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Social networks, heterogeneity, and adoption of technologies: Evidence from India

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ABSTRACT

This study examines the role of caste-based affiliations in the smallholders' social network interactions for adoption choices. In particular, whether lower-caste, namely Scheduled Castes/Scheduled Tribes, farmers rely more on social networks for information than their counterparts. We further explore whether social network effects are more pronounced when farmers interact within their caste than otherwise. Finally, the study tests whether the effects (intra-caste and inter-caste) vary by caste—SC/ST versus non-SC/ST farmers. The study uses a survey of 478 mustard farmers in Rajasthan, India. Econometric concerns related to unobserved heterogeneity are addressed by employing specifications with village fixed effects and a series of robustness tests. Simultaneity concerns are addressed by analyzing the social network effects in a dynamic adoption framework. Results show that the adoption choices regarding hybrid mustard seeds are more pronounced for the lower-caste farmers than for their counterparts. Findings reveal that social network effects are significant in intra-caste but not in the case of inter-caste. Finally, the result shows that the likelihood of accepting advice in technology adoption is higher when SC/ST farmers interact with non-SC/ST network members than when non-SC/ST farmers interact with SC/ST network members.

1. Introduction

New technologies are vital to increasing agricultural productivity and farmers' income (Duflo et al., 2011; Asfaw et al., 2012; Shiferaw et al., 2014; Ogundari and Bolarinwa. 2018; Simtowe et al., 2019; Martey et al., 2020). Despite this, the adoption of new farming technologies remains consistently low in many developing countries (Bergoeing et al., 2010; Takahashi et al., 2020). Diffusion of new technologies remains a challenge because of farmers' limited access to credit, the risks involved in agriculture, lack of farmers' knowledge and proficiency, and difficulties with access to accurate and timely information dissemination (Katengeza et al., 2019; Simtowe et al., 2019; Martey et al., 2020).

Information diffusion through extension agents and other agricultural advisory services is well documented in developed and developing nations (see Anderson and Feder, 2007; Glendenning et al., 2010; Klerkx, 2020; Norton and Alwang, 2020). In the context of India, only one-tenth of farmers have access to information through formal sources of agricultural advisory and extension services. About 30 percent of farmers have access to information through informal sources such as social networks (Birthal et al., 2015). A study by Gulati et al. (2018) showed that India spends <1 percent (about 0.70 %) of its agricultural gross domestic product (AGDP) on agricultural research, education, extension, and training. About 0.54 % of the budget is spent on agricultural research and education, and 0.16 % is spent on extension and training programs. Therefore, identifying the channels of information spillovers is vital for the quicker and broader outreach of new agricultural technologies.

Literature on the role of social networks comprising friends, relatives, and neighbors in technology adoption demonstrates the need for disseminating new technology in developing countries (Munshi, 2004; Bandiera and Rasul, 2006; Conley and Udry, 2010; Maertens and Barrett, 2013; Negi et al., 2020; Banerjee et al., 2013; Beaman et al., 2021). In this strand of literature, a topic that is not well covered is heterogeneity in social network effects on technology adoption based on individual characteristics and the nature of their interactions. Social

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networks (socio-cultural and ethnic diversity) are essential in the development economics literature (Munshi and Rosenzweig, 2018). Specific exploration of the role of socio-ethnic diversity in the adoption and diffusion of agricultural technology has received comparatively less attention in the literature. A notable exception is Bandiera and Rasul (2006), whose study focused on religious diversity. The socio-ethnic diversity is critical in India with diverse religions, cultures, and languages but most notably with the deep-seated division based on caste and sub-castes. India is home to more than 1.3 billion people and has a long history of ethnic division based on caste classification (Deshpande, 2000). These divisions work both in the formation of social networks and social interactions. Ignoring differences based on social identity (caste system in our case) constitutes an essential omission in assessing the roles of social networks in affecting outcomes, including technology adoption in agriculture.

Caste-based heterogeneities are pretty pronounced in India, with lower castes like Scheduled Castes/Scheduled Tribes (SC/ST) having higher poverty rates, inadequate access to credit, and even public goods like infrastructure. Lower castes lack access to information from the formal source extensions and advisory services (Birthal et al., 2015; Krishna et al., 2019). It is thus paramount to explore the differential impact of social networks—formal sources of information and extension—on technology adoption. Information on new technology and proper usage are more inhibited for certain caste groups because social engagements are delineated across lines of caste and religion. A priori, we hypothesize that lower-caste farmers are more reliant on their social networks to access information on new agricultural technologies.

In the Indian context, mustard seeds are used to produce edible oil used in cooking, ground mustard is used as a condiment in vegetable and curry preparations, and split mustard seeds are used for pickling. Regarding consumption, mustard oil is one of the most-consumed edible oils in India (Chow et al., 2010). Mustard contributes one-third of the total oilseeds production. Green revolution displaced crops like pulses and oilseeds have been characterized by neglect in policy and being increasingly forced into marginal environments where technology adoption, though required more, is also comparatively difficult. Crowded out by Green revolution crops (paddy and wheat) and high population growth, India removed edible oil from the import prohibition list in 1992. India is now the largest edible oil importer in the world, with import penetration as high as 60 percent. In response, Indian crop scientists developed hybrid mustard seeds with higher adaptability to agronomic stresses. Since 1991–92 the Government of India (GoI) has made several efforts through the national mission agenda and food security goals to increase the production of oilseeds and oil palm. GoI plans to increase the production and productivity of oilseed crops like mustard by adopting new agricultural technologies. However, the adoption of hybrid mustard seed technology has been slow.

Therefore, the objectives of this study are threefold. First, to investigate farmers' adoption decisions relative to the adoption choices of their social networks. In particular, the study assesses the effect of the social networks of lower-caste farmers (Scheduled Castes/Scheduled Tribes [SC/ST]) on the adoption decision of hybrid mustard seeds. Second, the study tests whether the social network effects are higher when farmers interact within their caste (intra-caste) or between castes (inter-castes). Finally, the study tests whether the effects (intra-caste and inter-caste) vary by caste—SC/ST versus non-SC/ST farmers. The study uses data from a primary survey conducted in 2015–2016 along with recall-based information on the adoption choices of farmers and social network members in Rajasthan, India. The current study employs the econometric analysis of social learning by accounting for individual characteristics of the social network members. Lastly, the study performs robustness tests to address the endogeneity and simultaneity concerns related to adoption decisions.

This paper contributes to the literature in several ways. First, it adds to the literature on social networks' role in adopting agricultural technologies, especially for oilseeds, in India.[1] Pulses and oilseeds[2] lack the support of public extension services and private sector engagement in oilseeds. Hence both production and marketing risks are comparatively high in oilseeds like rapeseed-mustard, implying the greater importance of social learning in oilseeds. The analysis considers the adoption and dis-adoption of oilseed cultivars which is an essential part of experimentation based on social learning and is usually not covered in the analyses. Secondly, this paper extends the literature on heterogeneous effects[3] of social networks on technology adoption by assessing the social network effects disaggregated by households' caste affiliations.

The paper is organized as follows. The second section describes the caste system in India and the importance of social networks. The third section details the primary survey of farmers in Rajasthan, India. This section compares the demographic characteristics of farmers with their social network members and provides a prelude for exogenous effects. The fourth section discusses the empirical framework for identifying heterogeneous social network effects on the adoption of hybrid mustard seeds by oilseed farmers in India. The fifth section presents and discusses the results of the study. The final section summarizes the findings and concludes with some policy implications.

2. Caste and social networks

Caste is a social stratification based on occupation and carries through generations. Munshi (2019) notes that a caste possesses five distinct attributes. These attributes include specialized occupations, hierarchy, hereditary, and mutualness, designation. In fact, a person's caste dictates the social status of the person and the family (Debnath and Jain, 2015). The Indian caste system comprises four hierarchical classes the Brahmins, Kshatriyas, Vaisyas, and Shudras. Dalits considered 'untouchables' are not included in the above four classes. Thus, a person's caste is dictated by birth or marriage, and the classification follows a rigid system. Munshi (2019) and Deshpande (2011) conclude that historically the upper castes (also known as the general category) followed and maintained strict religious rituals, eating habits (e.g., vegetarianism), and social norms (marriage), afforded certain privileges and positions of power in Indian society. On the other hand, the lower castes (Shudras) and other marginalized castes have been denied status and privilege in Indian society. The above differences in the upper and lower castes bear no direct economic consequences (Munshi, 2019). However, in his study, Gupta (2000) notes that upper castes tend to exploit lower castes economically.

In the late 20th century, the Indian government legislated and passed an affirmative action program that provided relief to lower caste Indian folks. The disadvantaged castes included lower or marginalized castes (Munshi, 2019). The disadvantaged castes have Scheduled Castes (SCs), Scheduled Tribes (STs), and Other Backward Classes (OBCs). SCs are groups treated as 'untouchables' and among the lowest ranked jati. STs refer to tribal communities, while OBCs comprise the low (but not untouchables) to middle-ranking caste groups. The disadvantaged castes are socially and economically 'backward,' lack resources—land, educational attainment, income, and access to productive assets—and

[1] Matuschke and Qaim (2009) paper studied the case of pearl millet and wheat hybrids for Maharashtra.

