AGRICULTURAL ECONOMICS

Agricultural Economics 40 (2009) 493–505

The impact of social networks on hybrid seed adoption in India

Ira Matuschke[a,*], Matin Qaim[b]

[a]Global Perspective Studies Unit, Food and Agriculture Organization of the United Nations (FAO), Viale delle Terme di Caracalla, 00153 Rome, Italy
[b]Department of Agricultural Economics and Rural Development, Georg-August-University of Goettingen, 37073 Goettingen, Germany

Received 30 May 2008; received in revised form 26 January 2009; accepted 20 April 2009

Abstract

This article adds to the literature about the impact of social networks on the adoption of modern seed technologies among smallholder farmers in developing countries. The analysis centers on the adoption of hybrid wheat and hybrid pearl millet in India. In the local context, both crops are cultivated mainly on a subsistence basis, and they provide examples of hybrid technologies at very different diffusion stages: while hybrid wheat was commercialized in India only in 2001, hybrid pearl millet was launched in 1965. The analysis is based on surveys of wheat and millet farmers in the state of Maharashtra. Comprehensive data on farmer characteristics and social interactions allow for identifying individual networks, thereby improving upon previous research approaches that employed village-level variables as proxies for network effects. Using econometric models, we find that individual social networks play an important role for technology adoption decisions. While village-level variables may be used as suitable proxies at later diffusion stages, they tend to underestimate the role of individual networks during early phases of adoption.

JEL classification: Q13, Q16, Q33

Keywords: Social networks; Adoption of hybrid seed technologies; Wheat; Pearl millet; India

1. Introduction

Agriculture is the motor of growth and poverty reduction in developing economies (Maxwell, 2004). In the past decades, technological change—induced by the adoption of innovations—was a critical element to increase agricultural productivity and economic growth (Self and Grabowski, 2007). Yet, productivity increases were far from uniform. While some countries and regions benefited immensely from the adoption of new technologies, for example, during the time of the Green Revolution, others have been left behind (Chavas, 2001). This worrisome trend triggered a large amount of economic studies aimed at identifying barriers to technology adoption and consequently to agricultural and economic growth. Micro-level studies of adoption in rural areas analyze factors that determine farmers' adoption decisions (Feder et al., 1984). Originating in rural sociology and mainly considering individual-specific determinants in the beginning, over time adoption studies have become more and more complex by including dynamic elements like learning by doing and learning from others (Foster and Rosenzweig, 1995). In fact, recent empirical studies showed that social learning, that is, interacting with others to learn about an innovation, is an important element to innovation adoption and diffusion (Barrett, 2005; Feder and Savastano, 2006; Granovetter, 2005). Interaction-based models examine how the individual's behavior is influenced by the characteristics or behavior of others (Brock and Durlauf, 2001).

Adoption studies that empirically considered social learning processes or social networks mainly used adoption rates at the village level as a proxy variable for network effects (e.g., Foster and Rosenzweig, 1995; Isham, 2002; Pomp and Burger, 1995). This approach essentially implies that *all* farmers in a village influence an individual in the decision to adopt an innovation. Recent studies, however, contest this approach by stating that farmers do not rely on the whole village for gathering information and making an adoption decision. They rather rely on small *individual* social networks, which do not necessarily coincide with geographic boundaries (e.g., Bandiera and Rasul, 2002; Boahene et al., 1999; Conley and Udry, 2001; Miguel and Kremer, 2003). This seems to be particularly relevant in the context of rural India, where social stratifications, for example, by caste, influence village dynamics. One reason why only few studies to date have analyzed individual social networks is that a large amount of data are required. It is necessary to have information not only on the individual itself but also on its social contacts. Such specific information is not readily available if not particularly asked for in a household survey.

*Corresponding author: Tel.: +39-366-4541213; fax: +39-06-57056172.
E-mail address: ira.matuschke@fao.org (I. Matuschke).

 DOI: 10.1111/j.1574-0862.2009.00393.x

The objectives of this article are twofold. First, we aim to provide further evidence on the importance of individual social networks in the adoption process by examining the adoption of hybrid wheat and hybrid pearl millet in the state of Maharashtra, India. In the local context, both crops are cultivated mainly on a subsistence basis. Hybrid wheat was launched in India in 2001, and to date adoption rates are still relatively low (Matuschke et al., 2007). Hybrid pearl millet, on the other hand, was introduced to the Indian market already in 1965, and adoption rates are high, particularly in semiarid areas (Matuschke and Qaim, 2008). Considering these two staple food crops allows us to look at the importance of networks at different diffusion stages. Second, we consider endogenous and exogenous network effects to determine which of these effects has a more significant impact on adoption. An endogenous effect is defined as the effect the behavior of a network member has on the individual's decision (e.g., whether the member himself/herself is an adopter or not). An exogenous effect is the impact that specific characteristics, like education or age, of the network member may have on the individual adoption decision (Manski, 2000). Our analysis complements Bandiera and Rasul (2002), who identified endogenous effects but were unable to estimate exogenous effects due to data constraints.

Analyzing social networks in detail can improve the understanding of social learning in adoption decisions and can help policy makers to develop more targeted strategies to promote agricultural innovations and rural growth. Such an analysis could also lend support to new demand-driven extension approaches, like farmer field schools, which actively consider farmer communication flows and farmer-specific needs. The impact of these new approaches on innovation adoption are currently being evaluated and tested in different set-ups (see Davis, 2008, for a discussion).

2. Methodology

Our approach is based on the simple model of social learning laid out in Bandiera and Rasul (2006). The notation follows Bandiera and Rasul (2002). Assume that the adoption decision a of farmer i living in village v is expressed as

$$a_{iv} = \beta X_i + \gamma a_{n(i)} + \delta X_{n(i)} + e_{iv}. \tag{1}$$

The adoption decision is dependent on the farm household's characteristics X as well as the adoption decision of the social network partners $a_{n(i)}$ and their characteristics $X_{n(i)}$. γ hereby measures the *endogenous* effects, that is, the impact that the adoption decision of the others has on the individual. For example, a farmer might be more willing to adopt a new seed technology if there are other adopters in the social network with whom he or she can share information on crop cultivation. δ measures the *exogenous* effects, that is, the effects that the characteristics of the social network members have on the individual, independent of whether the social network partners are adopters or not (Bandiera and Rasul, 2002; Manski, 1993). For example, a farmer might be more willing to adopt a new seed technology if there is a seed dealer in the social network whom he or she could ask for advice, regardless of whether or not the seed dealer is an adopter. In the simple model of social learning it is assumed that farmers do not know the optimal input level associated with a new technology. After every harvest, farmers therefore update their beliefs on the optimal input use based on their experience in the last season, all other previous seasons, and the experiences of their network partners (i.e., Bayesian updating). Based on this update, farmers try to move closer to the optimum input level to maximize the profitability of their farming operations in the next season. Yet, in evaluating the behavior of their network members, farmers do not only consider past planting decisions in their network. They also rely on expectations about the network members' planting decisions in the future, which can be inferred from the characteristics of the network members (Foster and Rosenzweig, 1995). Therefore, in Eq. (1), exogenous network variables are expected to have an independent effect on adoption decisions. e_{iv} is an error term, which is assumed to be normally distributed and uncorrelated with any of the variables.

