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ABSTRACT

In this paper we study the role of social networks in the context of the low adoption rate of hybrid varieties of pearl millet, an important dry land crop in India. We focus on Rajasthan, which has the lowest adoption rate of hybrid pearl millet varieties among all of the pearl millet-producing states in India. We find evidence of the existence of significant network effects on the adoption of hybrid varieties. However, going a step further, we explain this low rate of adoption in terms of the nature of effective networks for adoption. We find that only close-knit networks, which in light of social fragmentation can limit benefits to only a few farmers, have a significant effect on the adoption of hybrid seeds. The ineffectiveness of farmer groups, mass media, and public extension services—which in principle should be less exclusionary and thus could reach a larger group—can be a contributing factor underlying the low adoption rate of hybrid pearl millet varieties.

KEY WORDS: social networks, technology adoption, reflection problem, endogenous effect, exogenous effect, correlated effect

JEL CLASSIFICATION: D83, O13, O33, Q16

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1. INTRODUCTION

A persistent question in development economics is why some distinctly profitable technologies are not widely adopted in agriculture. Duflo, Kremer, and Robinson (2008) and Dercon and Christiaensen (2011) present strong evidence for strikingly low adoption rates for eminently profitable technologies in Kenya and Ethiopia, respectively. Low adoption rates of agricultural technologies, such as fertilizers and improved seed varieties, are very important from a development perspective, accounting for stagnation in agricultural productivity in different countries (World Bank 2008). While there can be several explanations for low adoption rates of several new technologies (such as access to credit, supply constraints, and lack of information), one of the important explanations is social learning (or the absence of it) through social networks.

Processes of social learning have been extensively studied in the context of agricultural technology adoption in developing countries (Bandiera and Rasul 2006; Conley and Udry 2010; Foster and Rosenzweig 1995; Munshi 2004). If social learning is sufficiently strong, low adoption equilibria may persist, in spite of potentially high returns (Zeitlin et al. 2010). In this paper we study one such case: low adoption of hybrid varieties of pearl millet in Rajasthan, India.

Significant research efforts worldwide have been targeted toward enhancing the productivity of this crop through breeding of high-yielding cultivars suited to arid and semi-arid environments. These efforts resulted in an increase in the productivity of pearl millet for dry and marginal land in India from 323 kilograms per hectare (kg/ha) during 1950–1954 to 991 kg/ha in 2010 (Bidinger, Sharma, and Yadav 2008). Nationally, hybrid pearl millet varieties now cover about 50 percent of the total pearl millet area in India, which is the highest hybrid adoption rate among coarse cereal crops. Area under high-yielding varieties (HYVs—including both hybrid and improved open-pollinated varieties) is largest in the state of Gujarat, with more than 90 percent of farmers using these varieties.

On the other hand, although Rajasthan has the largest area (in absolute terms) of pearl millet under cultivation, historically, its adoption rate of HYVs has been extremely low, with only 25–30 percent of farmers planting HYVs. In fact, among the pearl millet-producing states, Rajasthan exhibits the lowest rate of hybrid seed adoption. While this figure has somewhat improved recently, until 2010, Rajasthan had only 1.75 million hectares under HYV cultivation, which accounts for only 39 percent of the area under pearl millet cultivation (Manga and Kumar 2011). Asare-Marfo et al. (2010a) find the adoption of hybrid pearl millet varieties to be higher (51 percent) in Rajasthan, but this can be explained by oversampling of farmers in major pearl millet-growing areas where hybrid adoption rates are higher.

In this paper, we investigate farmers' hybrid pearl millet adoption choice from a social network perspective. As part of a survey of pearl millet-producing households, we map out the complete (or as comprehensive as possible) network of individuals/households in the selected communities. Based on previous research and qualitative investigations, we specify the possible nature of networks, thereby constituting a reference group for each household that takes into account both geographical proximity and social identity.

The definition of *reference group/network* is in general open ended, and is subject to researcher discretion. Broadly, *reference group* for a person is defined by the individuals whose average outcome and characteristics influence the individual's choices. Here, we argue that basing a definition of reference groups solely on geographical proximity does not fit the Indian context, given the social fragmentation that is at the forefront of the social structure, especially in the rural areas. The reference group of a farmer in a particular village could comprise farmers in a village other than the farmer's own village who belong to the same caste group. Our construction of reference groups is along the lines of Fontaigne and Yamada (2011), who in the context of urban India define reference groups based on education, age, geographical proximity, and caste.

Within this broadly defined group, each farmer can have specific individual interactions with varying intensity. We start by being completely agnostic about what *subnetworks* can be relevant for technology adoption, but emphasize the importance of these subnetworks being comprehensive in scope as well as coverage (i.e., types of nodes and intensity of interaction that each node contains). This is so not only because networks of different types—local as well as non-local, personal as well as institutional—can have a bearing on technology adoption, but also because the individual effects of each of the networks or information sources are best estimated conditional on the state of other networks. For example, the effectiveness of media could depend on the types of friends and family interactions.

Once we define the network/reference groups in terms of social identity and geographical proximity, we utilize the intensity of interaction with different network nodes to identify the presence of endogenous effects. In particular, we use the intensity of the interaction of social exchange with group-level adoption to establish the presence of endogenous effects. Note that, with adequate controls for individual and group characteristics, greater intensity of interaction having a bearing on technology choice can only happen when social learning exists (endogenous effect), and cannot be associated with other forms of social effects (i.e., exogenous and correlated effects). However, our intent is not to show the size of endogenous effects, but to show that they exist.

To emphasize the usefulness of this strategy, we first note that estimating endogenous social effects in a linear-in-means regression is subject to a *reflection problem* (Manski 1993; Bramoullé, Djebbari, and Fortin 2009): endogenous effects may not be isolated from exogenous and correlated effects, in particular, due to unobserved group characteristics. We use group fixed effects to account for group unobserved heterogeneity. However, this also means that group averages are subsumed in the fixed effects and cannot be identified. Therefore, we need variation in individual-level variables that links group average outcomes to individual outcomes. The detailed information we have on each individual's network provides us with individual-level variation in the intensity of network interaction. Under the assumption that the individual's network is embedded within his or her group, we can identify the existence of endogenous social effects by crossing the intensity of network interaction with the group average of hybrid varietal adoption. The coefficient of this interaction is identified even with group fixed effects.

At some level, our identification of endogenous social effects is along the lines of Bandiera and Rasul (2006), who observe a pattern of relationships between adoption by networks and individual farmer's choices, which they argue can emerge only due to endogenous social effects. In this paper, the significance of both the intensity of the interaction of some elements of a network and the adoption levels of the network on technology adoption works on a similar elimination principle.

Further, from a policy perspective, our main implication is not from finding the potential effects of more inclusive networks (such as farmers' associations), sources of information (media), and services (public extension services) on technology choice. In a state where traditional varieties dominate, the breadth of networks could be an important driver of the choice of hybrid varieties. If effective networks tend to be local and segmented, the adoption of modern technology could be spatially restricted. Thus, information or other inputs relevant for adoption could largely come from close-knit networks. Aggregating up, this would show up as overall low levels of adoption, since only a selected group would reap network benefits. Prima facie, this seems to be the situation in the adoption of hybrid varieties of pearl millet in Rajasthan.