[2] Oilseed crops have been neglected in policies that are cereal (wheat and rice) centric. In the minimum support process combined with procurement policies that absorb the marketing risk, oilseeds only have announced support prices and the government does not procure oilseed for the public distribution system.

[3] See for example, Jackson and Lopez-Pintado, 2011; Young, 2009; Magnan et al., 2015; Grzybowski, 2015; Kumar et al., 2021.

tend to be spatially segregated (Goel and Deshpande, 2016). One can argue that the societal structure based on the caste system has led to significant discrimination in business ownership, wealth creation, and choice of occupation (Desai and Dubey, 2012). In a study, Kumar and Venkatachalam (2019) found that farmers belonging to STs and SCs castes are 16–20 % less likely to apply for credit than farmers of higher castes.

The caste system also restricts people's movement by place of residence, exchange of resources, information, and social interactions Munshi and Rosenzweig (2016). For instance, Indian villages are often divided by people belonging to a particular caste category. Thus, in Indian villages, caste or religion-based social activities (like marriage, see Bidner and Eswaran, 2015; Debnath and Jain, 2015) and sharing of information are widespread. In addition, as noted by Banerjee and Munshi (2004) and Ligon (1998), people in the village engage in risk pooling and investments. As a result, in the villages, informal transactions (insurance, labor, credit, etc.) are intense within the caste. In fact, there is evidence of robust social ties within castes and weak social interactions between castes (Munshi, 2019).

Caste-based social networks play an essential role in pushing participation in government programs. For instance, Debnath and Jain (2015) describe caste as a 'naturally occurring social network,' a unit increase in peer families' utilization of health insurance within the caste, leading to a 20 % increase in first-time users of health insurance programs. Therefore, it is not surprising that in the farming sector, caste-based social networks may have an important impact on adopting agricultural technologies. For example, Banerjee et al. (2014) found that diffusion of knowledge (seeds in this case) was three times more when people discovered crop seeds from networks than choosing randomly. Caste networks thus play an important role in technology adoption, economic mobility, and information gathering.

3. Survey data

The International Food Policy Research Institute (IFPRI), New Delhi, conducted the primary survey in Rajasthan, India. The Indian Council of Agricultural Research (ICAR) supported the study. Rajasthan is India's largest state in terms of area, and farming is the primary source of livelihood. In Rajasthan, only 34 % of the net sown area is irrigated, and agricultural production is primarily rainfed. The study focuses on mustard farmers from Rajasthan, the state that occupies the largest share of India's mustard cropped area. The survey collected information for the 2015–2016 farming season, and data collection was done from November 2016-February 2017. The survey was carried out in 13 of Rajasthan's 29 districts.[4] The districts, spread across all agro-ecological zones (AEZs) of Rajasthan, were selected randomly from each zone.[5] The number of districts per zone was decided based on the total cropped area of major crops.[6] 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 families were selected randomly from each quintile.[7] In Rajasthan, the survey collects information for the following crops: wheat, mustard, pearl millet, and gram.

The total sample size for Rajasthan is 1496 farmers. Out of these 1496 farmers, 1004 farmers cultivate wheat, mustard (537 farmers), pearl millet (1046 farmers), and gram (140 farmers). The survey collects information from three modules: farmers, village, and census listing. The farmers' module collected information on the adoption of cultivars for 2015–2016. It also gathered information on the first year of the cultivar's adoption. Further, it collected information on cultivar dis-adoption before adopting the newer cultivar.

Detailed information on three other farmers with whom each of the surveyed farmers spent the most time. For mustard farmers, an additional module was administered to collate the information on farmers' social networks. While structuring the networks based on the intensity of connections, like Foster and Rosenzweig (2010) and Bandiera and Rasul (2006), these papers do not account for individual characteristics of social network members in their framework while identifying social learning from other farmers.[8] Studies including Matuschke and Qaim (2009) argued the importance of accounting for exogenous effects of members' individual characteristics in determining social network effects.

Towards this, the module included information on the farmers' characteristics and those of the social networks. The survey collected information on farmer and family attributes, such as the farmer's caste, religion, age, source of income, land holding, and educational attainment. The survey also asked farmers about the average length of time they spent together and whether they sought mutual advice on agricultural issues (for example, input usage and crop management strategies). We could collate the information on social networks for 478 of 537 mustard farmers. These 478 mustard farmers (including 1,434 network members) serve as the present paper's analysis sample. The village module collected information on village-level characteristics. These include information on the share of different social groups in the village, employment levels and composition, average land size, and distance of the village from major institutions (i.e., block headquarters, district headquarters, Krishi Vigyan Kendra [KVK] or Agricultural Science Center), agricultural extension services, banks, and input dealers. The listing module gathers information on demographic characteristics, cultivated crops, and mustard cultivars planted on the largest field for the 2015–2016 farming season.[9] To assess the issues of dynamic adoption, the module also queried farmers on the cultivar grown in 2012–2013. Information from the social network module finds that about 90 % of farmers have social networks from the village of the residence itself, creating a basis for combining farmers' and listing modules.

To collect recall-based information, we have provided detailed training to enumerators to enquire about this information. As a robustness exercise to assess the recall bias, we compare the information collected from the farmers' module (using the year in which the cultivar was first planted) and the listing module (direct question on adoption for 2012–13). We found that 96 percent of farmers reported the same response. Moreover, we argue that if there is no systematic pattern of recall biases across adopters versus non-adopters, it will not affect the results.

3.1. Socio-economic characteristics of mustard farmers

The overall sample suggests Rajasthan is a patriarchal society, and agriculture is a male-dominated activity—97 % of the household heads (HH) were male (Table 1). The oilseed producers, including rapeseed mustard, comprise poor households with low levels of human capital.

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

[5] 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.

[6] The selected crops in Rajasthan were wheat, mustard, and gram in the rabi season (winter), and pearl millet in the kharif (rainy) season.

[7] The listing module queried about the land owned and the total cultivable land.

[8] Social learning refers to learning from the network of family, friends, neighbors, and other farmers.

[9] Our survey captures information only for those cultivars that occupied maximum area for mustard cultivation. The share of farmers who cultivated more than one cultivar for mustard is only 3 percent.

Table 1
Variable description and summary statistics, sample farmers, Rajasthan, India.

Variable	Mean	Standard deviation	Minimum	Maximum
Household characteristics				
Female (yes = 1)	0.03	0.16	0	1
Education (year)	5.86	4.91	0	16
Age (year)	45	15	18	80
Schedule caste/tribe (yes = 1)	0.24	0.43	0	1
Religion (Hindu = 1)	0.90	0.30	0	1
Below poverty line (yes = 1)	0.17	0.38	0	1
Borrowed loan (yes)	0.50	0.50	0	1
Farm experience(year)	25	13	3	60
Primary income (agriculture = 1)	0.77	0.42	0	1
Household size (#)	6.62	3.06	2	22
Member of farmer's group (yes = 1)	0.03	0.16	0	1
Crop insured (yes = 1)	0.18	0.39	0	1
Soil health card (yes = 1)	0.13	0.34	0	1
Marginal farmer (yes = 1)	0.38	0.49	0	1
Small farmer (yes = 1)	0.27	0.45	0	1
Medium and large farmer (yes = 1)	0.35	0.48	0	1
Asset index (value)	0.58	2.47	−2.5	13.7
Plot characteristics				
Plot ownership (yes = 1)	0.92	0.28	0	1
Plot constraint (drought = 1)	0.47	0.50	0	1
Access to ground water (yes = 1)	0.73	0.45	0	1
Soil type (clay = 1)	0.10	0.30	0	1
Soil type (loam = 1)	0.14	0.34	0	1
Soil type (sandy = 1)	0.08	0.28	0	1
Soil type (sandy loam = 1)	0.68	0.47	0	1
Village characteristics				
Seed dealer (distance from village, kilometre)	8.25	7.02	0	30
Farm science centre (distance from village, kilometre)	12.73	8.75	0	40
Block head quarter (distance from village, kilometre)	14.73	8.63	3	40
Outcome variable				
Adoption of mustard hybrids (yes = 1)	0.59	0.49	0	1
No. of farmers	478			

Source: ICAR-IFPRI survey, 2017.
Notes: Asset index is constructed using principal component analysis by considering a wide range of assets owned (television, refrigerator, tractor) by farmers.

Household heads averaged merely-six years of schooling. This is important since several studies find a positive association between education and technology adoption (Bucciarelli et al., 2010; among others). The average age of household heads was 45. Age can be used as a proxy for experience, and it is likely to be positively associated with adopting hybrid mustard seed technology. On average, sampled mustard farmers have 25 years of experience in cultivation activities. Nakano et al. (2018) showed that farming experience is positively associated with technology adoption. Concerning farm size, 65 % of the mustard farmers are marginal or small farmers.[10]

Family size averaged 7, indicating a comparatively large endowment of family labor. The number of family members is potentially crucial for labor-intensive hybrids. Distribution by social group shows that about 24 % of farmers belong to the lowest caste (i.e., SC/ST class). Regarding religion, 90 % of the farmers belong to the Hindu community. Regarding plot characteristics, some 47 % of farmers report drought as the critical constraint in cultivating the plot. Rabi crops in Rajasthan are grown in residual moisture after the monsoon and use supplemental irrigation. Some 73 % of farmers report having access to groundwater for cultivating these plots. Some 68 % of farmers report their soil type as sandy loam, followed by loam (14 %), clay (10 %), and sandy (8 %).