To estimate Eq. (1), information on the individual and the social network is essential. Often, such comprehensive data are not available. In that case, analysts are restricted to estimate

$$a_{iv} = \beta X_i + \gamma \bar{a}_v + e_{iv}, \tag{2}$$

whereby $\bar{a}_v$ captures the average adoption rate at the village level. This data-driven simplification implies that the network effect is no longer individual specific. It becomes impossible to differentiate whether individuals behave similarly due to endogenous or exogenous effects or solely due to correlated effects at the village level, for example, village infrastructure. Consequently, social network impacts cannot be clearly identified, and estimation results may be biased or inconclusive.

Bandiera and Rasul (2002), who use a rich data set on sunflower adoption in Mozambique, are able to avoid this shortcoming by using individual-specific data. They estimate the following equation

$$a_{iv} = \beta X_{iv} + \gamma a_{n(i)} + \kappa G_v + e_{iv}. \tag{3}$$

Having identified *n(i)* allows them to estimate social network effects, and by including village fixed effects G_v they are able to control for unobservables at the village level that may influence adoption. However, in their model specification, Bandiera and Rasul are unable to specify the exogenous effect, δ. Yet, differentiating between endogenous, exogenous, and village effects can be very relevant from a policy perspective (Manski, 2000). Assume, for example, that seed samples of a new crop variety are handed out to some farmers. If the selected farmers are cultivating the new variety successfully and thereby encourage other farmers in their network to adopt, then $\gamma > 0$ and the seed handout achieved its aim. If, however, the adoption decision is solely dependent on exogenous effects or underlying village effects, then seed handouts would be less effective.

Our research extends the approach of Bandiera and Rasul (2002) by estimating both the endogenous and exogenous effects. Thus, we are able to identify which effects have a greater impact on adoption. We estimate the following equation

$$a_{iv} = \beta X_{iv} + \gamma a_{n(i)} + \delta X_{n(i)} + \kappa G_v + e_{iv}, \tag{4}$$

whereby adoption is modeled as a binary choice problem, a_{iv} $\{0, 1\}$.

When identifying social network effects the researcher generally faces two potential econometric problems, namely correlated unobservables and simultaneity. The first problem may arise in an individual or contextual framework (Manski, 2000). A farmer may adopt due to unobserved individual characteristics that influence the adoption decision, such as ability or outgoingness. In our analysis, we try to proxy for such characteristics. Furthermore, a farmer may choose a certain group based on individual features, for example, farmers who cultivate mainly wheat may group with other wheat farmers to be able to exchange information. If this is the case, then group membership itself becomes endogenous. Assuming that the network is correctly specified, we are able to address this problem because we have information on the farmer's group composition. Correlated variables in a contextual framework comprise village unobservables, which we can manage by including village fixed effects.

The second potential problem is simultaneity. The mean behavior of the group influences the individual, who in turn influences the group. This problem has been termed the reflection problem by Manski (1993).[1] To circumvent this problem, different approaches have been suggested. One is to use an instrumental variable approach where the instrument is correlated with the farmer's network but uncorrelated with any unobservable variables that influence group membership and individual adoption. Another approach, as suggested by Manski (2000), is to assume a dynamic adoption framework, where an individual farmer is influenced by the behavior of his network but with a lag. This "seeing is believing" type of learning assumes that a farmer first observes his fellows and then decides to adopt in the next growing season depending on their success. Such behavior has been illustrated in a number of empirical studies (e.g., Dong and Saha, 1998; Foster and Rosenzweig, 1995; Neill and Lee, 2001). We try to apply such a dynamic approach in Section 5 when testing for the robustness of our results.

3. Data collection and descriptive statistics

3.1. Study region

Data collection on wheat and pearl millet production took place in the Indian state of Maharashtra. Agriculture plays an important role in Maharashtra; it employs more than half of the state's labor force and contributes 13% to gross domestic product. Maharashtra is located in the semiarid tropics, and about 84% of the state's cultivable areas depend directly on monsoon rainfalls. We chose Maharashtra as study region because wheat and pearl millet are two of the state's principal crops in terms of production and consumption. In addition, Maharashtra is the state with the largest hybrid wheat and second largest pearl millet area in India (Fertiliser Association of India, 2004; Matuschke et al., 2007). Crop yields in Maharashtra are generally lower than national averages, because of less favorable soil, geographic, and climatic conditions (Government of Maharashtra, 2005). To increase agricultural productivity, the state government is actively seeking to increase the distribution of hybrids and improved certified seeds. However, this goal has been met with only moderate success. One reason could be information constraints among farmers. According to a survey of the National Sample Survey Organisation (NSSO), only 46% of all farmers in Maharashtra have access to (or do access) information on modern agricultural technologies (NSSO, 2005). The sources most frequently used to receive information are the input dealer followed by the most progressive farmer in the village. Our own primary data collection took place in 2004; the two data sets comprise the 2003/2004 production period.