We find that farmers who adopt a hybrid variety have specifically been influenced by close-knit networks, such as family and friends and religious gatherings. The greater the intensity of this interaction, the higher is the likelihood of adoption of hybrid technology. Common pool sources of information, networks, or services (such as media, government extension services, and associations) have had no significant effect on the adoption of hybrid varieties of pearl millet in Rajasthan. From a policy perspective, this finding is quite important, since these networks or information and service channels are generally the mainstay of policies geared toward large-scale technology adoption programs.

Apart from the close-knit connections, the sheer lack of effects of other networks outlines the constraints for using these networks when the objective is large-scale adoption in a fragmented society. Of course, the endogenous effects would have social multipliers, but from the revealed outcomes (working only in the case of friends and relatives and religious gatherings), they seem to be working slowly and sparsely.

This paper contributes to a growing body of literature that has tried to identify specific social influences on technology adoption (see, for example, Foster and Rosenzweig 1995; McNiven and Gilligan 2012; Pomp and Burger 1995). Identifying the effects of group-level adoption on an individual farmer's technology choices is subject to the classical reflection problem, as shown in the pioneering work of Manski (1993).

Recently, an alternative approach to identification of social effects—i.e., through individual networks—has been gaining ground (see Bramoullé, Djebbari, and Fortin 2009; Calvó-Armengol et al. 2009). Our dataset, with its detailed network structure and constitution of each social exchange, is well suited for this approach. Few studies have taken this approach in the context of technology adoption in the rural areas of developing countries, mainly because of the need to collect large amounts of data to capture information from all possible networks and the types of social exchange.

Some of the recent studies on technology adoption referred to above have started using individual networks to identify the effect of individual social networks on technology adoption (Bandiera and Rasul 2006; Conley and Udry 2010). For example, Matuschke and Qaim (2009) look at this issue in the context of adoption of hybrid varieties of wheat and pearl millet in Maharashtra, one of the two states in India where almost all farmers have adopted hybrid varieties of pearl millet. This paper deals in a starkly different setting, where adoption of hybrid varieties is low.

The paper is distinct from Matuschke and Qaim (2009) in other ways as well. The focus on Rajasthan implies that this study aims to address both lack of technology adoption as well as choices in favor of hybrid varieties.

Our mapping of networks at the individual level with an extensive set of nodes is comparatively comprehensive. Matuschke and Qaim (2009), much like Bandiera and Rasul (2006), proxy for group effects by adding village fixed effects as a regressor. Underlying this idea is the notion that groups are circumscribed at the village level. As discussed above, the span for networks in this paper is broader and not confined to village of residence. Social networks measure an individual's connectedness to others in the society. We measure an individual's connectedness along five dimensions: interaction within family, interaction with friends and relatives, telephone communication with networks of less frequent interactions, exposure to media, and participation in organizations.

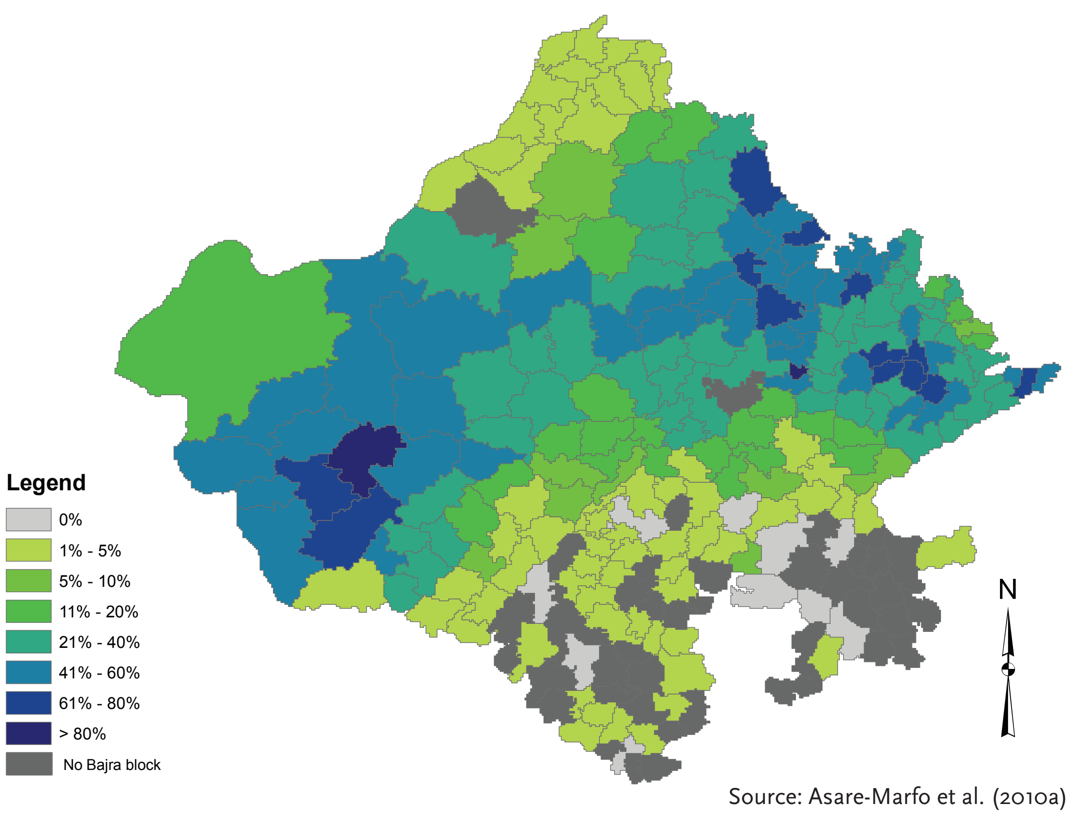
The paper is organized as follows. Section 2 presents the data and summary statistics based on the primary survey geared toward mapping of networks, their contributions, and the outcome in terms of varietal choice. Section 3 outlines the methodology for analyzing the social effects on technology adoption, first in terms of establishing the networks that are effective in technology adoption, and then followed by methods for establishing the presence of endogenous social effects, if any. Section 4 presents the results of regression analysis, and section 5 concludes with some policy implications.

2. DATA SUMMARY & STATISTICS

The sampling methodology used to select the farm households that were interviewed was a combination of stratified random sampling and probability proportionate to size methods. The sampling design was for a large random sample comprising 1,750 households, where about 350 households were chosen for a survey related to social networks. The sampling design consisted of four stages. First, based on background research, out of the ten agro-climatic zones in Rajasthan, six were found to be conducive to pearl millet production. The sampling frame comprised all six pearl millet zones. Second, we used 2007–2008 block-level data from the Government of Rajasthan on the area under pearl millet production in the six agro-ecological zones in which pearl millet is produced. These zones comprise 213 blocks of the 245 blocks that make up the state of Rajasthan.

