals. For these reasons, we also include network member's characteristics in specification 3 as follows:

$$a_{ivb} = \beta X_{ivb} + \gamma a_{nvb(i)} + \delta X_{nvb(i)} + \Phi Z_{vb} + \lambda G_{vb} + \varepsilon_{ivb} \tag{4}$$

where $X_{nvb(i)}$ is the characteristics of social network member *n* corresponding to individual farmer *i*, which also captures exogenous effects in addition to the social endogenous effects. Yet since Bandiera and Rasul (2006) do not have data on characteristics of the individual social network members, they are not able to account for the exogenous effect δ in their paper.

Further, it is important to note that there is some public good element in the adoption of new technology, and adopter cares about how many other farmers adopt the same technology, possibly for the reasons related to the availability of inputs required in the market for its implementation. Besley and Case (1993) document how adoption in the current period is related to the past experiences of other farmers. For these concerns, we also include village adoption rate for 2014–2015 in specification 4, which captures the influence of village adoption rates in previous years for the current adoption of hybrids in 2015–2016 as follows:

$$a_{ivb} = \beta X_{ivb} + \gamma a_{nvb(i)} + \delta X_{nvb(i)} + \Phi Z_{vb} + \eta \overline{a_{vb,2014-15}} + \lambda G_{vb} + \varepsilon_{ivb} \tag{5}$$

This serves as the final specification for identifying social network effects for the adoption of mustard hybrids.

In estimating the above equation there are two potential econometric problems stemming from unobserved heterogeneity and simultaneity. The first problem results from the fact that farmer may adopt due to unobserved individual characteristics that influence the adoption decision, such as ability to decipher the information, to address this we use education as a proxy for the ability. We also run specification 5 including village effects to show that our results still holds even for accounting for those endogenous effects that may drive the adoption choices for the village as a whole.

Simultaneity is another big challenge in estimating social network effects (Manski, 1993; Manski, 2000; Neill and Lee, 2001). Social network members' adoption choices may influence individual farmers; in turn, individual farmers' adoption choices may influence the members of their social network. The extent of this problem can be seen by testing for simultaneity between adoption choice of farmer's and their social network members. Since we have the adoption data for network members for 2012–2013. We can test the extent of this problem by dropping those farmers who adopted mustard hybrids before 2012–2013 from the sample, and consider the adoption choice of network members for 2012–2013 to estimate the social network effects. In other words, we keep only those farmers who have adopted mustard hybrids in 2012–2013 or in later years and test how farmers' adoption choices in the current year (2015–2016) is related to the adoption choices of their network members in previous years (2012–2013).

Heterogeneous Network Effects

We allow for the heterogeneous network effects that vary according to farmer's characteristics. As discussed earlier, the lower castes (SC/ST) household is hypothesized to be comparatively reliant on their social networks as compared to higher caste (non-SC/ST) households. In particular, we test whether SC/ST farmers have stronger network effects than the non-SC/ST farmers using the specification below:

$$a_{ivb}=\beta X_{ivb}+\gamma a_{nvb(i)}+\Phi\left(X_{ivb} * a_{nvb(i)}\right)+ \delta X_{nvb(i)} +\Phi Z_{vb} + \lambda G_{vb}+\varepsilon_{ivb} \tag{6}$$

The interaction term captures the difference in social network effects for SC/ST farmers as compared to non-SC/ST farmers.

In the Indian context, there is a significant body of literature that shows strong ties among within the social groups.[13] Bandiera and Rasul (2006) shows that the adoption choices of network members of the same religion are strongly correlated. Therefore, it is interesting to explore whether the same pattern appears among the social groups in the context of India. To test whether social network effects are more pronounced when farmers interact within same caste as compared to outside the caste, we run the following specification:

$$a_{ivb}=\beta X_{ivb}+\gamma Share_{ivb}+\delta X_{nvb(i)}+\Phi Z_{vb}+\eta\overline{a_{vb,2014}}+\lambda G_{vb}+\varepsilon_{ivb} \qquad (7)$$

where we define *Share* as the share of same-caste social network members who adopt hybrids. All the other notations remain the same. This variable captures the social network effect when same-caste members adopt hybrids. If the hypothesis is true, then it is expected that the coefficient here should be greater than in specification 5.