3.2. Wheat and pearl millet data sets

Wheat hybrids were launched by the Maharashtra Hybrid Seed Company (Mahyco) in 2001. Company breeders achieved heterosis in wheat by using cytoplasmic male sterility. The resulting wheat hybrid is adapted relatively well to moisture stress (Zehr, 2001). Nation-wide adoption rates grew on average 31% per annum from 2001 to 2008. To date, Mahyco is the sole producer of hybrid wheat seeds in India. For our data collection, we selected 284 wheat farmers using stratified random sampling methods. Maharashtra is divided into four geopolitical regions and 35 districts. In each of the three largest regions, we purposively selected one important wheat-growing district (Government of Maharashtra, 2005). The three districts surveyed are Nashik, Yavatmal, and Aurangabad. In each district, we randomly chose seven villages, where 12–15 interviews were carried out with randomly selected farmers. Since the number of hybrid wheat adopters was still relatively small in 2004, they were over-sampled from complete seed sales lists. In total, the hybrid wheat data set comprises 87 adopters and 197 nonadopters. Of the 87 adopters, 72 farmers had adopted hybrid wheat for the first time in the year of the survey. Eight farmers had already cultivated hybrid wheat for one season, and seven farmers for two seasons. Information was collected on wheat production, household characteristics, as well as social networks. Table 1 displays selected descriptive statistics for the wheat data set.

Hybrid pearl millet was introduced in India in 1965. It is one of the few hybrid food crops that became available early on in the country. Pearl millet hybrids spread rapidly during

[1] Brock and Durlauf (2001) offer an excellent summary on the reflection problem.

Table 1
Descriptive sample statistics for wheat farmers

	Adopters ($n = 87$)	Nonadopters ($n = 197$)
Individual characteristics		
Education (in years)	7.54 (4.30)	7.70 (4.81)
Experience (of growing wheat in years)	14.63 (9.76)	15.99 (12.12)
Farm size (land owned in acres)	12.74 (12.49)	7.81 (8.97)***
Irrigation (irrigated area/farm size)	0.69 (0.33)	0.68 (0.35)
Household expenditures (annual per capita household expenditures in 1,000 Rs[a])	12.55 (9.00)	8.94 (5.05)***
Information constraint (dummy, 1: constraint)	0.05 (0.21)	0.29 (0.45)***
Credit constraint (dummy, 1: constraint)	0.32 (0.47)	0.48 (0.50)**
Association membership (dummy, 1: member in at least one village association)	0.53 (0.50)	0.36 (0.48)***
Village and regional characteristics		
Village adoption rate in 2003/2004	0.12 (0.12)	0.10 (0.10)
Number of households in the village	434.86 (330.09)	374.89 (281.65)
Distance to input dealer (in km)	10.39 (8.53)	10.30 (8.44)
Distance to output market (in km)	17.90 (9.68)	17.68 (10.05)
Average soil quality (village soil quality dummy)	0.32 (0.47)	0.27 (0.44)
Poor soil quality (village soil quality dummy)	0.16 (0.37)	0.22 (0.41)
Yavatmal (district dummy)	0.38 (0.49)	0.30 (0.46)
Aurangabad (district dummy)	0.32 (0.47)	0.38 (0.49)

Note: Numbers in parentheses are standard deviations. *, **, *** mean differences are significant at the 90%, 95%, and 99% confidence levels, respectively.
[a]Rs = Indian Rupees. 1 USD ~ 48.18 Rs (January 2009).

Table 2
Descriptive sample statistics for pearl millet farmers

	Adopters ($n = 207$)	Nonadopters ($n = 59$)
Individual characteristics		
Education (in years)	7.12 (4.66)	4.05 (4.23)***
Experience (of growing pearl millet in years)	19.89 (13.88)	23.83 (14.01)*
Farm size (land owned in acres)	9.94 (12.16)	9.30 (8.88)
Irrigation (irrigated area/farm size)	0.28 (0.34)	0.10 (0.24)***
Household expenditures (annual per capita household expenditures in 1,000 Rs[a])	9.65 (6.12)	7.68 (5.68)***
Information constraint (dummy, 1: constraint)	0.41 (0.49)	0.75 (0.43)***
Credit constraint (dummy, 1: constraint)	0.49 (0.50)	0.75 (0.44)***
Association membership (dummy, 1: member in at least one village association)	0.43 (0.50)	0.27 (0.45)**
Village and regional characteristics		
Village adoption rate in 2003/2004	0.86(0.23)	0.45 (0.36)***
Number of households in the village	306.79 (147.81)	263.93(86.22)**
Distance to input dealer (in km)	9.47 (9.50)	15.58(11.79)***
Distance to output market (in km)	23.18 (19.44)	34.46(23.95)***
Average soil quality (village soil quality dummy)	0.28 (0.45)	0.34 (0.47)
Poor soil quality (village soil quality dummy)	0.27 (0.44)	0.37 (0.49)
Ahmednagar (district dummy)	0.24 (0.43)	0.69 (0.46)***
Dhule (district dummy)	0.35 (0.48)	0.20 (0.41)**

Note: Numbers in parentheses are standard deviations. *, **, *** mean differences are significant at the 90%, 95%, and 99% confidence levels, respectively.
[a]Rs = Indian Rupees. 1 USD ~ 48.18 Rs (January 2009).

the late 1960s and 1970s. Today, hybrid pearl millet is sold by a large number of private and public companies (Gautam, 2003). Adoption rates of hybrid pearl millet in Maharashtra are high, but vary widely by district (Gujral, 1999). For our data collection, we selected 266 pearl millet farmers using stratified random sampling methods. We purposively selected three large pearl millet-growing districts from three different regions of Maharashtra. These districts are Ahmednagar, Aurangabad, and Dhule. In each district, we randomly chose seven villages, and in each village 12–15 farmers were randomly selected and personally interviewed. In total, the hybrid millet data set comprises 207 hybrid adopters and 59 nonadopters. Information was collected on pearl millet production, household characteristics, social networks, and adoption history. Table 2 illustrates selected descriptive statistics for the pearl millet data set.

In both surveys, in addition to the household-level information, data on village variables were obtained by interviewing the village council heads. This was further supplemented by

Table 3
Number of network members reported by wheat and pearl millet farmers (in %)

Number of network members	Wheat farmers	Pearl millet farmers
Zero	8%	5%
One	18%	24%
Two	32%	40%
Three	42%	31%

village census data (Banthia, 1995). Village characteristics of interest in our context include variables like the local hybrid adoption rate, the number of households,[2] distances to output and input markets, and soil conditions. These characteristics, which serve as explanatory variables in the regression analyses, are also summarized in Tables 1 and 2.