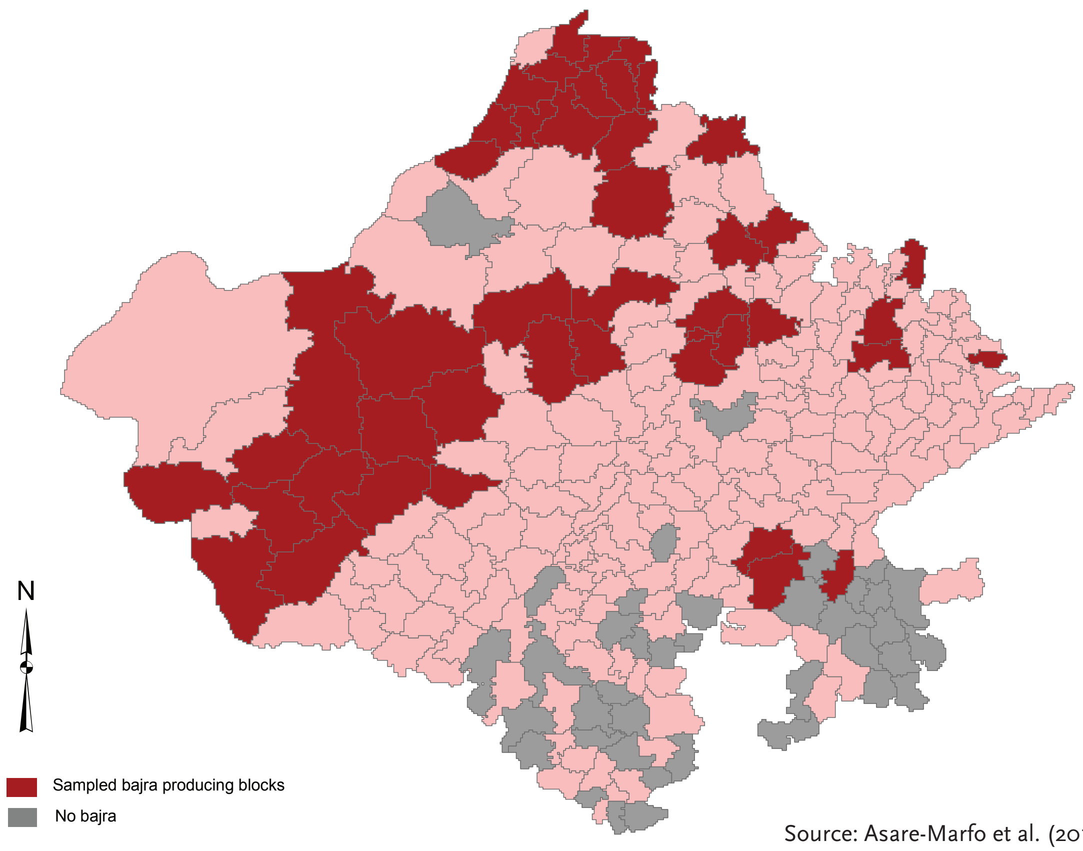
In the third state, the 213 pearl millet-producing blocks were ranked in an ascending order according to the total area under pearl millet production and, in the fourth stage, were split into four groups based on 25, 50, and 75 percent cut-off points of total land under pearl millet production: high, high-medium, low-medium, and low. All of the 5 blocks in the high and 13 of the 14 blocks in the

Figure 1. Share of agricultural area dedicated to pearl millet production



Source: Asare-Marfo et al. (2010a)

Figure 2. Pearl millet-producing blocks in Rajasthan



Source: Asare-Marfo et al. (2010a)

high-medium pearl millet area groups were selected. The mechanism of selection ensured that we also included 4 blocks from the low-medium and 23 blocks from the low pearl millet areas. Figure 1 shows the share of agricultural area dedicated to pearl millet in each of the 213 pearl millet-producing blocks, and Figure 2 shows the 45 selected blocks that constitute the sample.

Depending on the total number of villages in each block, four to six villages were randomly selected in each block. The selection of villages was based on stratification according to their distance to the center of the block. In each block, two or three villages closer to the block (market) center and one or two villages farther away from the block (market) center were randomly selected among long lists of such villages. Finally, in each village, depending on the population of the village, three to five households were randomly selected to be interviewed. To select the respondents, a cross-sampling method was used—i.e., a cross "X" was drawn on the village map, and every nth household was interviewed.

Not all households were administered the questionnaire with social network questions.

Since the choice of variety was critical for analysis in this paper, we conducted supplementary surveys with which we triangulated in order to identify the varieties correctly. We interviewed about 1,400 households just to gather information about varietal choice and some basic socioeconomic characteristics. In addition, surveys of the input suppliers and block-level public extension officers (Block Agricultural Officers) were conducted to validate patterns of varietal choices from our social network-oriented household survey (Asare-Marfo et al. 2010a; Asare-Marfo, Birol, and Roy 2010b).

In total, 320 households had usable data on modules related to social networks in 15 districts and 45 blocks. In each household, two to three adult members of the family were interviewed, given that we conceptualize networks at the individual level. Under the assumption that the varietal choice is a decision made by the household head, we used the network map of the household head that emerged from the responses to the social network module.

To obtain a comprehensive map of the individuals' network, questions were asked about the following categories of interaction and activities:

1. Intra-household network
2. Network of friends, family, and neighbors
3. Network of less frequent interactions (through telephone, etc.)
4. Involvement in (non-religious) local organizations
5. Involvement in organized religious activities (temples, churches, mosques, etc.)
6. Exposure to different forms of media

Our extensive coverage of connections across a large set of network (information) nodes contrasts with most studies dealing with social networks in technology adoption. Usually the focus in these studies has been on networks of friends, family, and neighbors, either as a primal node or at times as the sole node. Our premise is that because of such factors as improvement in communication and transportation, different types of networks are potentially important. Based on census data for 2011, more than 61 percent of rural households in Rajasthan had access to mobile phones. For example, a network of less frequent interaction, though sporadic, could be an important source of information, especially when individuals with whom such interaction occurs could be located in places that are better informed.

Additionally, we try to identify the clearly actionable nodes for policy, such as media and farmer organizations. Thus, it is important to assess their effectiveness with the proviso that their roles can only be judged conditional on other nodes. Apart from extending the scope of relevant networks, following Putnam (1995), our dataset also contains the intensity of social interaction.

Table 1 presents some descriptive statistics from the social network data. It lists the intensity of interaction at each of the extensive sets of social network nodes. As discussed above, we measure intensity in terms of time spent interacting with the network. For example, if the number of hours the head of the household spent with a household member is higher than that spent with another network member, then we treat that network node as being more intense.

Table 1. Descriptive statistics of the sample

Descriptive statistics	N	Mean	SD	Min	Max
Hybrid pearl millet variety =1, 0 otherwise	320	0.49	0.50	0.00	1.00
Caste-area group average of hybrid variety (m)	320	0.50	0.24	0.11	0.83
Area group average of hybrid variety (n) in hectares	320	0.47	0.21	0.14	0.81
Hours/week with friends and relatives (p)	320	11.74	7.63	0.00	45.00
Phone calls to friends and relatives out of village (q)	320	85.48	98.54	0.00	365.00
Hours/week at temple/mosque/church, etc. (r)	320	0.69	1.92	0.00	23.00
Number of organizations where participation occurred	320	0.10	0.38	0.00	3.00
Hours/week with household members	320	43.44	24.97	0.00	119.00
Hours/week with newspaper/radio/TV	320	13.57	8.19	0.00	49.00
Interaction = m*p	320	5.85	5.00	0.00	26.72
Interaction = m*q	320	40.08	52.03	0.00	268.38
Interaction = m*r	320	0.34	1.12	0.00	16.91
Interaction = m*s	320	0.06	0.24	0.00	1.74
Interaction = n*p	320	5.53	4.52	0.00	24.35
Interaction = n*q	320	39.60	52.03	0.00	222.17
Interaction = n*r	320	0.33	0.99	0.00	14.00
Interaction = n*s	320	0.05	0.22	0.00	1.83
Household size	320	6.66	7.50	2.00	70.00
Years lived in this village	320	54.52	31.56	1.00	200.00
Farmland size in hectares	320	0.32	1.17	0.02	20.24
Off-farm monthly income (in thousand rupees)	320	4.95	6.24	0.00	40.00
Farm monthly income (in thousand rupees)	320	5.97	6.31	0.00	70.00
Group average of consumption trait	320	4.31	0.09	4.19	4.60

Figure 3. Districts in Rajasthan

Source: Government of Rajasthan

In the sample, less than half of the farmers have chosen a hybrid variety of pearl millet (Table 1). There is very low participation in organizations in general and in farmer associations in particular. As expected, close-knit networks, such as those of household members, friends, and relatives, comprise the most intensive interactions. On average, an individual in our sample spends about 43 hours a week interacting with household members, about one-third of that time interacting with friends and relatives, and 14 hours a week interacting with all media.