4 Results and Discussion

4.1. Baseline Probit Regressions

We begin our analysis by running a simple probit model to explore the association of farmer characteristics and information channels, and the adoption of hybrids for mustard cultivation. Table 3 presents the marginal effects of the adoption of hybrid for the mustard cultivation where the dependent variable takes value 1 for hybrid and 0 otherwise, with the farmers' social, economic, and agricultural characteristics, as well as the various information channels (see Table 1 for complete list of explanatory variables). Column 1 presents the result without AEZ fixed effects, and Column 2 presents the result including AEZ fixed effects.

[13]See for example, Deshpande (2000).

Table 3: Baseline probit regression for the adoption of mustard hybrids

Explanatory variables	Dependent Variable: Hybrid=1 and 0 Otherwise	
	Model (1)	Model (2)
Male (Yes=1)	−0.0550 (0.407)	−0.254 (0.422)
Education (Year)	−0.0160 (0.0146)	−0.0215 (0.0148)
Age (Year)	−0.0183 (0.0263)	−0.0220 (0.0264)
Age square (Year)	0.000112 (0.000282)	0.000147 (0.000284)
KCC (Yes=1)	0.352*** (0.131)	0.372*** (0.137)
SC/STs (Yes=1)	−0.405*** (0.154)	−0.410** (0.160)
BPL (Yes=1)	−0.0986 (0.176)	−0.224 (0.178)
Source of income (Agriculture=1)	0.190 (0.220)	−0.0201 (0.230)
Member of farmer group (Yes=1)	−0.845** (0.369)	−0.714* (0.378)
Members involved in farming (#)	−0.000747 (0.0385)	−0.0177 (0.0385)
Smartphone (Yes=1)	−0.140 (0.204)	−0.148 (0.205)
Asset index (estimated value)	−0.0167 (0.0300)	−0.0311 (0.0305)
Second quintile	−0.297 (0.238)	−0.269 (0.241)
Third quintile	−0.0818 (0.207)	0.0395 (0.214)
Fourth quintile	−0.526** (0.226)	−0.397* (0.236)
Farmer's (neighbor) (Yes=1)	−0.0574 (0.164)	0.0472 (0.171)
Progressive farmer (Yes=1)	0.0173 (0.143)	−0.0478 (0.146)
Friends/relatives (Yes=1)	0.399** (0.195)	0.353* (0.203)
Extension officer (Yes=1)	−0.105 (0.276)	0.0936 (0.282)
KVK (Yes=1)	−0.402 (0.444)	−0.219 (0.465)
Radio/television/newspapers (Yes=1)	0.290* (0.173)	0.309* (0.176)
Input dealer (Yes=1)	0.0747 (0.132)	0.120 (0.139)
Rainfed	–	0.256 (0.191)
Irrigated	–	0.850*** (0.198)
Constant	0.704 (0.835)	0.697 (0.851)
Number of farmers	470	470

Notes: The dependent variable takes value 1 when mustard farmers adopted hybrids for cultivation in 2015–2016, and 0 when they adopted improved or traditional varieties. Column 3 also includes interaction of land quintiles and agro ecological zones (AEZs). Standard errors in parentheses. * p<.1, ** p<0.05, *** p<0.01.

Column 2 shows that SC/ST farmers are less likely to adopt hybrids. Given that hybrid seeds are more expensive than the improved and traditional varieties, farmers may not be able to afford the higher fixed cost involved in the cultivation of hybrids. Given that SC/ST farmers have less access to information, credit and insurance, it is possible that their lower ability to take risks may also affect their adoption of hybrids.[14] Indeed, results suggests that access to Kisan Credit Cards (KCCs) appear to be more likely to adopt hybrids. Feder et al. (1985) in this context highlighted a key role of credit facilities for the adoption of modern technology. Because mustard hybrids require higher fixed and variable costs, farmers with credit constraints may not be able to afford to adopt hybrids.

Information is also a key constraint for the adoption of technology (Feder et al., 1985). The result shows that friends and relatives are the main sources of information for the adoption of hybrids in mustard cultivation, and information channels such as radio, television, and newspapers are also significant source of information. Hybrids for mustard cultivation are mainly developed by the private sector,[15] private seed developers may spread word of their varieties through advertising. As expected, the adoption of hybrids is higher in rainfed and irrigated regions than in arid regions.