3.3. Social networks

To obtain information on individual-specific social networks, in both surveys we asked each farmer to name a maximum of three persons to whom he or she talks most frequently about agricultural decisions.[3] This approach is defined as the sociometric method to measure network links (Rogers, 2003). It was pioneered by Coleman et al. (1957) and applied in an agricultural context by Conley and Udry (2001) in their study on the adoption of pineapples in Ghana. The advantage of restricting a farmer to name three persons is that he or she will probably name the three strongest network members, which ensures that the analyst gets a close picture of the individual network. The disadvantage, however, is that the farmer might exchange crucial information that leads to adoption with a more distant network partner (Rogers, 2003; Santos and Barrett, 2004).[4] A solution to this problem would be to let the farmer name an unlimited number of network members and then differentiate between strong and weak ties. Yet, as Table 3 shows, more than half of the sample farmers actually reported fewer than three network members. In a final step, we asked the farmer about the characteristics of his or her network members, allowing us to identify exogenous network variables.[5]

[2] The village household numbers are based on the Village Census of Maharashtra 1991. We take the number of households instead of the total village population, because we assume that the number of households fluctuates less over a decade. The reason for this is that traditionally only the daughters leave the household upon marriage.

[3] As Udry and Conley (2005) rightly point out, there are a number of social networks available to the farmer, for example, information, finance, land, and labor networks. Survey questions need to specify the particular network of interest in the analysis. Here, we are interested in information networks available to the farmer.

[4] This theory is called "The strength of weak ties," which was established by Granovetter (1973).

[5] These characteristics of network members are as *perceived* by the farmer. Hogset and Barrett (2007), in their study on the adoption of natural resource management techniques in Kenya, established that respondents may not exactly know the characteristics of their peers. Yet, we argue here that individual adoption decisions are not driven by the actual behavior of network partners, but by behavioral perceptions that an individual farmer has.

Table 4
General information sources on modern technologies

	Wheat farmers	Pearl millet farmers
	Information source (%)	
Hybrid seed adopters	Input dealer (55)	Input dealer (40)
	Seed company (14)	Other farmers (19)
	Other farmers (13)	Most progressive farmer (11)
Nonadopters	Input dealer (52)	Other farmers (40)
	Most progressive farmer (19)	Input dealer (38)
	Other farmers (17)	Most progressive farmer (7)

Note: Percentages do not add up to 100, because only the three most important information sources are listed here.

How relevant are other farmers in the information gathering and adoption of modern seed technologies? Table 4 differentiates between sources that sample farmers use to receive general information on modern agricultural technologies. The results presented are in line with those of the NSSO survey described above. For information on modern technologies, farmers rely on the input dealer, the most progressive farmer in the village, and other farmers. Looking at adopters and nonadopters separately reveals that adopters receive their information mostly from formal sources like the input dealer, while for nonadopters other farmers play a somewhat more important role.

Table 5 looks at the social networks of adopters and nonadopters more closely. Comparing social network characteristics with the individual characteristics presented in Tables 1 and 2, it appears that networks are formed along homophilous lines, that is, among people who are similar to each other (Feder and Savastano, 2006; Rogers, 2003). When being asked who their network members are, 64% of the sample farmers said that they are mainly friends/other farmers, and 29% said that their network partners are mainly family or extended family members. In addition, network members tend to be of the same caste, they live close to each other, and communicate often. Networks are actively used for borrowing and lending activities. This relation has been examined in greater detail by Hogset (2005) and De Weerdt (2005). The large majority of farmers seek advice from network partners, which is unsurprising as we primarily consider information networks. Striking in Table 5 is that adopting farmers have significantly more other adopters in their social network than nonadopters. This holds for both crops—the recently marketed hybrid wheat and the long-established hybrid pearl millet.

4. Modeling adoption

In this section, we present the regression analyses and discuss their results. The adoption of hybrid wheat and pearl millet is examined separately before the results are briefly compared and synthesized. To model adoption, we estimate three probit models, which correspond to Eqs. (2), (3), and (4) in Section 2.

Table 5
Descriptive statistics of social network members (NM) for adopting and nonadopting farmers

Variable	Description	Hybrid wheat		Hybrid pearl millet	
		Adopters ($n = 87$)	Nonadopters ($n = 197$)	Adopters ($n = 207$)	Nonadopters ($n = 59$)
Age	Average age of NM (years)	38.40	38.30	41.38	39.88
		(8.82)	(9.92)	(11.07)	(12.25)
Caste	Share of NM who have the same caste as the individual farmer	0.76	0.71	0.74	0.77
		(0.37)	(0.41)	(0.41)	(0.40)
Farm size	Average farm size of NM (acres)	14.19	11.61	11.50	12.37
		(10.98)	(12.67)	(11.36)	(9.99)
Distance	Average geographical distance to the NM (in km)	1.28	1.03	2.50	1.32
		(2.92)	(3.46)	(19.12)	(4.40)
Communication	Average frequency of communication with the NM (days per month)	20.14	20.62	13.79	14.67
		(9.35)	(9.56)	(9.92)	(10.52)
Adoption	Share of the NM that are hybrid adopters	0.41	0.14***	0.91	0.40***
		(0.40)	(0.27)	(0.27)	(0.47)
Association	Share of NM that are members in a village association	0.53	0.45	0.44	0.32
		(0.41)	(0.37)	(0.45)	(0.43)
Borrowing	Share of NM that the individual borrows money from	0.46	0.42	0.48	0.53
		(0.41)	(0.39)	(0.48)	(0.48)
Lending	Share of NM that the individual lends money to	0.48	0.48	0.45	0.44
		(0.46)	(0.47)	(0.48)	(0.47)
Advice	Share of NM that the individual seeks agricultural advice from	0.93	0.92	0.88	0.91
		(0.21)	(0.25)	(0.30)	(0.28)

Note: Numbers in parentheses are standard deviations. *, **, *** mean differences between the network characteristic of adopters and nonadopters are significant at the 90%, 95%, and 99% confidence levels, respectively.

4.1. Hybrid wheat adoption

Table 1 displays a summary of the explanatory variables used in the regression analysis. In their seminal review paper, Feder et al. (1984) pointed out that individual variables like education, farm size, income, and experience are significant and positive determinants of adoption. For example, in a study on the adoption of high-yielding varieties during the Green Revolution, Feder and O'Mara (1981) showed that larger-scale farmers generally tended to be early adopters. Although the technology itself was scale neutral and divisible, larger farmers were better endowed to take the associated innovation risks.