Apart from the number of hours spent per week with a network node, an alternative measure of the importance of a social network for technology adoption is the number of nodes from which relevant information was obtained. Strikingly, the number of nodes in the network of organizations is quite small, with information coming from some religious organizations being most salient. Networks of family and friends have the maximum number of nodes as the sources of information regarding seeds and/or technology. At the general level of information about technology, the number of nodes in media is somewhat important.

Table 1 also presents the basic socio-economic profile of the households that were sampled. All the listed variables are at the household level. Given that two to three members were interviewed in each household, the total sample size equaled 1,251 data points. Among the household characteristics, the average landholding size is quite small, with only 0.32 ha devoted to cultivation of pearl millet.

In considering social learning, how we define the reference group is important. We assumed that the agrarian households in our sample are divided into three caste categories (k = 1,2,3): upper caste, scheduled castes/ scheduled tribes (SC/ST), and other backward castes (OBC) (Table 2)[1]. We also categorized the state of Rajasthan into six geographical areas (j = 1,...,6). These classifications are based on districts of geographical proximity that shared borders (Table 2 and Figure 3). We interacted the variables (k, j) to construct groups for each caste category within each area.

[1] Scheduled castes and scheduled tribes comprise the lowest caste, followed by other backward castes.

Table 2. Area classifications used

Area	Districts	Caste category	Description
1	Alwar, Bharatpur, Bundi, Kota	1	Upper caste
2	Hanumangarh, S. Ganganagar	2	Scheduled castes and scheduled tribes (SC/ST)
3	Bikaner, Churu	3	Other backward castes (OBC)
4	Jhunjhunu, Sikar		
5	Jodhpur, Nagour		
6	Barmer, Jaisalmer		

Recent work by Foster and Rosenzweig (2010) notes that in adopting technology, it might be worthwhile to explore whether information flow within a village is constrained by networks based on kinship or social status. They argue that it seems particularly relevant in the light of studies showing the importance of caste networks in determining access to credit in India (Munshi and Rosenzweig, 2009).

Table 3 presents the descriptive statistics by socio-economic groups and by the six geographical areas. There is significant heterogeneity across castes and geographical areas. Areas 3 and 6—i.e., the districts of Bikaner, Churu, Jaisalmer, and Barmer—have substantively lower adoption of hybrid varieties of pearl millet, partly because of agro-ecological constraints. Kelley et al. (1996) found that landrace varieties perform better in the western and most arid areas of Rajasthan, where they are better suited to marginal agro-ecological conditions. To the extent that hybrid varieties require more water, these drier districts would naturally exhibit lower adoption rates. Yet, spatial differences in adoption patterns exist over and above pure agro-ecological factors. Areas, such as Jodhpur, have comparatively high adoption rates, along with Jhunjunu and Sikar districts, which are comparatively arid. Further, spatially the differences in adoption rates are quite significant. These data indicate that factors other than agro-ecological factors (such as social networks) could be playing a role in determining technology choice.

In terms of the levels of intensity and engagement that the node of a social network provides, apart from a significant amount of time spent interacting with other household members, a unique characteristic observed in the data is the low association of households with common pool networks, such as media, farmer organizations, and public agricultural extension officers. Nearly three-quarters of farmers stated that they obtain technology-related information from media, although in the case of information on seeds for pearl millet varieties, this share never reaches double digits in any one of the categories of common pool networks.

Table 3. Means by caste and geographical categories

Descriptive statistics	Caste categories			Geographical (area) categories					
	Upper caste	SC/ST	OBC	Area 1	Area 2	Area 3	Area 4	Area 5	Area 6
Number of observations	41	49	230	26	65	40	63	69	57
Hybrid pearl millet variety	0.37	0.61	0.49	0.88	0.45	0.30	0.71	0.59	0.14
Hours/week with friends and relatives	11.21	11.63	11.85	9.95	12.12	10.25	12.11	12.19	12.21
Phone calls to friends and relatives out of village	65.44	92.85	87.48	53.50	102.69	76.26	52.83	114.77	87.53
Hours/week at temple/mosque/church, etc.	0.63	0.73	0.69	0.62	0.23	0.38	1.46	0.42	0.95
Number of organizations where participations occurred	0.05	0.08	0.12	0.08	0.02	0.07	0.32	0.04	0.07
Hours/week with household members	42.66	40.87	44.13	41.71	34.94	50.26	64.29	38.22	32.44
Hours/week for newspaper/radio/TV	12.34	13.16	13.88	12.73	14.17	14.07	14.00	14.19	11.70
Household size	7.32	8.06	6.24	5.23	5.75	7.55	9.00	6.48	5.33
Years lived in this village	57.32	53.06	54.34	55.58	42.05	66.13	61.52	45.35	63.51
Farmland size in hectares	0.82	0.23	0.25	0.06	0.23	0.27	0.15	0.32	0.76
Off-farm monthly income	6.79	4.56	4.70	3.50	4.29	4.71	3.67	5.43	7.36
Farm monthly income	4.01	5.26	6.48	3.83	10.09	5.76	3.92	7.72	2.57