In summary, SC/ST farmers are less likely to adopt hybrids, farmers with access to KCCs are more likely to adopt hybrids, and farmers who report information sources such as friends/relatives and radio/television/newspaper are more likely to adopt hybrids.

4.2. Social Network Effects

Before presenting final specifications on the role of social networks on the adoption of hybrids, it is useful to know how farmers' adoption choices are related to village adoption rates. We follow specification 1 to regress the farmer's adoption choice for 2015–2016 (hybrid=1 and 0 otherwise) as the dependent variable. The independent variable of interest is the village adoption rate for 2014–2015. Table 4's upper panel presents the result for this specification using individual characteristics listed in Table 1 in Columns 1, 2, and 3 for AEZ, district, and block fixed effects, respectively. The lower panel includes village characteristics in addition to individual characteristics, with results in Columns 4, 5, and 6 for AEZ, district, and block fixed effects, respectively.

[14] Thorat and Lee, 2005
[15] There are a few exceptions, include Dhara Mustard Hybrid, but their adoption is rare.

Table 4: Significance of village adoption rate of hybrids in 2014–2015 for the adoption of hybrids in 2015–2016

	Dependent variable: Hybrid=1 and 0 Otherwise		
	Model (1)	Model (2)	Model (3)
Village adoption rate of hybrids for 2014–2015	2.69*** (0.24)	2.12*** (0.35)	1.15 (1.55)
Individual characteristics of farmers	Yes	Yes	Yes
Village characteristics	No	No	No
AEZ fixed effect	Yes	–	–
District fixed effect	–	Yes	–
Block fixed effect	–	–	Yes
Constant	−0.33 (0.82)	−0.019 (0.83)	−1.26 (1.10)
No. of farmers	470	470	328
	Model (4)	Model (5)	Model (6)
Village adoption rate of hybrids for 2014–2015	3.93*** (0.36)	3.44*** (0.47)	0.41 (1.55)
Individual characteristics of farmers	Yes	Yes	Yes
Village characteristics	Yes	Yes	Yes
AEZ fixed effect	Yes	–	–
District fixed effect	–	Yes	–
Block fixed effect	–	–	Yes
Constant	−0.13 (0.87)	−2.09** (1.04)	−2.79* (1.59)
No. of farmers	470	470	328

Notes: The dependent variable takes value 1 when mustard farmers adopted hybrids for cultivation in 2015–2016, and 0 when farmers adopted improved or traditional varieties. Standard errors in parentheses. * p<.1, ** p<0.05, *** p<0.01. The dependent variable of interest in model 1 through 6 is the village adoption rate of hybrids for 2014–2015, and the model estimates the effect of village adoption rate of hybrids for 2014–2015 on the adoption of mustard hybrids in 2015–2016.

Columns 3 and 6 show that village adoption rates for 2014–2015 are insignificant in driving the adoption choice of farmers for 2015–2016. It suggests that previous year village adoption rate has no role in the adoption of hybrids for mustard farmers. This result is consistent with the literature that shows that in the early stages of diffusion there usually is limited role of previous year village adoption rates.[16]

Table 5 panel (a) presents the result based on specification 2. The dependent variable is the adoption choice of farmers for 2015–2016 (hybrid=1 and 0 otherwise). The independent variable of interest is the adoption choice of network members for 2015–2016, which takes value 1 when at least one network member adopts hybrids and 0 otherwise. This specification controls for individual characteristics as listed in Table 1. Columns 1, 2, and 3 present results from a separate regression, including AEZ, district, and block fixed effects, respectively. We find strong positive social network effects in all columns.

[16] See Matuschke and Qaim (2009), for more discussion.