In addition, we expect farmers with higher levels of education and/or experience to be earlier adopters, because they are usually more informed and understand better how to use new technologies successfully (e.g., Abdulai and Huffman, 2005). Different empirical studies have further shown that household living standard has a significant positive impact on adoption (see Feder et al., 1984, for examples). In our context, we use annual per capita household expenditures as an indicator of living standard, as this is usually considered a more reliable measure than income (Grosh and Glewwe, 2000). Yet, both income and expenditures are associated with a potential endogeneity problem in the adoption context, as technology adoption is not only influenced by living standard, but might also influence living standard itself. However, since over 80% of the hybrid wheat farmers in our sample were first-time adopters, we do not expect endogeneity to be a serious problem here.

In addition to living standard, Feder and O'Mara (1981) emphasized the importance of proper access to information and credit as facilitating elements in the adoption process. We therefore define information and credit constraint dummy variables. The information constraint variable is founded on self-reported access to information on modern agricultural technologies. The credit constraint is based on the farmers' self-reported access to a loan from the bank or credit from the input dealer. As farmers in Maharashtra mainly rely on rain fed agriculture, we also include the share of the total farm size that is irrigated. We expect this variable to have a positive effect on adoption, because farmers with better irrigation facilities may face fewer risks associated with varying weather conditions (Antle and Crissman, 1990). To describe the openness of farmers, Dasgupta (1989) suggested using the membership of farmers in rural associations or the village council. Participation in such associations might expose the farmer more easily to new ideas and concepts. Therefore, an association membership dummy, which captures whether or not the farmer is a member in a village organization, is added and expected to have a positive impact on adoption behavior.

To control for village characteristics, we enter the village-level variables. Among these is the village adoption rate to test for the validity of some of the previous adoption studies. Other village-level variables include the distance to the input dealer and to the output market, the number of households in the village, and the soil quality of the village compared to neighboring villages. Farmers who live in villages with shorter distances to the input dealer and output market may receive

Table 6
Modeling the adoption of hybrid wheat

Explanatory variable	Model (1)		Model (2)		Model (3)	
	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
Individual characteristics						
Education	1.52E-03	0.25	7.93E-04	0.13	−4.54E-04	−0.07
Experience	−2.25E-03	−0.86	−1.91E-03	−0.70	−1.53E-03	−0.48
Farm size	3.77E-03	1.23	3.98E-03	1.24	4.33E-03	1.18
Irrigation	−6.47E-03	−0.07	0.01	0.12	0.02	0.21
Household expenditures	0.01***	2.70	0.01*	1.83	0.01*	1.79
Information constraint	−0.25***	−3.36	−0.23***	−3.04	−0.25***	−2.89
Credit constraint	−0.03	−0.60	−0.03	−0.52	−0.05	−0.82
Association membership	0.11*	1.87	0.10*	1.66	0.12*	1.80
Village and regional characteristics						
Village adoption rate 2003/2004	0.15	0.51				
Distance to input dealer			6.72E-03	1.43	7.22E-03	1.42
Distance to output market			−2.68E-03	−0.78	−3.07E-03	−0.81
Number of households in the village			2.13E-04*	1.65	2.43E-04*	1.79
Average soil quality[a]			0.07	0.88	0.05	0.58
Poor soil quality[a]			0.06	0.70	0.07	0.72
Yavatmal[b]	0.08	0.94	0.12	1.31	0.14	1.33
Aurangabad[b]	0.02	0.32	0.12	1.39	0.15	1.47
Network characteristics						
Share of adopting network members (NM)			0.37***	4.18	0.39***	4.13
Age of NM					1.26E-03	0.37
Caste of NM					0.08	1.00
Farm size of NM					−1.71E-03	−0.56
Communication with NM					−3.07E-04	−0.08
Distance to NM					4.90E-04	0.05
Log likelihood	−150.81		−138.75		−130.66	
Pseudo (R^2)	0.13		0.20		0.20	

Note: Coefficients can be directly interpreted as marginal effects on the probability to adopt (evaluated at sample means). Standard errors are robust. *, **, *** coefficients are significantly different from zero at the 90%, 95%, and 99% confidence levels, respectively.
[a]Reference variable is high soil quality.
[b]Reference variable is Nashik district.

more information on new seed technologies and may also be easier able to market their surplus produce. In the same line, farmers who live in larger villages may be able to access infrastructures that facilitate innovation uptake easier. Finally, district dummies capture possible regional effects.

Table 6 displays the regression results. Coefficients can be directly interpreted as marginal effects on the probability to adopt (evaluated at sample means). In model (1), which corresponds to Eq. (2), the village adoption rate 2003/2004 is used as a proxy variable of social network effects. The village adoption rate has the expected sign, but is insignificant. Factors that significantly influence the adoption of hybrid wheat are association membership (as a proxy for openness), per capita expenditures (to capture the household living standard), and information. Farmers who are information constrained are 25 percentage points less likely to adopt.[6] Richer farmers are more likely to adopt hybrid wheat, which might be explained by the fact that they are more able to bear the risks associated with innovations, for example, the risk of crop failures in the light of high seed prices. Farm size, education, and experience do not play a significant role in the setup of model (1).

Model (2), which corresponds to Eq. (3), includes the share of adopting network members into the regression analysis and adds village fixed effects. We depart slightly from the approach of Bandiera and Rasul (2002, 2006) in this estimation. In their study, they had asked the individual farmer how many adopters he or she knows. They then used the number of adopters known as a proxy for the farmers' wider network. Instead of using the number of adopters known, we use the share of adopters in the farmer's close social network. This also facilitates comparisons with the previously used village adoption rates as a proxy. Table 6 demonstrates that the network adoption rate variable is highly significant. A larger share of adopters in the personal network increases the farmer's probability to adopt. Moreover, as in model (1), access to information, household expenditures, and association membership are important determinants of adoption. With respect to the village and regional characteristics, the size of the village (expressed as the number of households) has a small, but positive impact on adoption.

[6] To test the hypotheses that more open farmers might be less information constrained, we added an interaction term of the variables membership and information in models (1), (2), and (3). This term was insignificant in all cases.