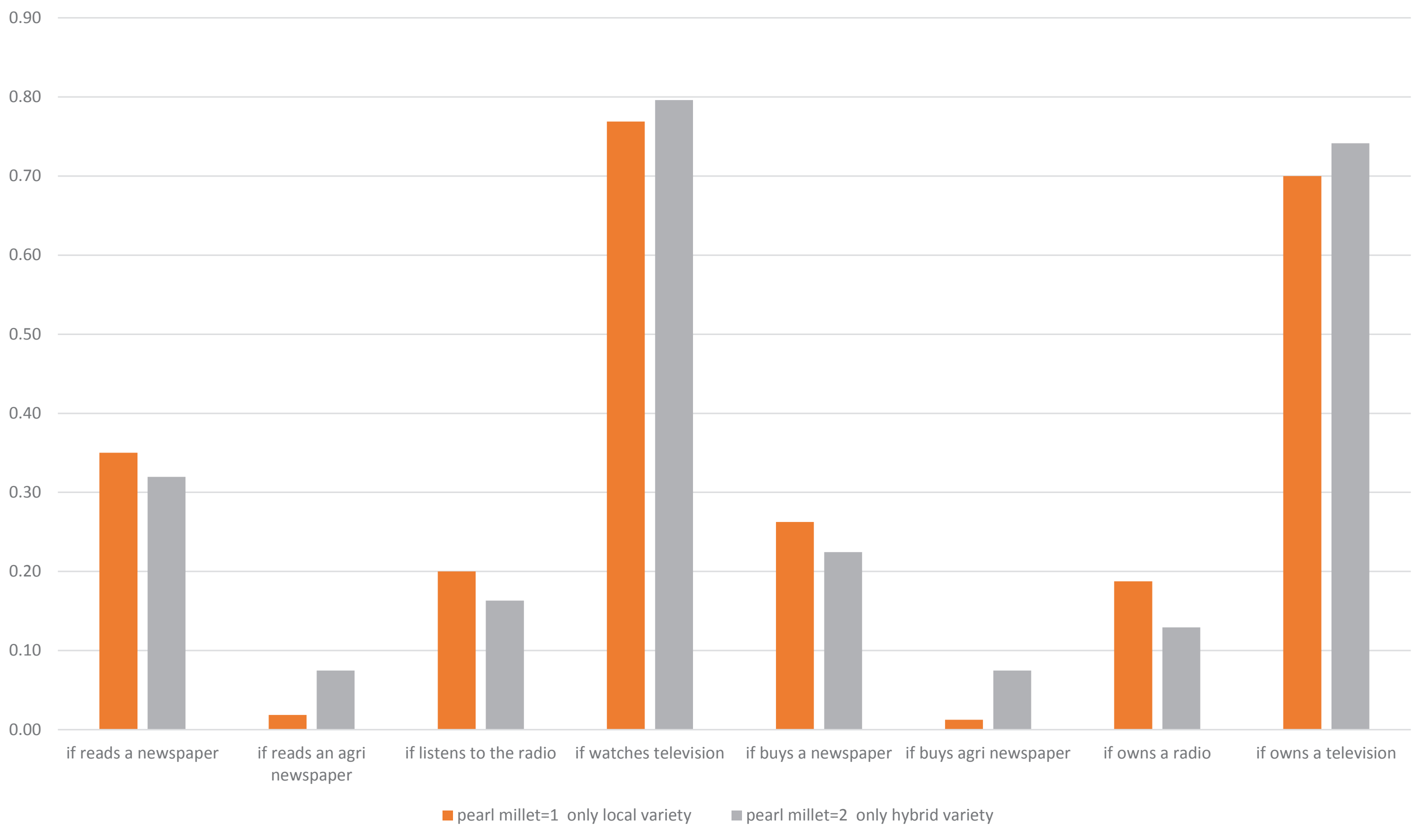
Farmer organizations exhibit a similar pattern. Across socioeconomic and geographical groups, a small proportion of farmers obtained information on technology from these networks. Also, as expected, the level of membership in farmer organizations is quite small, measured as percentage share. Birner and Anderson (2007) studied the sources of extension services and found that only 0.4 percent of farm households in Rajasthan reported being a member of any registered farmer organization. In the case of other organizations, such as self-help groups, this figure was just marginally higher, at 0.6 percent.

Figure 4 presents the use of media and the contribution of farmer organizations in transmitting information related to technology. These figures compare farmers who grow hybrid varieties with farmers who do not. Among media outlets, television has the maximum exposure. Across all media there is little difference between the proportions of farmers with access to these information sources and growers of hybrid and traditional varieties. At a modest level, exposure to agricultural newspapers is higher for farmers who grow hybrid varieties vis-à-vis growers of landrace varieties. On average, for either type of farmer, agriculture-centric media outlets are not important information sources.

Table 4 lists the potential of organizations, such as farmer associations, for transmitting information on matters related to technology. To obtain this information, we disaggregated different aspects of farming technology, and presented a detailed set of questions to farmers about whether the organization membership provided them the benefit of information. This information is pertinent, because technology is a package involving several elements, and choice of seed could be affected not solely by information about seed per se, but also by other related information on inputs and outputs.

We broke down agricultural technology and related information into crop spacing, crop rotation, irrigation, marketing of crops, and several other similar factors, such as buying and selling of agricultural inputs and weather-related information. Strikingly, membership in a farmer organization was found to be ineffective as a source of

Figure 4. Farmers' sources of information about new technologies (proportions)



Source: primary survey by authors

Table 4. Organizations and information

	Member	Non-member
Number of events taking place in the village last year	0.13	**0.22**
Number of events attended by the individual	0.08	**0.14**
Time per year spent **(in days)**	0.09	**0.14**
Number of benefits received in a year	1.00	1.00
Amount of information received on crops	0.01	0.01
... on seed spacing	0.00	0.01
... on seeds	0.01	**0.02**
... on irrigation	0.01	0.01
... on soil management	0.01	0.01
... on other inputs	0.01	**0.03**
... on other farming techniques	0.00	0.01
... on availability of inputs	0.02	**0.05**
... on prices	0.03	**0.06**
... on traders and brokers	0.01	0.02
... on means of transportation	0.01	0.01
... on market fees	0.02	**0.06**
... on time and frequency of the market	0.00	0.01

Note: Items in bold present cases with statistically significant differences.

information for each of these factors. This is because very few farmers in Rajasthan are members of farmer organizations in the first place. None of the farm households in the sample obtained agriculture-related information from religious or non-religious organizations, such as farmer organizations or self-help groups.

3. METHODOLOGY

In this section we outline the methodology for identifying the effects of networks on choice of hybrid technology. Our motivation comes from Calvó-Armengol, Patacchini, and Zenou (2009). Below we present a brief description of their model. Let $y_i^0 > 0$ denote the effort, such as adoption of technology by individual i. Let z_i^0 denote the outcome due to peer influence. The individual outcome is the sum of two efforts

(1) $y_i^* = (x,g) = y_i^{0*}(x) + z_i^{0*}(x),$

where the individual outcome is assumed to be a combination of peer influence ($y_i^{0*}(x)$) and factors that are separate from it, x denotes idiosyncratic characteristics of the individual that comprises M attributes (please see equation (2), below). The variables on the right-hand side of equation (1) are defined as,

(2) $y_i^{0*}(x) = \theta_i(x) = \Sigma_{m=1}^{M} \beta_m x_i^m + \dfrac{1}{g_i} \Sigma_{m=1}^{M} \Sigma_{j=1}^{n} y_m g_{ij} x_i^m,$

(3) $z_i^*(x) = \mu g_i + \phi\, \Sigma_{j=1}^{n} g_{ij} z_j.$

Where μg_i denotes that the network itself (its size or intensity—in our formulation we will capture it in terms of intensity) and $\phi\, \Sigma_{j=1}^{n} g_{ij} z_j$ depends on the outcomes of the peers (in our case the varietal choice), $g_i = \Sigma_{j=1}^{n} g_{ij}$ is the number of direct links of individual i. Now, suppose that there are K networks. In the above formulation, θ_i introduces the heterogeneity that captures the observable differences across individuals. The empirical counterpart of the formulations (for n individuals with K networks) above is as given below. For $i = 1,2,\ldots,n,$ $k = 1,2,\ldots,K,$ and $v_{i,k}$ defining an error component,

$$(4) \qquad y_{i,k} = \underbrace{\Sigma_{m=1}^{M}\beta_m x_{i,k}^m}_{\text{individual characteristics}} + \underbrace{\frac{1}{g_{i,k}}\Sigma_{m=1}^{M}\Sigma_{j=1}^{n_k} y_m g_{ij,k} x_{j,k}^m}_{\text{group characteristics (exogenous effect)}} + \underbrace{\eta_k}_{\substack{\text{correlated effect}\\ \text{Network FE}}} + \underbrace{\mu g_{i,k}}_{\substack{\text{measure of}\\ \text{network}\\ \text{size/intensity}}} + \underbrace{\phi\, \Sigma_{j=1}^{n} g_{ij}\varepsilon_{j,k}}_{\text{endogenous effect}} + v_{i,k}$$