Table 5: Effects of social networks on the adoption of hybrids among mustard farmers

	Dependent variable: Hybrid=1 and 0 Otherwise		
Panel A	Model (1)	Model (2)	Model (3)
Network member adopt hybrid	1.01*** (0.13)	0.51*** (0.15)	0.43** (0.19)
Individual characteristics of farmers	Yes	Yes	Yes
Village characteristics	No	No	No
Network member characteristics	No	No	No
AEZ fixed effect	Yes	–	–
District fixed effect	–	Yes	–
Block fixed effect	–	–	Yes
No. of villages	51	51	51
No. of farmers	470	470	328
Panel B	Model (4)	Model (5)	Model (6)
Network member adopt hybrid	0.929*** (0.143)	0.592*** (0.166)	0.409* (0.210)
Individual characteristics	Yes	Yes	Yes
Village characteristics	Yes	Yes	Yes
Network member characteristics	No	No	No
AEZ fixed effects	Yes	–	–
District fixed effect	–	Yes	–
Block fixed effect	–	–	Yes
Constant	1.013 (0.812)	−1.358 (1.013)	−3.043** (1.542)
Number of farmers	470	470	328
Panel C	Model (7)	Model (8)	Model (9)
Network member adopt hybrid	0.972*** (0.144)	0.668*** (0.173)	0.529** (0.224)
Individual characteristics	Yes	Yes	Yes
Village characteristics	Yes	Yes	Yes
Network member characteristics	Yes	Yes	Yes
AEZ fixed effects	Yes	–	–
District fixed effect	–	Yes	–
Block fixed effect	–	–	Yes
Constant	2.676** (1.323)	0.692 (1.607)	−1.746 (2.434)
Number of farmers	470	470	327
Panel D	Model (10)	Model (11)	Model (12)
Network member adopt hybrid	0.550*** (0.165)	0.480*** (0.184)	0.527** (0.224)
Village adoption rate of hybrids for 2014–2015	4.001*** (0.394)	3.696*** (0.567)	0.531 (1.706)
Individual characteristics	Yes	Yes	Yes
Village characteristics	Yes	Yes	Yes
Network member characteristics	Yes	Yes	Yes
AEZ fixed effects	Yes	–	–
District fixed effect	–	Yes	–
Block fixed effect	–	–	Yes
Constant	2.867 (1.867)	0.380 (1.749)	−1.641 (2.464)
No. of farmers	470	470	327

Notes: The dependent variable takes value 1 when farmers adopted hybrids for mustard cultivation, and 0 when they adopted improved or traditional varieties. Standard errors in parentheses. * p<.1, ** p<0.05, *** p<0.01. The dependent variable of interest is *network member adopt hybrid*, which takes value 1 if any member of the network adopted mustard hybrids and 0 otherwise. It captures the effect of social networks on the adoption of mustard hybrids. The variable *village adoption rate of hybrids for 2014–2015* is mustard farmers' adoption rate of hybrids for 2014–2015.

Panel (b) presents the results based on specification 3 that controls for village characteristics as well. The results are still positive and significant in all specifications. Panel (c) presents results based on specification 4 that include individual characteristics of network members, in addition to the individual characteristics of farmers, and the village characteristics. All the columns show a strong and positive impact of social network. Comparing the coefficients in panel b and c suggests that the inclusion of individual characteristics of network members does not make much difference in the magnitude of social network coefficients.

Panel (d) presents the result based on specification 5 that includes individual characteristics of farmers, village characteristics, and individual characteristics of network members, and the village adoption rate for 2014–2015. We find a positive and significant effect of social network on the adoption of hybrids. In other words, the result clearly shows the adoption choices of social network members are related to the adoption choice of farmers. Table 6 presents the result based on specification 5, and including village fixed effects instead of block fixed effects. The result appears to be the similar. It clearly suggests that the results are robust to the inclusion of village fixed effects.

Table 6: Effects of social networks on the adoption of hybrids (including village fixed effects)

	Hybrid=1 and 0 Otherwise	
	Model (1)	Model (2)
Network member adopt hybrid	0.481** (0.241)	0.481** (0.241)
Village adoption rate of hybrids for 2014–2015	–	3.641* (1.973)
Individual characteristics	Yes	Yes
Village characteristics	Yes	Yes
Network member characteristics	Yes	Yes
AEZ fixed effects	–	–
District fixed effect	–	–
Village fixed effect	Yes	Yes
Constant	4.432* (2.598)	1.501 (3.243)
No. of farmers	240	240

Notes: The dependent variable takes value 1 when farmers adopted hybrids for mustard cultivation, and 0 when they adopted improved or traditional varieties. Standard errors in parentheses. * p<.1, ** p<0.05, *** p<0.01. The dependent variable of interest is *network member adopt hybrid*, which takes value 1 if any member of the network adopted mustard hybrids and 0 otherwise. It captures the effect of social networks on the adoption of mustard hybrids. Models 1 and 2 run on the full sample with village fixed effects.