Table 7
Modeling the adoption of hybrid pearl millet

Explanatory variable	Model (4)		Model (5)		Model (6)	
	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
Individual characteristics						
Education	0.02***	3.02	2.53E-03	0.49	7.41E-03	1.47
Experience	−6.98E-04	−0.40	−3.22E-03**	−2.48	−2.01E-03	−1.43
Farm size	−1.14E-03	−0.61	−8.64E-04	−0.51	6.12E-04	0.36
Irrigation	0.07	0.69	0.05	0.63	0.02	0.25
Household expenditures	1.36E-03	0.28	4.62E-03	1.16	3.60E-03	0.97
Information constraint	−0.09*	−1.83	−0.04	−1.07	−0.06*	−1.68
Credit constraint	−0.05	−0.94	−0.02	−0.41	−0.04	−1.11
Association membership	0.02	0.37	−0.03	−0.57	−0.05	−1.17
Village and regional characteristics						
Village adoption rate 2003/2004	0.41***	4.54				
Distance to input dealer			−1.04E-04	−0.06	−4.05E-04	−0.26
Distance to output market			−1.07E-03	−1.22	−7.04E-04	−0.74
Number of households in the village			8.29E-04***	2.69	7.10E-04***	2.61
Average soil quality[a]			−0.11**	−2.05	−0.11***	−2.02
Poor soil quality[a]			−0.21***	−2.92	−0.23***	−2.91
Ahmednagar[b]	−0.08	−1.15	−0.34***	−3.49	−0.25***	−3.27
Dhule[b]	0.01	0.13	0.04	0.61	0.08	1.38
Network characteristics						
Share of adopting network members (NM)			0.25***	5.25	0.33***	6.34
Age of NM					2.27E-03	1.42
Caste of NM					−0.04	−0.80
Farm size of NM					−2.52E-03	−1.55
Communication with NM					2.20E-03	1.14
Distance to NM					−7.08E-04	−1.32
Log likelihood	−90.66		−72.98		−57.99	
Pseudo (R^2)	0.35		0.48		0.56	

Note: Coefficients can be directly interpreted as marginal effects on the probability to adopt (evaluated at sample means). Standard errors are robust. *, **, *** coefficients are significantly different from zero at the 90%, 95%, and 99% confidence levels, respectively.
[a]Reference variable is high soil quality.
[b]Reference variable is Aurangabad district.

Model (3), which corresponds to Eq. (4), adds network characteristics to the regression analysis. The results are somewhat surprising; all coefficients associated with these characteristics are individually and jointly insignificant, while the influence of the share of adopting network members remains largely unaffected. We conclude that only the behavior of network members, not their characteristics, matters for the adoption decision. Household expenditures, openness, access to information, and village size remain significant determinants of adoption, as in model (2).

4.2. *Hybrid pearl millet adoption*

Table 2 displays the summary statistics of the variables chosen for analysis of hybrid pearl millet adoption. Table 7 shows the regression results. As in the case of hybrid wheat, coefficients can be directly interpreted as marginal effects on the probability to adopt (evaluated at sample means). Model (4) is equivalent to "conventional" models, which consider village adoption rates as a proxy for network effects. The village adoption rate is highly significant. Farmers who live in a village with a high number of hybrid pearl millet adopters are more prone to be adopters themselves. Moreover, farmers who are better educated and are not constrained in their access to information are more likely to adopt. Interestingly, the effect of per capita household expenditures is insignificant. The price of hybrid pearl millet seeds is relatively low (in fact, much lower than that of hybrid wheat), so that the household income situation is of lesser relevance for the adoption decision. Furthermore, the familiarity with the technology might play a role: for a long-established seed technology like hybrid pearl millet, farmers may find it easier to assess and manage potential risks.[7]

Model (5) includes the share of adopters in the network and village variables. The network variable is highly significant and indicates that farmers who have a higher share of adopters in their personal network are more likely to adopt. Adopters are more likely to live in larger villages, though this effect is

[7] As argued above, the household expenditure variable might potentially be endogenous. Unfortunately, due to the lack of a suitable instrument, we cannot properly test for endogeneity. However, since removing the expenditure variable from the models hardly changes any of the other coefficients, we can at least conclude that there is no systematic bias on the overall results.

relatively small. In addition, farmers who live in villages with average or poor soil quality (compared to farmers in villages with high soil quality) are less probable to be adopters. Farmers who live in Ahmednagar district are less likely to adopt hybrid pearl millet than farmers in Aurangabad. This is probably due to agro-ecological factors, as the two districts are located in two different agricultural zones (ICRISAT, 1999). Farmers, who are more experienced are less likely to adopt, but this effect is relatively small. Model (5) fits the data better given the fact that it has a higher log likelihood and a higher Pseudo R^2 value. Model (5) is therefore preferred over model (4).

In model (6), the network characteristics are added to the regression analysis. Access to information, village size, and soil quality significantly influence adoption. Also, the share of adopters in the farmers' social network has a positive effect. With respect to the network characteristics, as in the case of hybrid wheat, coefficients are individually and jointly insignificant at the 95% confidence level. We therefore conclude that network behavior is more important for the adoption of hybrid pearl millet than network characteristics.

4.3. Comparing the results of the regression analyses

Analyzing the adoption of hybrid wheat and hybrid pearl millet—a new and a long-established seed technology—renders a couple of interesting observations. First, information constraints are an important barrier to technology adoption in most regression set-ups and at different diffusion stages. The marginal effects on the probability to adopt, which were displayed in Tables 6 and 7 showed that a farmer who is constrained in his access to information is 25 and 9 percentage points less likely to adopt hybrids of wheat and pearl millet, respectively. The higher negative effect of an information constraint in the case of hybrid wheat makes intuitive sense: at an early stage of technology diffusion, information is not easily available (but needed most) compared to later stages of adoption. To further test the sensitivity of this conclusion, we redefined the information variable in additional estimates. Instead of including the self-reported information constraint, we constructed a new dummy, using farmers' statements about their most important information sources. This dummy takes a value of one if public extension agents, seed company agronomists, input dealers, or other formal sources were named, and zero for more informal information sources (e.g., other farmers). Assuming that farmers who use formal sources are better informed and receive higher-quality information about new technologies, one would expect a positive estimation coefficient in the adoption models. And indeed, for both types of hybrids this formal information source dummy is positive and highly significant, and it is bigger in magnitude for the newly released hybrid wheat.[8] These additional results confirm that access to information is an important determinant of technology adoption.