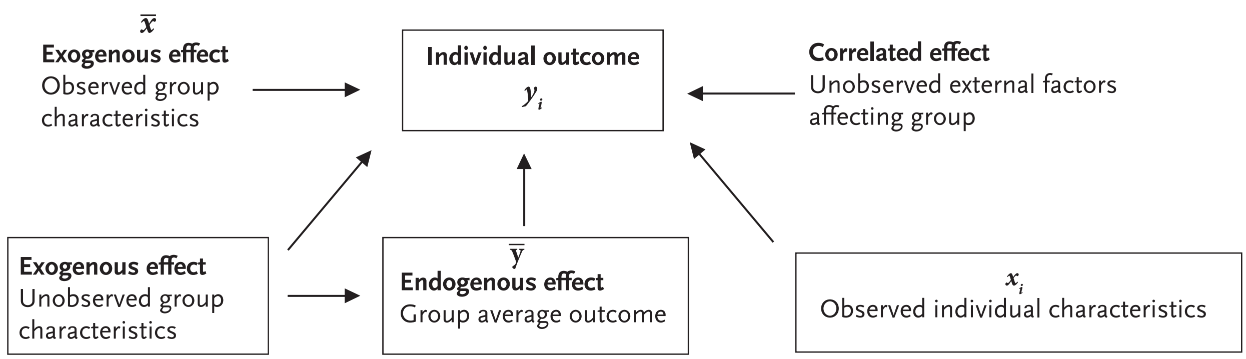
Figure 5 presents the schematic explaining the social effects in individual choices related to technology adoption. The social effects comprise the following:

Endogenous effect: group behavior influencing individual behavior.

Exogenous effect: individual behavior varying with the exogenous characteristics of the group (for example, family background).

Correlated effects: individuals in the same reference group tend to behave similarly because they are alike or face a common environment (can be unobserved).

Figure 5. Estimation issues in social effects



Typically, social effects are estimated using the following linear-in-means regression:

$$(5) \qquad y_{i,k} = \beta_0 + \Sigma_{m=1}^{M}\beta_1^m x_{i,k}^m + E(x_{i,k}|\, k)'\beta_2 + \beta_3 E(y_{i,k}|\, k) + \beta_4\eta_k + \xi_{i,k},$$

where, β_2,β_3 and β_4 measure exogenous, endogenous, and correlated effects, respectively, and $\xi_{i,k}$ is the error term.

As Manski (1993) shows, these effects are not identified in this regression, primarily due to the reflection problem, which arises because even in the absence of correlated effects, simultaneity in the behavior of interacting agents introduces a perfect collinearity between the expected mean outcome of the group and its mean characteristics. This reflection problem hinders the differentiation of the endogenous effect from the exogenous effects. Is group behavior actually affecting individual behavior, or is it simply the aggregation of individual behaviors (if the individual outcomes increase, will the group average also increase)? In other words, even after accounting for observed group characteristics, there can always be unobserved characteristics that can be correlated with both individual outcome and group outcome. So, we cannot distinguish if a group member's action is the cause or the effect of peers' influence, which is the well-known reflection problem.

The important distinction between equation (4) and equation (5) is that, in the former, the assumption is that people interact in networks (k denotes network). Different individuals can belong to the same network, but their relative positions in the network are usually different. As a result, this approach can utilize individual-level variation even within the network. In equation (4), the assumption is that people interact within a group. As a result, individual variation within a group cannot be exploited (see Bramoullé, Djebbari, and Fortin (2009) for details).

In our analysis, while we do not have the information to span the dyadic relations within a network, we do have a variety of intensity measures. Therefore, we adopt an approach that is a combination of both of the approaches above. In the spirit of equation (4), we utilize the intensity measures to identify the endogenous effect at the *group* level. The advantage is that we are able to exploit the individual-level variation. We start by assuming that networks are embedded in groups, which given the social structure in agrarian rural societies in Rajasthan, seems a reasonable assumption.

Individuals interact in networks with different intensities. Under this setup, consider the regression

$$(6) \qquad y_{i,k} = \beta_0 + \Sigma_{m=1}^{M} \beta_1^m x_{i,k}^m + z'_{i,k}\pi_1 + \delta_k + \xi_{i,k},$$

where measures the intensity with which individual interacts in network (the empirical counterpart of in equation (4)), and is the indicator variable for group. Clearly, endogenous, exogenous, and correlated effects cannot be estimated in equation (6), since the network dummy subsumes all of these effects. Now, consider the following rendition of equation (6):

$$(7) \qquad y_{i,k} = \beta_0 + \Sigma_{m=1}^{M} \beta_1^m x_{i,k}^m + z'_{i,k}\pi_1 + E(y_{i,k} | k)^* z'_{i,k}\pi_2 + \delta_k + \xi_{i,k},$$

In this regression, $\pi_2 \neq 0$ only when there exists an endogenous effect.

By using group-level fixed effects, we purge the elements that would undermine establishing the presence of true endogenous effects. With group fixed effects, group-level adoption does not have an identifiable coefficient, but its interaction with the intensity of social exchange does. A significant coefficient of the interaction would establish the presence of endogenous social effects. Unless there are endogenous effects, there should be no variation in the effects of group choices with the intensity of interaction in individual networks. The logical element of this argument is akin to the one in Bandiera and Rasul (2006). The non-linear relationship that Bandiera and Rasul (2006) obtain is used as evidence for the existence of endogenous social effects. This pattern is expected only when endogenous effects are working, since adoption rates fall with the strategic waiting that happens with endogenous effects. Similarly, given the interaction of group adoption with the intensity of social exchange having a bearing on technology choice, we can take this as evidence of the presence of endogenous social effects.

4. RESULTS

4.1 Main Results

In this section we present the results of the regressions of individuals' position in the network (in terms of intensity of interactions) on technology choices—first in isolation, and then in combination with group averages and group fixed effects. We want to highlight the importance of caste in the construction of reference groups. Hence, we also compare results between different compositions of the reference groups, once where the reference groups are defined based on both geographical proximity and caste, followed by the case where groups are defined solely by geography (Tables 5, 6, and 7, respectively). While these are the main results, we start with some preliminary regression in Table 5 that controls merely for area fixed effects, followed by a specification in Table 6 that accounts for caste-area fixed effects. Table 6 includes group fixed effects while table 7 presents the case where groupings are defined solely on geographical proximity (i.e. excluding caste).

The marginal effect from preliminary probit regressions presented in Table 5 look at the associations between group-level adoption and individual farmer's choice of hybrid or traditional varieties. Column 1 presents the most basic model without inclusion of the intensity of individual network variables. With some basic controls of socioeconomic characteristics, there is a significant correlation between group (based on caste and geographical proximity) adoption of hybrid variety and individual farmer's choice.