About 17 % of farmers possess Below Poverty Line (BPL) and *Antyodaya* cards—a government food subsidy for the poorest. A priori, more impoverished and lower-caste farmers are less likely to adopt hybrids owing to disadvantages in accessing credit, information, and extension services. Regarding access to credit, 50 % of the sampled mustard farmers took out loans in 2015–16. About 77 % of farmers in the sample reported farming as their primary source of livelihood. Importantly, only 3 % of farmers are associated with the farmers' group or organizations, which could be an important source of information and extension services. Mwaura (2014) shows that participation in a farmers' group positively impacted technology adoption. Some 18 % of the sampled mustard farmers insured their crops in 2015–16. The government of India introduced a soil health card scheme to help analyze the farmers' soil.[11] The result shows that 13 % of farmers have access to soil health cards. As a proxy for farmers' wealth, we constructed an asset index. The asset index is created using principal component analysis by considering a wide range of farmers' assets (televisions, refrigerators, tractors). Feder et al. (1985) show that wealthier farmers are more likely to bear the risks of adopting new technology. Regarding plot characteristics, 92 % of farmers owned their plot, and the remaining 8 % leased-in plots to cultivate mustard.

Table 1 also reports the village's connectivity to block headquarters, the nearest farm science center, and seed dealers. An average village is about 8 km (km) from the seed dealers, 13 km from the farm science center (or KVK), and 15 km from block headquarters. The adoption profile of mustard farmers suggests that about 59 % have adopted hybrid mustard seeds, with the remaining 41 % as non-adopters at a point in time.[12] Appendix Fig. A1 presents the major sources of information used for adopting hybrid mustard seeds. Results reveal that 65 % of farmers reported social networks as their principal source of information for agricultural practices, followed by progressive farmers (59 %), input dealers (45 %), mobile/radio/television/newspaper (21 %), and agricultural extension officers (16 %).[13] These figures indicate multiple sources of information for farmers though the importance of different sources of information varies by the farmer. Yet, social networks remain an overwhelmingly important source for most farmers.

3.2. Social network members

Our survey queried farmers about three other farmers with whom they interacted the most. For 478 mustard farmers, the survey thus collated information for 1,434 network members. Farmers were asked about their relationship with the other farmers, demographic characteristics, and adoption patterns. About 90 % of significant social network members comprise friends (64 %) and relatives (26 %), followed by neighbor farmers (8 %), and 2 % others (*panchayat* [village council] workers or local leaders). Table 2 presents the characteristics of social network members. To assess the possible exogenous effects, we compared the characteristics of the social network members with those of the farmers in question. This comparison, among other things, provided information on whether the farmers have an intra-caste or an inter-caste network and whether the network comprises farmers with similar age, education, and landholding profile.

Table 3 presents summary statistics comparing the characteristics of sample farmers versus network farmers. Panel A, B, C, and D of Table 3

[10] Marginal farmers own <1 ha of land. Small farmers own between 1 and 2 ha of land.

[11] The scheme was introduced in February 2015.

[12] Out of non-adopters, 39% adopt open-pollinated varieties (OPVs), and 2% adopted traditional varieties.

[13] Progressive farmers are defined as those farmers who adopt modern agricultural technologies and are the source of information for other farmers. Social networks include the networks of friends and relatives and neighbors.

Table 2
Variable description and summary statistics, network members, Rajasthan, India.

Variable	Mean	Standard deviation	Minimum	Maximum
Household characteristics				
Male (yes = 1)	0.98	0.11	0	1
Age (year)	47	9	1	73
Age square (year)	2253	888	1	5378
Education (year)	6.09	3.23	0	15
Schedule caste/tribe (yes = 1)	0.22	0.39	0	1
Primary income (agriculture = 1)	0.76	0.37	0	1
Religion (Hindu = 1)	0.90	0.28	0	1
Land owned (hectare)	2.28	3.25	0	37.76
Outcome variable				
Adoption of mustard hybrids (yes = 1)	0.22	0.41	0	1
No. of Network members	1434			

Source: ICAR-IFPRI survey, 2017.
Note: The survey collects information on 3 social network members from each surveyed farmers.

show the results of the caste, education, age, and land size. There is a definite sorting by caste in the rural networks. For upper-caste farmers, 74 % of network members are from the same upper caste, 22 % reported from the other backward castes (OBC), and 3 % from the lower caste farmers. For OBC, 95 % of network members are from the same OBC, and the remaining 5 % are from the other caste groups. For Scheduled Castes (SC), 81 % of network members are from the same scheduled caste, followed by OBC (14 %) and upper castes (4 %), and 2 % of Scheduled Tribes (ST). For STs, 85 % of network members are from the same ST and followed by SC (11 %), OBC (3 %), and upper caste (1 %). Overall, the dominance of intra-caste networks holds uniformly for all caste groups but seems more pronounced as one goes down the caste ladder (not monotonically).

Table 3 Panel B presents the result regarding education. For illiterate, 39 % of network members are from the same illiterate category, followed by secondary and above (22 %), primary (20 %), and middle (18 %). For primary, 29 % of network members are from the secondary and above, followed by primary (27 %), illiterate (26 %), and middle (19 %). For middle, 33 % of network members are from the secondary and above, followed by middle (26 %), primary (25 %), and illiterate (16 %). For secondary and above, 44 % of network members are from the same secondary and above, followed by middle (21 %), illiterate (19 %), and primary (16 %). Table 3 Panel C presents the result of the age profile. For the 15–19 age group, the highest number of network members (33 %) is between 29 and 44. For the 29–44 age group, the highest number of network members (42 %) are from 29 to 44. For the 44–59 age group, the highest number of network members (42 %) are from 44 to 59. For age 59 and above, the highest number of network members (37 %) are from the 44–59 age group.

Table 3 Panel D presents the distribution of network members by farmer classification in terms of land ownership, where land ownership is classified into four categories—marginal farms (<1 ha), small farms (1–2 ha), medium farms (2–4 ha), and large farms (greater than 4 ha). Marginal farmers primarily interacted within the same category of network farmers (67 %). Small farmers mainly interacted with the network members of the marginal farmers' category (40 %). Medium farmers primarily interacted with the network members of the small farmers' category (37 %). Large farmers mainly interacted with the same

Table 3
Comparing farmers profile with network members profile, Rajasthan, India.

Caste profile	Farmers profile									
	Upper caste (n = 90)		Other backward class (n = 273)		Scheduled castes (n = 88)		Scheduled tribes (27)		All farmers (n = 478)	
	Mean	sd	Mean	sd	Mean	sd	Mean	sd	Mean	sd
Upper caste (share)	0.74	0.44	0.04	0.19	0.04	0.19	0.01	0.12	0.17	0.38
Other backward class (share)	0.22	0.41	0.95	0.23	0.14	0.34	0.03	0.17	0.61	0.49
Scheduled caste (share)	0.02	0.15	0.01	0.09	0.81	0.39	0.11	0.32	0.17	0.37
Scheduled tribe (share)	0.01	0.12	0.01	0.09	0.02	0.12	0.85	0.36	0.05	0.22
All network farmers (#)	270		819		264		81		1434	
Education profile	**Illiterate (n = 154)**		**Primary (n = 88)**		**Middle (n = 73)**		**Secondary & above (n = 163)**		**All farmers (n = 478)**	
	Mean	**sd**	**Mean**	**sd**	**Mean**	**sd**	**Mean**	**sd**	**Mean**	**sd**
Illiterate (share)	0.39	0.49	0.26	0.44	0.16	0.37	0.19	0.39	0.26	0.44
Primary (share)	0.20	0.40	0.27	0.44	0.25	0.43	0.16	0.37	0.21	0.41
Middle (share)	0.18	0.38	0.19	0.39	0.26	0.44	0.21	0.41	0.21	0.40
Secondary & above (share)	0.22	0.42	0.29	0.45	0.33	0.47	0.44	0.50	0.32	0.47
All network farmers (#)	462		264		219		489		1434	
Age profile	**Age 15–29 (n = 78)**		**Age 29–44 (n = 150)**		**Age 44–59 (n = 132)**		**Age 59 and above (n = 118)**		**All farmers (n = 478)**	
	Mean	**sd**	**Mean**	**sd**	**Mean**	**sd**	**Mean**	**sd**	**Mean**	**sd**
Age 15–29 (share)	0.18	0.38	0.06	0.23	0.07	0.25	0.04	0.20	0.07	0.26
Age 29–44 (share)	0.33	0.47	0.42	0.49	0.30	0.46	0.29	0.45	0.34	0.47
Age 44–59 (share)	0.33	0.47	0.36	0.48	0.42	0.49	0.37	0.48	0.37	0.48
Age 59 and above (share)	0.16	0.37	0.17	0.37	0.21	0.41	0.30	0.46	0.21	0.41
All network farmers (#)	234		450		396		354		1434	
Land profile	**Marginal farmer (n = 145)**		**Small farmer (n = 152)**		**Medium farmer (n = 126)**		**Large farmer (n = 55)**		**All farmers (n = 478)**	
	Mean	**sd**	**Mean**	**sd**	**Mean**	**sd**	**Mean**	**sd**	**Mean**	**sd**
Marginal farmer (share)	0.67	0.47	0.40	0.49	0.21	0.41	0.15	0.35	0.40	0.49
Small farmer (share)	0.19	0.39	0.33	0.47	0.37	0.48	0.25	0.43	0.29	0.45
Medium farmer (share)	0.07	0.26	0.17	0.37	0.26	0.44	0.24	0.43	0.17	0.38
Large farmer (share)	0.06	0.24	0.10	0.30	0.17	0.37	0.37	0.48	0.14	0.34
All network farmers (#)	435		456		378		165		1434	

Source: ICAR-IFPRI survey, 2017.

large farmers' category (37 %). By and large, interactions among marginal and large farmers are similar, a function of factors such as caste. At the same time, small and medium category farmers mainly interact with the marginal and small network members category, respectively.