Second, social networks matter in adoption decisions, especially with respect to newly released technologies. Our results suggest that village adoption rates can serve as a suitable proxy for individual networks at later stages of technology diffusion, but they underestimate network effects at early adoption stages. Further disaggregating the network effects, the behavior of network members appears to be more important than network characteristics for adoption decisions. How far this latter finding can be generalized needs to be addressed in further research. There are no points of comparison yet, as previous studies were not able to include exogenous effects empirically due to data limitations. In principle, the insignificance of most of the exogenous network effects in our models might have several potential reasons. Exogenous effects might not matter much in general, so that the theory discussed above would need to be reconsidered. It is also conceivable that exogenous effects matter in some but not in other situations, depending on the types of technologies or institutional settings. Finally, there might be data problems. For instance, our approach of using average characteristics of network members seems appropriate against the background that networks form along homophilous lines, but it might still mask peculiar characteristics of individuals that might potentially play a role. While we tried different variable specifications without obtaining significant results, measurement or aggregation problems cannot be ruled out completely.

Third, in our samples living standard constraints form an obstacle to adoption only in the case of the recent innovation, which could be explained by the fact that richer farmers can bear potential risks associated with the innovation more easily than poorer farmers. Actual or perceived innovation risks tend to decline over time, as farmers become more familiar with a technology and how to use it properly. Yet, given potential endogeneity problems, this finding also deserves scrutiny in future analyses.

Fourth, contrary to widespread beliefs, small farm sizes and limited access to irrigation facilities as such are not inevitably factors that decrease the probability of hybrid adoption, even at early diffusion stages. This latter point is certainly situation specific. For instance, that irrigation has no significant impact on hybrid wheat and pearl millet adoption reflects the fact that these crops are primarily cultivated under rain fed conditions in Maharashtra. However, it shows that smallholder farmers in relatively unfavorable conditions can benefit from hybrid technologies, if these are targeted to their specific needs.

5. Testing for the robustness of the results

In this section, we test for the robustness of our results by first defining the dependent adoption variable differently and then by looking at the composition of the network from a more dynamic angle. For these robustness tests, we only consider the

[8] Pearl millet farmers who rely on formal sources of information are 14 percentage points more likely to adopt, while for wheat farmers this number is 41 percentage points.

Table 8
Modeling the adoption intensity (Tobit models)

Explanatory variable	Hybrid wheat ($n = 282$)		Pearl millet ($n = 264$)	
	Coefficient	t-value	Coefficient	t-value
Individual characteristics				
Education	0.02	0.87	0.04	0.90
Experience	−5.03E-03	−0.60	−0.02*	−1.82
Farm size	4.26E-03	0.53	−0.02	−1.38
Irrigation	−0.02	−0.06	0.45	0.87
Household expenditures	0.03**	2.54	0.03	1.07
Information constraint	−0.87***	−2.89	−0.34*	−1.06
Credit constraint	−0.06	−0.35	0.09	0.28
Association membership	0.22	1.28	0.02	0.05
Village and regional characteristics				
Distance to input dealer	0.01	0.65	−5.59E-03	−0.35
Distance to output market	−8.88E-03	−0.76	−0.02**	−2.03
Number of households in the village	5.54E-04	1.35	9.83E-03***	3.61
Average soil quality[a]	0.40*	1.78	−1.13***	−2.75
Poor soil quality[a]	0.14	0.57	−1.92***	−3.62
Yavatmal[b]	0.26	0.88		
Aurangabad[b]	0.25	0.94		
Ahmednagar[c]			−2.52***	−3.98
Dhule[c]			1.12**	1.98
Network characteristics				
Share of adopting network members	0.80***	3.27	1.95***	3.89
Constant	−1.58***	−2.69	−0.26	−0.30
Log likelihood	−195.66		−130.25	
$\chi^2(16)$	59.06		187.53	
	$p > \chi^2 = 0.00$		$p > \chi^2 = 0.00$	

Note: *, **, *** coefficients are significantly different from zero at the 90%, 95%, and 99% confidence levels, respectively.
[a]Reference variable is high soil quality.
[b]Reference variable is Nashik district.
[c]Reference variable is Aurangabad district.

models that include the share of adopting network members, as these proved superior in the analysis so far.

Adoption can be modeled in different ways. By using probit models above, we defined adoption as a binary choice problem. Adoption, however, can also be modeled by considering the intensity with which a farmer applies an innovation (Adesina and Baidu-Forson, 1995; Ghadim et al., 2005). We estimate the adoption intensity of hybrid wheat and hybrid pearl millet by using a Tobit model. For hybrid wheat, for example, the adoption intensity is defined as the hybrid wheat area over the total wheat area of the farm household, which by definition is truncated at 0 and 1. Table 8 displays the regression results.[9]

The estimates generally confirm our previous findings. Individual social networks do not only influence farmers in their adoption decision but also in their decision on the adoption intensity. For both crops, the social network variable is highly significant. In the case of hybrid wheat, household expenditures, the information constraint, and average soil quality are significant, too, while the association membership variable, as a proxy for openness, does not significantly determine the adoption intensity. With respect to hybrid pearl millet, as in the binary choice model, access to information, village and district characteristics influence the intensity of adoption. In addition, experience has a negative and significant impact.

In a final step, we try to address the potential simultaneity problem illustrated in Section 2 by looking at the composition of farmers' social networks more closely. In our questionnaire, we asked farmers whether their network members had adopted before, after, or at the same time as they themselves. According to this information, we now construct a new social network variable, which includes only those members for whom a positive or negative time lag in adoption was reported, that is, they had either adopted before or after the individual farmer. With this approach, the reflection problem may be circumvented, because it excludes the possibility that at the same time (i) the farmer was influenced by a member and (ii) the farmer influenced a member. Table 9 displays the regression results.

[9] Tobit model estimations may also help to address the issue of mimicry, which is often raised in network studies (e.g., Foster and Rosenzweig, 1995). Mimicry implies that farmers do not learn from each other, but just copy their adoption behavior for some unknown reason. Yet, rational-acting individuals would not increase or decrease the area under a new innovation, if they would not have learned about its profitability from their own experiences or their network partners.