4.3. Heterogeneous Social Network Effects

Table 7 present the results based on specification 6. The variable of interest is the interaction between SC/ST and network members, which captures the difference in the social network effect between SC/ST farmers and non-SC/ST farmers. The result, which confirms our hypothesis, shows that SC/ST farmers have a greater social network effect as compared to non-SC/ST farmers. Recall that SC/ST has less access to the information than non-SC/ST farmers to begin with.This finding is consistent with Nourani (2016), their theoretical model that predicts that the network effect diminishes as the information or belief of farmers about the technology increases.

Table 7: Heterogeneity in network effects by caste

	Hybrid=1 and 0 Otherwise		
	Model (1)	Model (2)	Model (3)
SC/ST network member adopt hybrid*	−0.0554 (0.331)	0.278 (0.340)	0.791* (0.453)
Network member adopt hybrid	0.986*** (0.166)	0.591*** (0.199)	0.304 (0.269)
SC/ST	−0.675** (0.335)	−0.667* (0.394)	−0.973 (0.599)
Individual characteristics	Yes	Yes	Yes
Village characteristics	Yes	Yes	Yes
Network member characteristics	Yes	Yes	Yes
AEZ fixed effects	Yes	–	–
District fixed effect	–	Yes	–
Block fixed effect	–	–	Yes
Constant	2.668** (1.323)	0.708 (1.596)	−1.299 (2.507)
No. of farmers	476	471	327

Notes: The dependent variable takes value 1 when farmers adopted hybrid for mustard cultivation, and 0 when they adopted improved or traditional varieties. Standard errors in parentheses. * p<.1, ** p<0.05, *** p<0.01. The dependent variable of interest is *SC/ST* network member adopt hybrid*, which captures the difference in network effects for SC/ST households as compared to non-SC/ST households.

Table 8 present the results based on specification 7. The right-hand side variable of interest is the share of the same caste network members who adopt hybrids. This variable captures the influence of the social network (when the same caste network member adopts hybrids) on farmers' adoption choices. The result shows a strong social network effect of the same-caste adopters, and the magnitude of coefficient than in specification 4, which measures social network effects without distinguishing caste. Similar caste interactions appear to be key in influencing farmers' adoption decisions. This is akin to the finding in Bandiera and Rasul (2006) who show that there is greater correlation in adoption choices of individuals of same religion.

Table 8: Network effects when network members of the same caste adopt mustard hybrids

	Dependent variable: Hybrid=1 and 0 otherwise		
	Model (1)	Model (2)	Model (3)
Share of the same caste network member who adopt hybrid	1.854*** (0.278)	1.356*** (0.287)	1.101*** (0.389)
Individual characteristics	Yes	Yes	Yes
Village characteristics	Yes	Yes	Yes
Network member characteristics	Yes	Yes	Yes
AEZ fixed effects	Yes	–	–
District fixed effect	–	Yes	–
Block fixed effect	–	–	Yes
Constant	2.829* (1.574)	0.835 (1.757)	−1.922 (2.029)
No. of farmers	450	444	303

Notes: The dependent variable takes value 1 when farmers adopted hybrid for mustard cultivation, and 0 when they adopted improved or traditional varieties. Standard errors in parentheses. * p<.1, ** p<0.05, *** p<0.01. The dependent variable s*hare of the same caste network member who adopt hybrid* is defined as the percentage of farmers of the same caste who adopted hybrids in the individual networks. It captures the how interaction with the same caste affects the adoption of hybrids.

4.4. Simultaneity Concerns

To address simultaneity concerns, we run the final specification 5 on a restricted sample: we consider the right-hand side variable of interest as the adoption choice of network members for 2012–2013, and the dependent variable as the adoption choice of farmers in 2015–2016 (hybrid=1 and 0 otherwise), but drop those who adopted hybrids before 2012–2013, in order to test for the simultaneity. Table 9 shows that the adoption choice of farmer in the current year is related to the adoption choice of social networks of the previous year.[17] This result reflects that the concerns related to the two-way simultaneity is likely not a problem here.