Fig. 1 presents the adoption of hybrids based on three different indicators. The first indicator, "*whether farmers learn about agricultural technology from network members*," shows that 63 % of the farmers adopted hybrid mustard by learning from their social network. The second indicator, "*whether farmers accept advice from network members*," indicates that 64 % of farmers adopted hybrids based on farmers' advice in their social networks. The third and final indicator, "*whether network members adopt hybrids,*" reveals that 80 % of farmers adopt hybrids because their social network members adopted hybrid mustard. If correctly identified, this would estimate the true endogenous effect of a social network. On average, only 43 % of farmers adopt hybrids even when their social network members did not adopt hybrid mustard.

4. Empirical framework

Conceptually, a farmer's initial decision to adopt new technology (hybrid mustard seeds, in this context) may depend on learning about the technology from several sources. For example, farmers may learn about the new technology directly from formal sources of information such as extension agents, participating in capacity-building programs, or demonstration trials of frontier technologies. They can also learn from informal sources of information, including social networks of friends, neighbors, relatives, progressive farmers, and farmers groups.[14]

Learning the technology from social networks allows a farmer to see the technology demonstrated and evaluate it more effectively and with credibility. When farmers have behavioral constraints in adopting modern agricultural technologies, their trusted social network may serve as the means to convince them about the new and better technology. Apart from demonstration, networks often serve as the primary source of information for adopting technology. In assessing the contribution of social networks in determining individual choices may be prone to the problem of simultaneity and correlated unobservables factors—identification issues. We estimate the following specification for identifying the effects of social networks on the adoption decision of hybrid mustard seeds.

$$Y_{ivb} = \beta X_{ivb} + \gamma N_{nvb(i)} + \delta X_{nvb(i)} + \Phi Z_{vb} + \eta \overline{a_{vb,2014-15}} + \lambda G_{vb} + \varepsilon_{ivb} \tag{1}$$

where i is farmer, v is the village, b is a block, Y_i is the adoption of hybrid mustard seeds by farmer $i$and takes the value of 1 if the farmer adopts hybrid mustard seeds in 2015–16 and 0 otherwise. X_{ivb}*istheset* of covariates related to farmers (see Table 1 for the list of covariates). $N_{nvb(i)}$is the adoption decision of a social network member, n corresponds to individual farmer i in 2015–2016, and takes value 1 if at least one social network member adopted hybrid mustard seeds and 0 otherwise.[15] $X_{nvb(i)}$ is the characteristics of social network member n, corresponding to individual farmer i, which also captures exogenous effects (see Table 2 for the list of covariates). Z_{vb} represents the village-level characteristics such as distance from input dealers, block headquarters, and agriculture institutions. $\overline{a_{vb,2014-15}}$ captures the average adoption rate at the village level in the previous year. G represents the block fixed effects. ε is an error term assumed to be uncorrelated with other covariates.

Following Manski (1993), γ in Equation (1) can be interpreted as endogenous social effects under certain conditions. γ estimates the impact of farmers' social networks on the farmer's adoption decision if the effect can be separated from exogenous and correlated effects. δ is the coefficient that captures the direct impact of the characteristics of social networks on the farmer's adoption decision. The similarity in characteristics constitutes an independent reason for the relationship between network choices and the subject in question beyond pure endogenous effect. Towards assessing endogenous effects, it is assumed that farmers do not know the optimal level of other complementary inputs required in growing hybrid mustard seeds.[16] However, farmers can update their beliefs on the requirements for hybrid mustard seeds based on the experiences of their social network (see Bandiera and Rasul, 2006 for details). Therefore, the mechanism of endogenous social effect is through the members of the social network who have adopted hybrid mustard seeds and who, in turn, increased the expected marginal benefits for the farmer from adopting hybrid mustard seeds.

We adopted the sociometric method to measure social network links to identify the individual-specific social network effect. Recall that to define social groups exclusively, and the survey queried farmers for a maximum of three people with whom they spent maximum time. Thus, we use the intensity of interaction-based measures suggested by Rogers (2003). Data on the characteristics of network members help us improve over several studies conducted in this field.[17] Individual attributes also may explain the process of selection into social networks. Therefore, including the personal characteristics of members of the social network is essential in addressing the endogenous selection of individual farmers. This is a well-known problem of sorting into networks. Tables 1 and 2 show a complete list of farmers' and network members' characteristics. We include block fixed effects to control for unobserved characteristics at the block level to account for correlated effects. Correlation in adoption choice among farmers may be related to the availability of input markets, access to agricultural institutions, and access to information related to farming. Ideally, one would include village-fixed effects to mitigate the above problem, but such regression could significantly reduce the sample of mustard farmers per village. Therefore, in addition to the block fixed effects, we include detailed village characteristics (such as distance from input dealer, block headquarters, and agriculture institutions) to account for correlated effects.

The dynamic choices with externalities show the role of the public-good element in adopting new technology (Besley and Case, 1993), and an adopter cares about how many other farmers adopt the same technology. This may be related to the availability of inputs required in the market for the technology to work. Therefore, we include the village adoption rate for 2014–2015 in Specification 1 to account for such externalities. An important caveat is that the strategy presented in the section above, at its best, may not be subject to full causal interpretation, for which it merits caution. Next, we test whether SC/ST farmers have stronger social network effects than non-SC/ST farmers using the specification below:

$$Y_{ivb} = \beta X_{ivb} + \gamma N_{nvb(i)} + \Phi\left(SCST_{ivb} {}^{*} N_{nvb(i)}\right) + \delta X_{nvb(i)} + \Phi Z_{vb} + \lambda G_{vb} + \varepsilon_{ivb} \tag{2}$$

where *SCST* takes a value of 1 if a farmer belongs to an SC/ST caste category. The interaction term in the above equation captures the difference in social network effects for SC/ST farmers compared to non-SC/ST farmers. Heterogeneity might not affect payoffs directly but can reduce social learning. For example, Rogers (1995) characterizes technology diffusion as the process by which an innovation is communicated through specific channels over time among the members of a social system.

[14] Progressive farmers are defined as those farmers who are in general adopts new agricultural agricultural technologies earlier than the other farmers.

[15] We also perform analysis using the total number of hybrid adopters in the network. Results are available from the authors upon request.

[16] Hybrid mustards have different traits than open pollinated varieties (OPVs), and may have a different requirement in terms of machine, irrigation, labour, fertilizer, and pesticides, farmers'.

[17] Papers like 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 to the extent assessed in the paper.

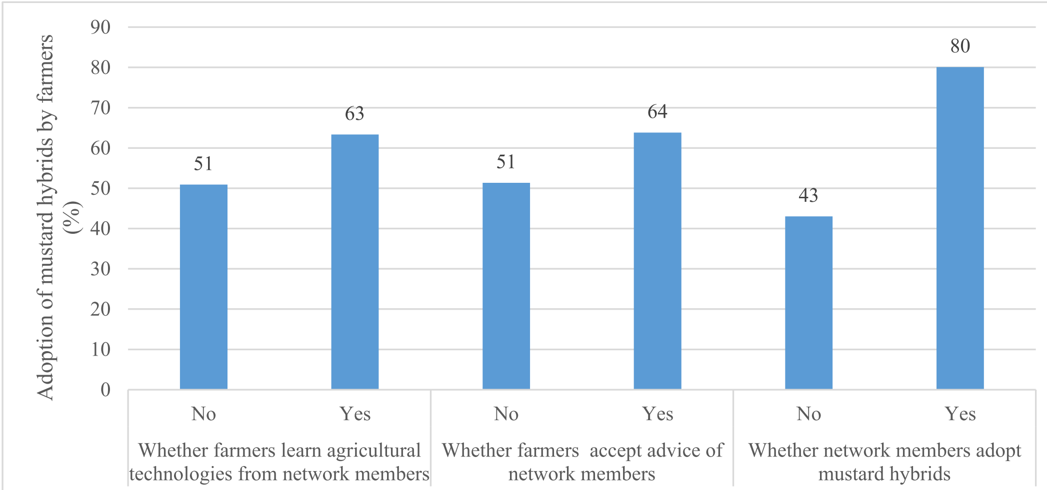

Fig. 1. Adoption of hybrid mustard by farmers (%) and learning from network members, Source: ICAR-IFPRI survey, 2017.