Subsequently, in column 2 we introduce the intensity of interaction with individual networks across various nodes. There is a significant association between the time spent with family and friends and the probability of adoption of a hybrid variety. Other than the close-knit connections, greater intensity of any other social interaction or information sources does not have a bearing on choice of hybrid varieties of pearl millet seed. In column 3, with the inclusion of components of group fixed effects (area and caste dummies separately), the fixed effects tend to explain most of the variation rendering group adoption insignificant.

Table 6 presents the results of the specification in column 2 that would establish the presence of endogenous social effects: group-level unobserved heterogeneity is controlled for through group fixed effects, with the group defined by both geography and social identity. After controlling for group-level unobserved heterogeneity, the interaction of intensity with group-level average adoption implies the presence of endogenous social effects.

For two measures of intensity—time spent with friends and relatives and in religious activities—interaction with group (caste and location) adoption results in significant effects at a 5 percent significance level. For a given level of group adoption, a unit increase in hours per week spent with friends and relatives increases the probability of adoption of a hybrid variety by about 4 percentage point. The marginal effects are higher at 29 percentage points in the case of religious activities. Alternatively, these results could be interpreted as the effects of group adoption on individual farmer choices for given intensities of interaction with friends and relatives and of participation in religious activities.

From the data, it is not possible to determine how distinct the identities of individuals in these networks are vis-à-vis the identities of others. Religious organizations in India

Table 5. Marginal effects of probit estimate of choice of hybrid varieties of pearl millet: basic regression

Descriptive statistics	(1)	(2)	(3)
Caste-area group average of hybrid variety (m)	0.533***	0.530***	0.054
Hours/week with friends and relatives (p)		0.008**	0.010**
Phone calls to friends and relatives out of village (q)		0.000	0.000
Hours/week at temple/mosque/church, etc. (r)		–0.008	–0.015
Number of organizations in which participation occurred (s)		0.033	–0.007
Hours/week with household members		0.001	0.000
Hours/week with newspaper/radio/TV		-0.001	–0.002
Household size	0.003	0.003	0.001
Years lived in this village	0.001	0.001	0.001
Farmland size in hectares	–0.351***	–0.309***	–0.189*
Monthly off-farm income	0.001	-0.003	–0.000
Monthly farm income	0.012**	0.011**	0.008**
Caste-area group average of consumption trait	0.337	0.298	0.069
Upper caste			0.013
SC/ST			0.104***
Area 1			0.263***
Area 2			–0.140***
Area 3			–0.219***
Area 4			0.105
Area 6			–0.373***
Observations	320	320	320
pseudo R-square	0.111	0.133	0.207

Notes: (a) Each regression has a constant. (b) OBC and Area 5 are the omitted categories because they have the largest shares in the sample. (c) Caste-area groups 7 and 18 are dropped due to insufficient observations (one each). (d) Standard errors clustered by Caste-area groups. (e) *** p<0.01, ** p<0.05, * p<0.1.

to a large extent tend to be exclusionary, not only along religious lines, but on caste lines as well. In temples for upper castes, the lowest castes are typically denied entry. In general, especially in rural societies, individuals attend masses in the temples of their own castes (Thorat and Sabharwal 2010).

There could be several channels for these endogenous effects. For a given level of adoption of hybrid varieties by the reference group, more interaction could result—for example, in better processing of signals. Interaction could also provide supplementary information and resources needed for translating the signal into an actual decision of adoption. These mechanisms essentially comprise the pathways for endogenous working of the social effects. Note that we are not quantifying the size of the endogenous effect, but are merely establishing its existence.

Among the other variables in Tables 4 and 5, we have included the average valuations of consumption traits on a Likert scale of the group members, except when group fixed effects are included. Since the varietal choice could be based on this valuation, it can account for some of the heterogeneity across groups (in specifications where we do not have group fixed effects). As the valuation of attributes can never be exhaustive, admittedly, this method can only create a partial proxy to account for unobserved heterogeneity. However, this variable does not have a significant coefficient.

There is evidence for farmers with larger land sizes being less likely to adopt a hybrid variety. Since pearl millet is a marginal crop, this evidence is most likely the result of its lower importance in the cropping portfolio of larger farmers. Incentives for adoption of a high-yielding, but riskier, variety could be lower for this group of farmers.

The evidence of no significant effect of common pool networks, such as nonreligious organizations, on farmers' choice of hybrid varieties of pearl millet is striking. The Government of India spends significant resources on mass media programs to support its outreach activities in agriculture. Recently, farmers have started taking advantage of the *Kisan* (farmer) call centers set up by the government. Further, the government runs television programs under the Mass Media Support to Agriculture Extension Scheme. Available on public channels, these programs include features, documentaries, success stories of farmers, research inputs, quizzes, crop seminars, and a live phone-in program. The programs are also available in local languages in different states.

Similarly, on extension, the Ministry of Agriculture set up an entire institute—the National Institute of Agricultural Extension Management.—to assist the state governments,

Table 6. Marginal effects of probit estimate of choice of hybrid varieties of pearl millet: group effects included

Descriptive statistics	(1)	(2)
Interaction = (Caste-area group average of hybrid variety)*p		0.044**
Interaction = (Caste-area group average of hybrid variety)*q		0.000
Interaction = (Caste-area group average of hybrid variety)*r		0.295**
Interaction = (Caste-area group average of hybrid variety)*s		–0.055
Hours/week with friends and relatives (p)	0.010**	–0.012
Phone calls to friends and relatives out of village (q)	0.000	–0.000
Hours/week at temple/mosque/church, etc. (r)	–0.014	–0.201**
Number of organizations in which participation occurred (s)	–0.006	0.043
Hours/week with household members	0.000	0.001
Hours/week with newspaper/radio/TV	–0.002	–0.001
Household size	0.001	0.002
Years lived in this village	0.001	0.001
Farmland size in hectares	–0.199**	–0.144*
Off-farm monthly income	–0.001	–0.001
Farm monthly income	0.009**	0.004
Caste-area group dummy 1	0.257***	0.246***
Caste-area group dummy 2	0.184***	0.191***
Caste-area group dummy 3	–0.302***	–0.269***
Caste-area group dummy 4	–0.069	0.195**
Caste-area group dummy 5	–0.238***	–0.143**
Caste-area group dummy 6	–0.276***	–0.136*
Caste-area group dummy 8	–0.331***	0.033
Caste-area group dummy 9	–0.030	0.346***
Caste-area group dummy 10	0.133***	0.223***
Caste-area group dummy 12	–0.042	0.056
Caste-area group dummy 13	–0.027	0.227***
Caste-area group dummy 14	–0.120	0.074
Caste-area group dummy 15	–0.389***	–0.345***
Caste-area group dummy 16	–0.391***	–0.051
Caste-area group dummy 17	–0.424***	–0.102
Observations	320	320
pseudo R-square	0.210	0.243

Notes: (a) Each regression has a constant. (b) Caste-area group 11 is the omitted category because it has the largest shares in the sample. (c) Caste-area groups 7 and 18 are dropped due to insufficient observations (one each). (d) In these regressions the Caste-area group averages are subsumed in the Caste-area group dummies. (e) Standard errors are clustered by Caste-area groups. (f) *** p<0.01, ** p<0.05, * p<0.1.

the Government of India, and other public-sector organizations in effectively managing their agricultural extension and other agricultural management systems. The state of Rajasthan has also tried to improve its extension services. Recently, it has adopted group-based approaches to extension with village extension workers operating mainly through *Kisan mandate* (group of 20 farmers). The state has also been encouraging non-governmental organizations to participate in extension activities, and has been contracting out some extension activities to them, particularly in the far-flung areas where public extension is comparatively weak (Sulaiman and Hall 2008).