Table 9: Effects of social network for those farmers who adopt hybrids post 2012–2013

	Hybrid = 1 and 0 Otherwise	
	Model (1)	Model (2)
Network member adopt hybrid	1.014*** (0.327)	0.439 (0.633)
Individual characteristics	Yes	Yes
Village characteristics	Yes	Yes
Network member characteristics	Yes	Yes
AEZ fixed effects	Yes	
District fixed effect		Yes
Village fixed effect		
Constant	6.258** (2.884)	-4.277 (9.714)
No. of farmers	192	164

Notes: Dependent variable takes value 1 when farmers adopt hybrid for the mustard cultivation, and zero when it adopts improved or traditional varieties. Standard errors in parentheses. * p<.1, ** p<0.05, *** p<0.01. The

[17] Because of sample size, we were able to run this regression with district-fixed effects but not block-fixed effects.

dependent variable of interest is n*etwork member adopt hybrid* that takes value 1 if any member of the network adopts mustard hybrids and 0 Otherwise. It captures the effect of social network on the adoption of mustard hybrids. Model 1 and 2 runs on the restricted sample such that we have consider only those farmers who have started adoption of mustard hybrid post 2012 and drop those farmers who have either started adoption of mustard hybrid pre-2012.

5 Conclusion and Policy Implications

The objective of this paper was to extend the research on the role of social networks in the adoption of agricultural technologies. It studies the role of social networks amid social differentiation in the adoption of mustard hybrids in India's Rajasthan. The paper first examined how mustard farmers' adoption decisions related to the adoption choices of their social network. Next, the paper investigates whether lower-caste (SC/ST) farmers relied more on their social networks for information as compared to higher-caste (non-SC/ST) farmers. Finally, it explores whether the network effects are more pronounced when the farmers interact within their caste or outside their caste.

The paper found a strong social network effect on the adoption of mustard hybrids in India's Rajasthan. In the context of Maharashtra, Matuschke and Qaim (2009) reveals a similar pattern of results for the adoption of wheat and pearl millet hybrids. Banerjee et al. (2013) also highlights the role of social networks for the microfinance diffusion. Note, however, that the role of social network in the adoption of agricultural technologies is more complicated as it also involves appropriate implementation of agricultural technology in addition to the awareness about technology itself. Conley and Udry (2010) elaborates that how farmer learns about the input adjustments from their neighbours in the cultivation of pineapple in Ghana. Therefore, the diffusion of modern agricultural technologies through the social network requires better understanding on the mechanisms through which it is influencing adoption choices. It is possible that the adoption of agricultural technologies by friends/neighbors/relatives may provide an opportunity to see its demonstration for the evaluation of technology in a better way. It is also possible that farmers have some behavioral constraints for the adoption of modern agricultural technologies and their social network may serve as the mean to better convince them about the technology. Further, it may be the case that they may serve as the primary source of information for the technology. More research will be needed to explore the role of social network particularly for the adoption of modern agricultural technologies, and further to explore the mechanism through which social network is making its impact in the adoption of technologies.

Our study further highlights that the social network effect was more pronounced for the lower castes (SC/STs) as compared to the higher castes (non-SC/ST). While there is limited literature in the context of heterogeneity in social network effects. Our finding is consistent with Nourani (2016) theoretical model that predicts that the network effect diminishes as the information of farmers about the technology increases.

This paper also establishes that the network effects were higher when farmers interacted within their caste rather than outside their caste, suggesting the network effect is stronger with homophily within the same caste. This is akin to Bandiera and Rasul (2006) that finds that network members of same religions have higher correlations in the adoption choices. Currarini et al. (2008) also reveals that the friendship formation in similar groups resulted in similar preferences. Our result provides evidence that the individual's identity matters for the social learning in the context of adoption of agricultural technologies. Therefore, the policy implication is to provide subsidies in terms of information or incentives to the early adopter farmers of every social group, for the speedy and wider diffusion of agricultural technologies within their networks. For example, if one farmer in a specific caste adopts a new technology, other farmers within that same caste may be more likely to adopt it as well.

Our evidence on farmers learning from their social network for the adoption of new technologies, may help policy makers to take advantage of these social spillovers for the information diffusion. The evidence on heterogeneous network effects may further help them to formulate targeted approaches for speedy and widespread diffusion. More research will be needed to identify the mechanisms of social network impact, and on the heterogeneous effects of social networks.

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