4.1. Inter-caste and intra-caste network effects

The pioneering work by Rogers and Bhowmik (1970) explains that social systems could be characterized as inter-caste or intra-caste. In other words, inter-caste systems encourage change from system norms, and intra-caste systems tend towards system norms. Most people interact with folks from similar backgrounds (McPherson and Smith-Lovin, 1987; Jackson and López-Pintado, 2013). In the Indian context, a significant body of literature (Deshpande and Sharma, 2013; Deshpande, 2011) shows strong ties within social groups. To test whether social network effects for technology adoption are more pronounced when farmers interact intra-caste than when they interact inter-caste. We implement the following specification in equation (3):

$$Y_{ivb} = \beta X_{ivb} + \gamma NA\_SAMECASTE_{nvb(i)} + \delta X_{nvb(i)} + \Phi Z_{vb} + \lambda G_{vb} + \varepsilon_{ivb} \quad (3)$$

All notations in the above equation are as defined above. *NA_SAMECASTE* is the number of intra-caste social network members who adopted hybrid mustard seeds. The variable *NA_SAMECASTE* captures the social network effect when farmers interact intra-caste. To examine the social network effects when farmers interact inter-caste, we implement the following specification:

$$Y_{ivb} = \beta X_{ivb} + \gamma NA\_DIFFCASTE_{nvb(i)} + \delta X_{nvb(i)} + \Phi Z_{vb} + \lambda G_{vb} + \varepsilon_{ivb} \quad (4)$$

where *NA_DIFFCASTE* is the number of inter-caste social network members who adopted hybrid mustard seeds. The variable *NA_DIFFCASTE* captures the social network effect when members interact with members from a different caste.

4.2. Intra-caste, inter-caste, and heterogeneity in network effects

In the social network literature, it is argued that farmers with more information are less sensitive than farmers with less information about the adoption choices of their social networks (Bandiera and Rasul, 2006). Therefore, even in the case of interaction within the caste, higher-caste farmers (who are perceived to be better informed) may react differently than lower-caste farmers. To assess the differential impact of networks/interactions by caste, we implement the following specification:

$$Y_{ivb} = \beta X_{ivb} + \gamma NA\_SAMECASTE_{nvb(i)} + \Phi(SCST_{ivb} {}^{*} NA\_SAMECASTE_{nvb(i)}) + \delta X_{nvb(i)} + \Phi Z_{vb} + \lambda G_{vb} + \varepsilon_{ivb} \quad (5)$$

All notations in the above equation are as defined above. The interaction term *SCST*NA_SAMECASTE* captures the differential effect of intra-caste networks on SC/ST farmers compared to non-SC/ST farmers. Farmers distinguished by caste may have biased interaction patterns (see Jackson and López-pintado, 2013). For example, when higher-caste farmers interact outside their caste, the effects on them could be very different than those for lower-caste network members (i.e., heterogeneous effects). To examine such asymmetric or differential effects, we implement the following specification:

$$Y_{ivb} = \beta X_{ivb} + \gamma NA\_DIFFCASTE_{nvb(i)} + \Phi(SCST_{ivb} {}^{*} NA\_DIFFCASTE_{nvb(i)}) + \delta X_{nvb(i)} + \Phi Z_{vb} + \lambda G_{vb} + \varepsilon_{ivb} \quad (6)$$

In the above equation, the interaction term *SCST*NA_DIFFCASTE* captures the differential effect based on caste affiliation.

4.3. Econometric concerns

In the adoption decision identifying the effects of social networks stemming from unobserved heterogeneity and simultaneity is problematic. This is especially true when the social networks are considered based on geographical proximity (for example, village). Therefore, this study defines social networks based on the actual group interaction with farmers and where farmers spend maximum time. We included the block fixed effects and village-level characteristics (such as proximity to input markets and district-level extension) to rule out the group effect. We also estimate equation (1) with village effects to check the robustness of our findings. Individual heterogeneity may arise from two primary sources. First, farmers may adopt hybrid mustard seeds due to unobserved individual characteristics in the empirical model that influence the adoption decision (such as the ability to process information). For this reason, we included farmer attributes, such as education and age.

We also estimate three variants of Equation (1), excluding adopters who reported the principal sources of information (agricultural extension, input dealer, mobile/media) other than the social networks. The first variant excludes adopters who reported agricultural extension services as one of their principal sources of information. The second variant excludes adopters who reported seed dealers as their source of information. Finally, the third variant excludes adopters who reported mobile phone/radio/television/newspaper as their source of information. Here, the idea is to see whether the network effects still hold after dropping such adopters. Simultaneity is another challenge in estimating the social network effects on technology adoption (Manski, 1993; Manski, 2000; Neill and Lee, 2001). Social network members' adoption choices may influence the individual farmer's decision to adopt hybrid mustard seeds, but the converse could also be true. The extent of the simultaneity between the adoption choices of farmers and members of the social network can be tested. The uniquely collected past adoption data for network members for 2012–2013 allows us to test the extent of the problem by dropping farmers who adopted mustard hybrids before 2012–2013 from the sample and considering the adoption choice of network members for 2012–2013 to estimate the social network effects. In other words, we keep only farmers who adopted hybrid mustard seeds in 2012–2013 or later years and test how farmers' adoption decisions are related to the adoption decisions of their social network members in 2012–2013.

5. Results and discussion

Table 4 presents the marginal effects of adopting hybrid mustard seeds by sampled Indian farmers.[18] Model 1 (Column 2, Table 4) shows the result with the agro-ecological zone (AEZ) fixed effects, and Model 2 (Column 3, Table 4) shows the results with district-fixed effects.[19] Model 2 indicates that SC/ST farmers are less likely to adopt hybrid mustard seeds. Apart from social network reasons, other factors such as the costs of hybrid mustard seeds could be a deterrent for economically strapped SC/ST farmers. Also, SC/ST farmers have reduced access to extension information, credit, and insurance compared to farmers belonging to general castes. SC/ST farmers lack knowledge of the new hybrid mustard seed technology and may be less willing to take risks (Thorat and Lee, 2005; Krishna et al., 2019). The result shows that farmers with loam and sandy loam soils are less likely to adopt mustard hybrids than farmers with clay soil (Feder and Umali, 1993). Distance from the village where farmers reside to the nearest seed dealer and block headquarters are associated with the adoption of mustard hybrids. The farmers who live closer to the block headquarters are more likely to adopt mustard hybrids. In contrast, the farmers who reside nearest to seed dealers are less likely to adopt mustard hybrids. It is possible that mustard hybrid seeds are available only at the block-level seed markets but not at the seed dealers locally (Kumar, 2016). Farmers with limited access to input markets at the block level will purchase seeds from the nearest seed dealers and, in turn, are less likely to adopt mustard hybrids. Regarding information channels for agricultural practices, the result shows (Model 2, Table 4) that social networks and mobile/radio/television/newspaper are positively associated with the adoption of mustard hybrids.

5.1. Effect of social networks on adoption of hybrid technology

Table 5, Model 3 presents the marginal effects of social networks on the adoption of mustard hybrids based on specification 1. Columns 1 and 2 present the results, including AEZ and district fixed effects. We interpret results from Column 3, which includes block fixed effects. The result shows that the village adoption rates (η) for hybrid mustard seeds for the previous year (2014–15) are insignificant in driving farmers' adoption decisions in 2015–16. Our finding is consistent with studies in the literature (Dadi et al., 2004; Burton et al., 2003; Beyene and Kassie, 2015; Varshney et al., 2019) that show that in the early stages of technology diffusion, the lagged effect of technology adoption at the village level on the individual adoption of technology is negligible or absent. The coefficient of interest, network member (γ), (row 1 of Table 5) shows that if a network member adopts mustard hybrid seeds, the likelihood of a farmer adopting mustard hybrid seed increases by nearly 11 percentage points. Our finding is consistent with Matuschke and Qaim (2009). They found the adoption of wheat and pearl millet hybrids in India was affected by network members' adoption of wheat and pearl millet hybrids.

To assess the robustness of the above results, Appendix Table A1 presents the outcome based on equation (1), including village fixed effects. Indeed, results show that the findings in Table 5 still hold. The network effect on adopting mustard hybrids is about 12 percentage points. Appendix Table A2 presents the result from three variants of equation (1). The second, third, and fourth columns show the results excluding adopters who used agricultural extension services, seed

Table 4
Marginal effects from the probit analysis of adoption of hybrid mustard, Rajasthan, India.