4.2 The Importance of Caste

We have emphasized the importance of caste in social networks in the Indian context. Beyond this conjecture, we assess the importance of caste more systematically. In this section, we conduct two tests based on alternative definitions of group: one in which groups are more broadly defined (based on location), and other in which they are more narrowly defined (based on location, caste, and landholding size) than the specifications used for the results in Table 6.

Thus, in Table 7 we redefine the reference groups based solely on geographical proximity (the standard in most papers), and apply the same methodology as before (when

Table 7. Marginal effects of probit estimate of choice of hybrid varieties of pearl millet: without caste-based grouping

Descriptive statistics	(1)	(2)	(3)
Area group average of hybrid variety (n)	0.915***	0.914***	
Interaction = (Area group dummy average of hybrid variety)*p			0.002
Interaction = (Area group dummy average of hybrid variety)*q			–0.003*
Interaction = (Area group dummy average of hybrid variety)*r			0.371
Interaction = (Area group dummy average of hybrid variety)*s			–0.142
Hours/week with friends and relatives (p)		0.010**	0.008
Phone calls to friends and relatives out of village (q)		0.000	0.001***
Hours/week at temple/mosque/church, etc. (r)		–0.010	–0.218
Number of organizations in which participation occurred (s)		0.004	0.068
Hours/week with household members		0.001	0.000
Hours/week with newspaper/radio/TV		–0.002	–0.002
Household size	0.002	0.002	0.001
Years lived in this village	0.002*	0.002*	0.001
Farmland size in hectares	–0.222**	–0.174**	–0.207***
Off-farm monthly income	0.003	–0.001	0.000
Farm monthly income	0.007*	0.006*	0.008**
Group average of consumption trait	0.222**	0.210	
Upper caste	–0.003	0.002	0.025
SC/ST	0.099***	0.106***	0.100***
Area group dummy 1			0.231***
Area group dummy 2			–0.149***
Area group dummy 3			–0.267**
Area group dummy 4			0.099
Area group dummy 6			–0.420***
Observations	320	320	320
pseudo R-square	0.172	0.192	0.222

Notes: (a) Each regression has a constant. (b) OBC and Area 5 are the omitted categories because they have the largest shares in the sample. (c) Caste-area groups 7 and 18 are dropped due to insufficient observations (one each). (d) In regression (3), the Area group averages are subsumed in the Area group dummies. (e) Standard errors are clustered by Caste-area groups. (f) *** p<0.01, ** p<0.05, * p<0.1.

groups were based on both social identity and geographical proximity). Again, the variables of interest, the coefficient of which identifies endogenous effect, are the interaction of intensity measures with group-level adoption. Treating location as the perimeter of networks/reference group, we find that a greater intensity of social exchange no longer has effect in its interaction with group-level adoption of hybrid varieties. As before, the results show a strong, positive association between group adoption and an individual farmer's choice of a hybrid variety.

The exclusion of caste from the reference group establishes the importance of caste in social network analysis in the Indian context. If farmers' adoption a hybrid variety in the locality is higher, great intensity of their social interaction in this context (Table 7) does not translate into greater likelihood of their adoption of a hybrid variety. This is in sharp contrast to the results in Table 6, where group definition incorporated caste as well. Similarly, the time spent at religious institutions reveals no significant effects. In our dataset, interactions for most of the farmers with friends were generally confined to their same castes. The redefining of reference group—i.e., bereft of caste—creates a situation where endogenous effects would tend to weaken.

In the case of meetings with friends and relatives, as well as interactions in religious centers, there is sorting along caste lines. Hence, it is informative that the intensity of interaction with a group that does not take caste composition into account has no effect on technology choices.

Next we define the reference group in greater detail. In particular, we decompose the largest caste group (in terms of share of population)—i.e., OBC—into two land-size classes: large and small. Large land size corresponds to land areas that are larger than median holdings in the sample. In a large caste group, such as OBC, this decomposition could be useful, since within the OBC group, social learning would require similarity on a larger set of characteristics, such as land size.

In Table 7, we present the results after redefining the group to be determined by location, caste, and land sizes. The interaction between group and intensity measures for the close-knit networks and measures related to socialization in religious places remain significant. Compared with the results in Table 6 where these effects were insignificant, the interaction of narrowly defined groups provides further evidence for the existence of endogenous social effects.

5. CONCLUSIONS & POLICY IMPLICATIONS

In this paper we study the low rate of adoption of hybrid varieties of pearl millet in the Indian state of Rajasthan from a social network perspective. We show that close-knit networks and religious organizations have been effective for farmers in determining their choice of technology. Specifically, these connections could comprise family and friends or religious gatherings, and are in general restrictive. For these connections, we also establish the existence of endogenous social effects. However, in India's socially fragmented rural agrarian society, there are limits for translating these social effects into social multipliers.

With such evident fragmentation within the population of pearl millet farmers, interventions aiming to deliver new technologies at a large scale—for example, hybrid pearl millet seeds with high iron levels—would require networks, sources of information, and services that are less exclusionary than friends, family, and religious-based organizations. We hypothesized these nodes to be the media and nonreligious organizations, in particular, along with the public-sector-managed agricultural extension services. Our empirical results show that these channels have no significant impact on a farmer's decision to adopt a hybrid variety. This finding is crucial for policy, since these channels comprise direct policy levers in a fragmented society, such as India. Indeed, several government programs in India have relied on these channels to run large-scale seed-adoption programs. The ineffectiveness of these sources could be a prime factor for the limited dissemination of hybrid technologies, such as hybrid pearl millet seeds in Rajasthan.

In different settings, social fragmentation could be an important factor in determining outcomes. The evolving consensus in the literature is that ethnic fragmentation potentially has negative consequences on macro-economic performance (see, for example, Alesina and Tabellini 1989 and Collier 2000). In microeconomics literature, the role of fractionalization is somewhat understudied. With fragmentation, micro-level impacts can be significant (e.g., low rates of adoption of a new technology, such as hybrid seeds of a crop), if inclusive channels are not well developed.

Finally, going forward, the marketing and delivery strategy for a new variety requires careful planning. The findings in this study show clearly the channels to be tapped into for maximizing the uptake of a new technology. As in different settings, farmer-to-farmer learning is very important. Given the evidence on strategic waiting by farmers in different contexts, as part of delivery strategy, taking continuous small steps could be more effective than implementing big packages all at once.

The finding that such inclusive channels as extension services, media, and organizations are not effective in determining choice of technology does not mean that they should not be tapped into in order to popularize a new seed variety. Our empirical findings suggest that in their current form in the state of Rajasthan, the roles played by these sources of information are limited. The implications would be to develop these sources in a way that encourages farmers to use them more extensively. Recall that less than 4 percent of this study's respondents obtained their information on seeds from media sources—an extremely low number. There is certainly scope for increasing the outreach of these channels that can play a significant role in spreading agricultural technology in a fragmented society.

The media outlets should be exploited by making their delivery of information more accessible and appealing to the farmers. There is sufficient mileage to be drawn from such widespread channels as television and radio. With more than 61 percent of rural households having access to mobile phones, this technology can be utilized as an important source of information.

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