Variable	Dependent variable: Hybrid = 1;0 otherwise Model 1	Model 2
Female (yes = 1)	−0.026 (0.100)	−0.079 (0.070)
Education (year)	0.002 (0.004)	−0.001 (0.004)
Age (year)	−0.002 (0.008)	0.005 (0.007)
Age square (year)	−0.000 (0.000)	−0.000 (0.000)
Schedule caste/tribe (yes = 1)	−0.132** (0.043)	−0.100** (0.038)
Religion (Hindu = 1)	−0.068 (0.067)	−0.196** (0.071)
Below poverty line (yes = 1)	−0.094* (0.049)	−0.045 (0.039)
Borrowed loan (yes)	0.015 (0.039)	0.028 (0.035)
Farm experience(year)	0.005** (0.002)	0.001 (0.002)
Primary income (agriculture = 1)	−0.052 (0.048)	−0.026 (0.042)
Household size (#)	−0.002 (0.006)	−0.004 (0.005)
Member of farmer's group (yes = 1)	−0.283** (0.128)	−0.202* (0.105)
Crop insured (yes = 1)	−0.066 (0.058)	−0.093* (0.051)
Soil health card (yes = 1)	−0.113* (0.059)	−0.049 (0.051)
Farmer classification (base category = marginal)		
Small farmer (yes = 1)	−0.013 (0.046)	−0.001 (0.041)
Medium and large farmer (yes = 1)	−0.087 (0.055)	−0.062 (0.051)
Asset index (value)	−0.016* (0.009)	−0.005 (0.008)
Plot ownership (yes = 1)	0.087 (0.063)	0.001 (0.060)
Plot constraint (drought = 1)	0.073* (0.041)	−0.025 (0.037)
Access to ground water (yes = 1)	0.253*** (0.041)	−0.033 (0.052)
Soil type (base category = clay)		
Soil type (loam = 1)	−0.285*** (0.072)	−0.229*** (0.063)
Soil type (sandy = 1)	−0.087 (0.076)	−0.059 (0.069)
Soil type (sandy loam = 1)	−0.309*** (0.060)	−0.209*** (0.057)
Seed dealer (distance from village in kilometer)	0.007** (0.003)	0.015*** (0.004)
Farm science centre (distance from village, kilometer)	−0.012** (0.004)	−0.003 (0.004)
Block head quarter (distance from village kilometer)	−0.004 (0.003)	−0.005** (0.003)
Source of information (social network = 1)	0.116** (0.043)	0.093** (0.043)
Source of information (progressive farmer = 1)	−0.012 (0.041)	−0.044 (0.038)
Source of information (input dealer = 1)	0.078*(0.040)	0.062* (0.037)
Source of information (extension services = 1)	0.060 (0.072)	0.089 (0.062)
Source of information (mobile/radio/ television/newspaper = 1)	0.115** (0.047)	0.102** (0.043)
AEZ Fixed Effects	Yes	–
District Fixed Effects	–	Yes
Pseudo R Square	0.33	0.47
No. of Farmers	478	473

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 1 and 2 results from a separate regression. Robust standard errors in parentheses. **$p < 0.05$, ***$p < 0.01$. Marginal farmers are defined as those farmers with land ownership <1 ha. Small farmers owns between 1 and 2 ha of land. Medium and large farmers own greater than 2 ha of land.

[18] The analysis includes social, economic, and agricultural profile of farmers listed in Table 1, and its major source of information for the agricultural practices presents in Appendix Fig. A1.

[19] We interpret the results from Model 2. Our sample comes from the three agro-ecological zones of Rajasthan, namely, arid, rain-fed, and irrigated.

Table 5
Marginal effects of social networks on the adoption of mustard hybrids.

	Dependent variable (Hybrid = 1; 0 otherwise)		
	Model 1	Model 2	Model 3
Network member adopt hybrid	0.084** (0.034)	0.065** (0.032)	0.107** (0.042)
Village adoption rate, hybrids 2014–2015	0.612*** (0.051)	0.568*** (0.068)	0.300 (0.321)
Household and plot characteristics of farmers	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
Pseudo R Square	0.526	0.572	0.557
No. of farmers	473	468	325

Notes: The dependent variable takes value 1 when farmers adopted hybrids for mustard cultivation, and 0 when they adopted improved or traditional varieties, for the period 2015–16. The variable of interest is *network member adopt hybrid*, which takes value 1 if any member of the network adopted mustard hybrids and 0 otherwise. The variable *village adoption rate of hybrids for 2014–2015* is mustard farmers' adoption rate of hybrids for a village for 2014–2015. Robust standard errors in parentheses. **$p < 0.05$, ***$p < 0.01$.

dealers, and mobile/radio/television/newspaper, respectively, as their source of the information channel. Columns 2 and 3 show a strong network effect at the 5 % or higher significance level. Column 3 shows a positive and significant network effect at the 10 % level of significance. Finally, Appendix Table A3 presents the results from the dynamic adoption framework. Specifically, we test how farmers' adoption decision in 2012–13 or later relates to network members' adoption decision in 2012–2013.[20] The coefficients in Model 1 and Model 2 are statistically significant at the 5 percent level of significance. Thus, findings are robust and likely mitigate concerns related to the possibility of two-way simultaneity. Overall, we conclude that the social network effects are robust, addressing unobserved heterogeneity and simultaneity concerns.

5.2. Heterogeneous social network effects on adoption of mustard hybrids

Table 6 presents the parameter estimates based on equation (2). The interaction term (SC/ST farming households and the adoption of mustard hybrids seeds by network members) is the variable of interest. Precisely, the interaction term captures the social network effect between SC/ST farmers and non-SC/ST farmers. Table 6 shows that compared to non-SC/ST farmers, SC/ST farmers have a more significant social network effect on technology adoption. In other words, SC/ST farmers are more likely, nearly 17 percentage points, to adopt hybrid mustard seeds because of social networks than non-SC/ST farmers (Model 3). The findings reveal that social learning is higher for lower caste farmers, especially SC/ST farmers. Another argument could be that risk-averse farmers may be convinced that technology is worthwhile once they see the effects of new technology on farmers in their social networks. Our finding is consistent with Nourani (2016), who predicted that the network effect diminishes as farmers' access to information about the technology increases. Our result is also consistent with Stoloff et al. (1999). They studied social networks in labor markets and suggested that disadvantaged women relied differentially on their social support networks to enter the labor market.

[20] We use the specification 1. Because of smaller sample size were able to run regressions using AEZ and district fixed effects, but not including block fixed effects.

Table 6
Heterogeneity in network effects by caste, marginal effects.

Variable	Dependent variable (Hybrid = 1; 0 otherwise)		
	Model 1	Model 2	Model 3
SC/ST* Network members adopt mustard hybrid	0.079 (0.070)	0.160** (0.068)	0.167** (0.082)
Network members adopt mustard hybrid	0.058 (0.039)	0.014 (0.038)	0.052 (0.048)
SC/ST	−0.176** (0.086)	−0.184** (0.076)	−0.254** (0.097)
Village adoption rate, hybrids 2014–2015	0.624*** (0.053)	0.605*** (0.073)	0.248 (0.322)
Household and plot 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
Pseudo R Square	0.527	0.579	0.564
No. of farmers	473	468	325

Notes: The dependent variable takes value 1 when farmers adopted hybrid for mustard cultivation, and 0 when they adopted improved or traditional varieties, for the period 2015–16. The variable of interest is *SC/ST* Network members adopt mustard hybrid*, which captures the difference in network effects for SC/ST as compared to the non-SC/ST farmers. Robust standard errors in parentheses. **$p < 0.05$, ***$p < 0.01$.

5.3. Intra-caste and inter-caste network effects

Table 7, Panel A presents the results based on equation (3). The right-hand side variable of interest is the number of same-caste network members who adopt mustard hybrid seeds. In contrast, Panel B of Table 7 shows the result based on specification 4. Specifically, Panel B shows results that control network effects from a different caste. Thus, the right-hand side variable of interest is the number of different caste network members who adopt mustard hybrid seeds. We only interpret the results obtained in Model 3. The result in Panel A shows a strong social network effect of the same-caste adopters on a farmer's decision to adopt hybrid mustard seeds, and the magnitude of the coefficient suggests that when one farmer of the same caste increases in the network, they are 6.1 percentage points more likely to adopt mustard hybrids. In contrast, the result is insignificant when they interact outside their caste. This result is akin to the findings of Bandiera and Rasul (2006), who show a greater correlation in adoption choices of individuals of the same religion. Our conclusion is also in line with Rogers and Bhowmik (1970), who argue that individuals who associate with similar individuals are more likely than individuals who associate with different individuals to follow the group's norm. Panel B (Table 7) show an insignificant social network effect when farmers interact outside their caste. Our finding is consistent with Davidson (2018). Davidson (2018) finds stronger ties (in the context of lending and borrowing money) when an individual interacts with members of the same caste interact than when the individual interacts with members of different castes. The relationship becomes weaker when higher and lower castes interact.

5.4. Intra-caste, inter-caste, and heterogeneity in network effects

Panel A of Table 8 presents the result of equation (5). The right-hand variable of interest in equation (5) is the interaction between SC/ST farmers and the number of same-caste network members who adopt mustard hybrids. Thus, the interaction term captures the differential effect of the same caste affiliations networks on SC/ST farmers compared to non-SC/ST farmers. The coefficient in Model 3 is insignificant, suggesting that when farmers interact within the caste, there is no differential impact for SC/ST farmers compared to the non-SC/ST farmers. Panel B of Table 8 presents the result based on equation (6).

Table 7
Intra-caste and Inter-caste in network effects on the adoption of mustard hybrids, marginal effects.

Panel A	Dependent variable (Hybrid = 1; 0 otherwise)		
	Model 1	Model 2	Model 3
Number of same caste network member who adopt mustard hybrids	0.044** (0.022)	0.034 (0.021)	0.061** (0.027)
Village adoption rate, hybrids 2014–2015	0.625*** (0.050)	0.572*** (0.070)	0.270 (0.311)
Household and plot 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
Pseudo R Square	0.523	0.570	0.555
No. of farmers	473	468	325
Panel B	**Model 4**	**Model 5**	**Model 6**
Number of different caste network member who adopt mustard hybrids	0.097 (0.057)	0.075 (0.063)	0.154 (0.083)
Village adoption rate, hybrids 2014–2015	0.658*** (0.046)	0.592*** (0.067)	0.416 (0.337)
Household and plot 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
Pseudo R Square	0.520	0.568	0.552
No. of farmers	473	468	325

Notes: The dependent variable takes value 1 when farmers adopted hybrid for mustard cultivation, and 0 when they adopted improved or traditional varieties, for the period 2015–16. In panel A, the variable of interest is the *number of same caste network member who adopt mustard hybrids* and captures the homophily in network effects. In panel B, the variable of interest is the *number of different caste network member who adopt mustard hybrids* and captures the heterophily in network effects. Robust standard errors in parentheses. **p < 0.05, ***p < 0.01.

The right-hand side, the variable of interest is the interaction between SC/ST farmers and the number of different-caste network members who adopt mustard hybrids. Thus, the interaction term captures the inter-caste network effect of SC/ST farmers compared to non-SC/ST farmers. Model 3 shows that when SC/ST farmers interact with non-SC/ST farmers, they are more likely to adopt mustard hybrids than when non-SC/ST farmers interact with SC/ST farmers. Our finding is consistent with Bandiera and Rasul's (2006).

6. Conclusions and policy implications

This paper examined the role of social networks in adopting agricultural technology. First, the study documented how mustard farmers' adoption decisions were related to the adoption choices of their social network members. The study then investigated whether lower-caste (SC/ST) farmers relied more on their networks for information than higher-caste (non-SC/ST) farmers. Our study showed positive social network effects for the adoption of mustard hybrids, with the effect being more pronounced in lower-caste farmers (SC/STs). Second, the study examined whether social network effects were more pronounced when farmers interacted in intra-caste networks versus inter-caste. The study showed that farmers are more likely to adopt mustard hybrids than when they interact within the caste. And when they interact outside the caste, results are insignificant. Finally, the study showed that the likelihood of accepting advice for the adoption of mustard hybrids is higher when SC/ST farmers interact with non-SC/ST network members compared to when non-SC/ST farmers interact with SC/ST network members. This is likely a progressive farmer asymmetric effect where

Table 8
Caste heterogeneity in the intra-caste and inter-caste network effects, marginal effects.

Panel A	Dependent variable (Hybrid = 1; 0 otherwise)		
	Model 1	Model 2	Model 3
Number of same caste network member who adopt mustard hybrids*SC/ST	0.034 (0.045)	0.072 (0.042)	0.083 (0.050)
Number of same caste network member who adopt mustard hybrids	0.036 (0.024)	0.019 (0.022)	0.041 (0.029)
SC/ST	−0.139 (0.082)	−0.119 (0.076)	−0.173 (0.102)
Village adoption rate, hybrids 2014–2015	0.631*** (0.052)	0.595*** (0.072)	0.224 (0.315)
Household and plot 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
Pseudo R Square	0.524	0.573	0.559
No. of farmers	473	468	325
Panel B	**Model 4**	**Model 5**	**Model 6**
Number of different caste network member who adopt mustard hybrids*SC/ST	0.353** (0.162)	0.407** (0.157)	0.729*** (0.184)
Number of different caste network member who adopt mustard hybrids	0.031 (0.049)	0.002 (0.050)	0.005 (0.086)
SC/ST	−0.219** (0.083)	−0.190** (0.072)	−0.344*** (0.099)
Village adoption rate, hybrids 2014–2015	0.654*** (0.046)	0.583*** (0.068)	0.472 (0.350)
Household and plot 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
Pseudo R Square	0.527	0.578	0.575
No. of farmers	473	468	325

Notes: The dependent variable takes value 1 when farmers adopted hybrid for mustard cultivation, and 0 when they adopted improved or traditional varieties, for the period 2015–16. In panel A, the variable of interest is the interaction of n*umber of same caste network member who adopt mustard hybrids and SC/ST* and it captures the differential impact of homophily on SC/STs as compared to the non-SC/STs. In panel B, the variable of interest is the interaction of n*umber of different caste network member who adopt mustard hybrids and SC/ST* and it captures the differential impact of heterophily on SC/STs as compared to the non-SC/STs. Robust standard errors in parentheses. **p < 0.05, ***p < 0.01.

progressive farmers are generally from upper castes.

The study underscores the crucial contextual heterogeneity of social networks in adopting technologies. We know that the social network's role in the adoption of agricultural technologies is complicated. This is because adopting technologies involves the appropriate implementation of agricultural technology and awareness about the technology. Results from this study provide evidence that the individual's social identity matters when it comes to social learning, especially in adopting agricultural technologies. Social identities are pre-determined, but interactions can be policy-driven. The results here find that the promotion of interactions beyond own caste can be an essential source of information and learning. Thus, policymakers should encourage policies that identify influential persons in the caste as the first and foremost point in disseminating new technologies. Confined within caste networks could restrict technology choices as the incidence of inter-caste networks is quite restricted. Socializing interactions are individual choices and thereby not directly policy driven. However, creating opportunities for specific social interactions is a policy option.

The findings have implications on information dissemination and incentives to early adopters for relevant social groups. To ensure better targeting of the adoption of technologies, informal networks among farmers should be identified, focusing on the caste composition of the members of their social networks, among other things. Perhaps policymakers facilitate and encourage the dissemination of new technologies, agronomic practices, and market information through public–private partnerships (government and state extension agents and input suppliers). Interactions between lower and upper castes could lead to faster adoption of technologies among smallholders in India. To this end, policymakers could subsidize information dissemination through media/radio/television/local newspapers.

The social value of creating opportunities for broadening social interactions between lower and upper castes cannot be understated and provide significant benefits like in technology adoption. If policymakers aim to provide speedy and broader diffusion of agricultural technologies, social networks within caste groups could be leveraged. Our evidence on farmers learning from their social networks regarding adopting new technologies may help those engaged in technology dissemination to take advantage of social spillovers for information diffusion. The evidence on heterogeneous network effects may further help policymakers formulate policy incentives and target social network approaches to speedy and broader distribution of modern technologies.

Going forward, several avenues of research are worth pursuing. Given the difficulties in identifying the network effects, a research design where individuals are randomly assigned to different situations of socializing interactions without caste could provide an ideal setting for isolating the network effects. In the same vein, it will also be worthwhile to analyze the changes in technology adoption around major exogenous events like reduced costs of information access which may also help identification. Importantly, utilizing individual longitudinal data that has information on social interactions and technology choices would allow for individual-level unobserved heterogeneity, which may help achieve more accurate estimates and unfold interesting dynamics.

CRediT authorship contribution statement

Deepak Varshney: Conceptualization, Methodology, Writing – original draft, Validation. **Ashok K. Mishra:** Writing – original draft, Writing – review & editing. **Pramod K. Joshi:** Supervision. **Devesh Roy:** Methodology, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2022.102360.

References

Anderson, J.R., Feder, G., 2007. Agricultural Extension. In: Evenson, R.E., Pingali, P. (Eds.), Agricultural Development: Farmers, Farm Production and Farm Markets. Handbook of Agricultural Economics, Vol. 3. Elsevier, Amsterdam, pp. 2343–2378.

Asfaw, S., Shiferaw, B., Simtowe, F., Lipper, L., 2012. Impact of modern agricultural technologies on smallholder welfare: evidence from Tanzania and Ethiopia. Food Policy 37 (3), 283–295.

Bandiera, O., Rasul, I., 2006. Social networks and technology adoption in northern Mozambique. Econ. J. 116 (514), 869–902.

Banerjee, A., Chandrasekhar, A.G., Duflo, E., Jackson, M.O., 2014. Gossip: Identifying Central Individuals in a Social Network (No. w20422). National Bureau of Economic Research.

Banerjee, A., Chandrasekhar, A.G., Duflo, E., Jackson, M.O., 2013. The diffusion of microfinance. Science 341 (6144), 1236498.

Banerjee, A., Munshi, K., 2004. How efficiently is capital allocated? Evidence from the knitted garment industry in Tirupur. Rev. Econ. Stud. 71 (1), 19–42.

Beaman, L., BenYishay, A., Magruder, J., Mobarak, A.M., 2021. Can network theory-based targeting increase technology adoption? Am. Econ. Rev. 111 (6), 1918–1943.

Bergoeing, R., Loayza, N., Piguillem, F., 2010. Why are developing countries so slow in adopting new technologies? The aggregate and complementary impact of micro distortions (August 1, 2010). World Bank Policy Research Working Paper, (5393). World Bank, Washington, DC.

Besley, T., Case, A., 1993. Modeling technology adoption in developing countries. Am. Econ. Rev. 83 (2), 396–402.

Beyene, A.D., Kassie, M., 2015. Speed of adoption of improved maize varieties in Tanzania: an application of duration analysis. Technol. Forecast. Soc. Chang. 96, 298–307.

Bidner, C., Eswaran, M., 2015. A gender-based theory of the origin of the caste system of India. J. Dev. Econ. 114, 142–158.

Birthal, P.S., Roy, D., Negi, D.S., 2015. Assessing the Impact of Crop Diversification on Farm Poverty in India. World Dev. 72, 70–92.

Bucciarelli, E., Odoardi, I., Muratore, F., 2010. What role for education and training in technology adoption under an advanced socio-economic perspective? Proc.-Soc. Behav. Sci. 9, 573–578.

Burton, M., Rigby, D., Young, T., 2003. Modelling the adoption of organic horticultural technology in the UK using duration analysis. Aust. J. Agric. Resour. Econ. 47 (1), 29–54.

Chow, J., Klein, E.Y., Laxminarayan, R., Husereau, D., 2010. Cost-effectiveness of "golden mustard" for treating vitamin A deficiency in India. PLoS ONE 5 (8), e12046. https://doi.org/10.1371/journal.pone.0012046.

Conley, T.G., Udry, C.R., 2010. Learning about a new technology: pineapple in Ghana. Am. Econ. Rev. 100 (1), 35–69.

Dadi, L., Burton, M., Ozanne, A., 2004. Duration analysis of technological adoption in Ethiopian agriculture. J. Agric. Econ. 55 (3), 613–631.

Davidson, T., 2018. Variation in caste homophily across villages and contexts in rural India.

Debnath, S., Jain, T., 2015. Social networks and health insurance utilization. Working Paper No. F-35304-INC-1. International Growth Center.

Desai, S., Dubey, A., 2012. Caste in 21st century India: competing narratives. Econ. Polit. Weekly 46 (11), 40–49.

Deshpande, A., 2000. Recasting economic inequality. Rev. Soc. Econ. 58 (3), 381–399.

Deshpande, A., 2011. The Grammar of Caste: Economic Discrimination in Contemporary India. Oxford University Press.

Deshpande, A., Sharma, S., 2013. Entrepreneurship or survival? Caste and gender of small business in India. Econ. Polit. Weekly 38–49.

Duflo, E., Kremer, M., Robinson, J., 2011. Nudging farmers to use fertilizer: theory and experimental evidence from Kenya. Am. Econ. Rev. 101 (6), 2350–2390.

Feder, G., Just, R.E., Zilberman, D., 1985. Adoption of agricultural innovations in developing countries: a survey. Econ. Dev. Cult. Change 33 (2), 255–298.

Feder, G., Umali, D.L., 1993. The adoption of agricultural innovations: a review. Technol. Forecast. Soc. Chang. 43 (3-4), 215–239.

Foster, A.D., Rosenzweig, M.R., 2010. Microeconomics of technology adoption. Annu. Rev. Econ. 2(1), 395–424.

Glendenning, C.J., Babu, S., Asenso-Okyere, K., 2010. Review of agricultural extension in India: Are 'farmers' information needs being met? (No. 1048). International Food Policy Research Institute (IFPRI).

Goel, D., Deshpande, A., 2016. Identity, perceptions and institutions: caste differences in earnings from self-employment in India IZA Discussion Paper 10198. Forschungsinstitut zur Zukunft der Arbeit GmbH.

Grzybowski, L., 2015. The role of network effects and consumer heterogeneity in the adoption of mobile phones: evidence from South Africa. Telecommun. Policy 39 (11), 933–943.

Gulati, A., Sharma, P., Samantara, A., Terway, P., 2018. Agriculture extension system in India: Review of current status, trends and the way forward. Indian Council for Research on International Economic Relations.

Gupta, D., 2000. Interrogating Caste: Understanding Hierarchy and Difference in Indian Society. Penguin Books, New Delhi.

Jackson, M.O., López-pintado, D., 2013. Diffusion and contagion in networks with heterogeneous agents and homophily. Netw. Sci. 1 (1), 49–67.

Katengeza, S.P., Holden, S.T., Lunduka, R.W., 2019. Adoption of drought tolerant maize varieties under rainfall stress in Malawi. J. Agric. Econ. 70 (1), 198–214.
Klerkx, L., 2020. Advisory services and transformation, plurality and disruption of agriculture and food systems: towards a new research agenda for agricultural education and extension studies. J. Agric. Educ. Extens. 26 (2), 131–140.
Krishna, V.V., Aravalath, L.M., Vikraman, S., Xin, B., 2019. Does caste determine farmer access to quality information? PLoS ONE 14 (1), e0210721. https://doi.org/10.1371/journal.pone.0210721.
Kumar, A., 2016. Production barriers and technological options for sustainable production of rapeseed-mustard in India. J. Oilseed Brassica 1 (2), 67–77.
Kumar, V., Nim, N., Agarwal, A., 2021. Platform-based mobile payments adoption in emerging and developed countries: role of country-level heterogeneity and network effects. J. Int. Bus. Stud. 52 (8), 1529–1558.
Kumar, S.M., Venkatachalam, R., 2019. Caste and credit: a woeful tale? J. Dev. Stud. 55 (8), 1816–1833.
Ligon, E., 1998. Risk sharing and information in village economies. Rev. Econ. Stud. 65 (4), 847–864.
Maertens, A., Barrett, C.B., 2013. Measuring social 'networks' effects on agricultural technology adoption. Am. J. Agric. Econ. 95 (2), 353–359.
Magnan, N., Spielman, D.J., Lybbert, T.J., Gulati, K., 2015. Leveling with friends: social networks and Indian farmers' demand for a technology with heterogeneous benefits. J. Dev. Econ. 116, 223–251.
Manski, C.F., 1993. Identification of endogenous social effects: the reflection problem. Rev. Econ. Stud. 60 (3), 531–542.
Manski, C.F., 2000. Economic analysis of social interactions. J. Econ. Perspect. 14 (3), 115–136.
Martey, E., Etwire, P.M., Kuwornu, J.K.M., 2020. Economic impacts of smallholder farmers' adoption of drought-tolerant maize varieties. Land Use Policy 94, 104524. https://doi.org/10.1016/j.landusepol.2020.104524.
Matuschke, I., Qaim, M., 2009. The impact of social networks on hybrid seed adoption in India. Agric. Econ. 40 (5), 493–505.
McPherson, J.M., Smith-Lovin, L., 1987. Homophily in voluntary organizations: Status distance and the composition of face-to-face groups. Am. Sociol. Rev. 52 (3), 370. https://doi.org/10.2307/2095356.
Munshi, K., 2004. Social learning in a heterogeneous population: technology diffusion in the Indian Green Revolution. J. Dev. Econ. 73 (1), 185–213.
Munshi, K., 2019. Caste and the Indian economy. J. Econ. Literat. 57 (4), 781–834.
Munshi, K., Rosenzweig, M., 2018. Ethnic diversity and the under-supply of local public goods. Available from: https://www.histecon.magd.cam.ac.uk/km/panchayat79.pdf.
Munshi, K., Rosenzweig, M., 2016. Networks and misallocation: insurance, migration, and the rural-urban wage gap. Am. Econ. Rev. 106 (1), 46–98.
Mwaura, F., 2014. Effect of farmer group membership on agricultural technology adoption and crop productivity in Uganda. Afr. Crop Sci. J. 22, 917–927.
Nakano, Y., Tsusaka, T.W., Aida, T., Pede, V.O., 2018. Is farmer-to-farmer extension effective? The impact of training on technology adoption and rice farming productivity in Tanzania. World Dev. 105, 336–351.
Negi, D.S., Birthal, P., Kumar, A., Tripathi, G., 2020. Farmers' social networks and the diffusion of modern crop varieties in India. Int. J. Emerg. Markets.
Neill, S.P., Lee, D.R., 2001. Explaining the adoption and disadoption of sustainable agriculture: the case of cover crops in northern Honduras. Econ. Dev. Cult. Change 49 (4), 793–820.
Norton, G.W., Alwang, J., 2020. Changes in agricultural extension and implications for farmer adoption of new practices. Appl. Econ. Perspect. Policy 42 (1), 8–20.
Nourani, V., 2016. Social Network Effects of Technology Adoption: Investing with Family, Learning from Friends & Reacting to Acquaintances. Cornell University, p. 54.
Ogundari, K., Bolarinwa, O.D., 2018. Impact of agricultural innovation adoption: a meta-analysis. Aust. J. Agric. Resour. Econ. 62 (2), 217–236.
Rogers, E.M., 1995. Diffusion of Innovations: modifications of a model for telecommunications. In: Stoetzer, M.-W., Mahler, A. (Eds.), Die Diffusion Von innovationen in Der Telekommunikation. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 25–38. https://doi.org/10.1007/978-3-642-79868-9_2.
Rogers, E.M., 2003. Diffusion of Innovations, fifth ed. Free Press, New York.
Rogers, E.M., Bhowmik, D.K., 1970. Homophily-heterophily: relational concepts for communication research. Pub. Opin. Q. 34 (4), 523–538.
Shiferaw, B., Kassie, M., Jaleta, M., Yirga, C., 2014. Adoption of improved wheat varieties and impacts on household food security in Ethiopia. Food Policy 44, 272–284.
Simtowe, F., Marenya, P., Amondo, E., Worku, M., Rahut, D.B., Erenstein, O., 2019. Heterogeneous seed access and information exposure: implications for the adoption of drought-tolerant maize varieties in Uganda. Agric. Food Econ. 7 (1), 1–23.
Stoloff, J.A., Glanville, J.L., Bienenstock, E.J., 1999. Women's participation in the labor force: the role of social networks. Soc. Netw. 21 (1), 91–108.
Takahashi, K., Muraoka, R., Otsuka, K., 2020. Technology adoption, impact, and extension in developing countries' agriculture: a review of the recent literature. Agric. Econ. 51 (1), 31–45.
Thorat, S., Lee, J., 2005. Caste discrimination and food security programmes. Econ. Polit. Weekly 4198–4201.
Young, H.P., 2009. Innovation diffusion in heterogeneous populations: contagion, social influence, and social learning. Am. Econ. Rev. 99 (5), 1899–1924.