Table 9
Modeling the adoption of hybrid wheat and hybrid pearl millet using dynamic adoption networks

Explanatory variable	Hybrid wheat ($n = 234$)		Pearl millet ($n = 251$)	
	Coefficient	z-value	Coefficient	z-value
Individual characteristics				
Education	1.36E-03	0.23	0.01***	2.88
Experience	−5.17E-04	−0.18	−5.34E-05	−0.04
Farm size	3.44E-03	1.08	1.13E-03	0.06
Irrigation	0.05	0.49	0.07	0.93
Household expenditures	0.01**	2.27	4.94E-03	0.15
Information constraint	−0.24***	−2.97	−0.07*	−1.76
Credit constraint	−0.02	−0.37	−0.04	−0.96
Association membership	0.13**	2.16	−0.02	−0.57
Village and regional characteristics				
Distance to input dealer	4.16E-03	0.84	−1.10E-03	−0.63
Distance to output market	−1.67E-03	−0.47	−9.70E-04	−1.09
Number of households in the village	1.28E-04	0.95	8.37E-04***	3.34
Average soil quality[a]	0.08	1.06	−0.11*	−1.95
Poor soil quality[a]	0.08	1.01	−0.21***	−2.91
Yavatmal[b]	0.06	0.63		
Aurangabad[b]	0.09	1.03		
Ahmednagar[c]			−0.36***	−4.10
Dhule[c]			0.04	0.79
Network characteristics				
Share of adopting network members (adopting with a lag)	0.18*	1.77	0.07**	2.09
Log likelihood	−114.06		−77.87	
Pseudo R^2	0.16		0.40	

Note: Coefficients can be directly interpreted as marginal effects on the probability to adopt (evaluated at sample means). Standard errors are robust. *, **, *** coefficients are significantly different from zero at the 90%, 95%, and 99% confidence levels, respectively.
[a]Reference variable is high soil quality.
[b]Reference variable is Nashik district.
[c]Reference variable is Aurangabad district.

Restricting the data to consider networks that are composed of only later or earlier adopters leads to similar regression results as those reported above. This approach may not be optimal, but it still supports our finding that social networks significantly influence the individual adoption decision. Another approach would be the use of instrumental variables. Yet, suitable instruments, which are related to the share of adopters in the network, but not the adoption decision, are not available in our case.

6. Conclusions and policy implications

The objective of this article was to extend the current research on social networks in rural areas by analyzing the adoption of hybrid seed technologies in wheat and pearl millet—two crops that are primarily grown as subsistence crops in the Indian state of Maharashtra. The results provide an informative overview of what farmers' information networks in a village look like and what role they play: communication takes place along homophilous rather than heterophilous lines, and individual social networks matter for the adoption decision as such, as well as for the adoption intensity. Relying on village-level technology adoption rates as a proxy for individual networks—as done in many previous adoption studies—may underestimate network effects, particularly at early stages of technology diffusion. The comprehensive primary data collected also allowed us to include exogenous network effects, while previous empirical studies were only able to look at endogenous effects. Our results suggest that the behavior of members in the farmer's individual network has a bigger and more important impact on the adoption decision than their characteristics. In other words, what the network members do is more important than who they are. The question whether this is a general finding or one which is specific only to our data or the conditions found in the particular setting will have to be addressed through further empirical research.

In terms of institutional barriers, we found that information constraints are one main obstacle to adoption, both in the case of hybrid wheat and hybrid pearl millet. This is a well-established finding in the adoption literature, and our study therefore reinforces and strengthens the conclusion that policies directed at facilitating technology adoption should give priority to mitigating such information barriers. Increased quality of and access to formal information, may decrease uncertainties and increase learning behavior. Social network effects would then amplify the adoption process. Subsidizing early adopters (e.g., through free seed samples) and establishing sample farms close to villages could be one approach to increase the quantity and immediate relevance of information. Moreover, according to the NSSO survey, farmers in India suggest to increase the quality of information by ensuring a better timeliness and reliability (NSSO, 2005). This requires that policy makers strengthen the effectiveness of the extension system and also actively involve other main information sources that farmers rely on, such as input dealers and other progressive farmers, for instance through farmer field schools.

The empirical analysis of social interactions is plagued by econometric problems like correlated unobservable variables and simultaneity. We attempted to tackle some of these problems by identifying social networks more precisely and also testing dynamic approaches. Nonetheless, further research is needed. While the theoretical literature on networks is well developed, more empirical studies, especially in rural areas of developing countries, could help increase the understanding of networks and the dynamics of technology adoption in village settings with imperfect markets for information. Innovative studies in the field of social network analysis are currently underway, and our study is a step in this direction.

Acknowledgments

This article was developed while the first author was a PhD student at the University of Hohenheim, Germany. The financial support of the German Research Foundation (DFG) for this project is gratefully acknowledged. The views expressed in this document are those of the authors, not necessarily those of the Food and Agriculture Organization of the United Nations (FAO).

References

Abdulai, A., Huffman, W.E., 2005. The diffusion of new agricultural technologies: The case of crossbred-cow technology in Tanzania. Am. J. Agric. Econ. 87, 645–659.

Adesina, A.A., Baidu-Forson, J., 1995. Farmers' perceptions and adoption of new agricultural technology: Evidence from analysis in Burkina Faso and Guinea, West Africa. Agric. Econ. 13, 1–9.

Antle, J.M., Crissman, C.C., 1990. Risk, efficiency and the adoption of modern crop varieties: Evidence from the Philippines. Econ. Devel. Cult. Change 38(3), 517–537.

Bandiera, O., Rasul, I., 2002. Social Networks and Technology Adoption in Northern Mozambique. CEPR Discussion Paper No. 3341. Centre for Economic Policy Research, London.

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

Barrett, C.B., 2005. On the relevance of identities, communities, groups, and networks to economics of poverty alleviation. In: Barrett, C.B. (Ed.), The Social Economics of Poverty; On Identities, Communities, Groups, and Networks. Routledge, Oxon, UK, 1–11.

Banthia, J.K., 1995. Census of India 1991, Series 14, Maharashtra District Census Handbook. Government Central Press, New Delhi, India.

Boahene, K., Snijders, T.A.B., Folmer, H., 1999. An integrated socioeconomic analysis of innovation adoption: The case of hybrid cocoa in Ghana. J. Pol. Modeling 21(2), 167–184.

Brock, W.A., Durlauf, S.N., 2001. Interaction-based models. In: Heckman, J.J., Leamer, E. (Eds.), Handbook of Econometrics. Elsevier, Amsterdam, 3297–3380.

Chavas, J-P., 2001. Structural change in agricultural production: Economics, technology and policy. In: Gardner, B., Rausser, G. (Eds.), Handbook of Agricultural Economics. Elsevier, Amsterdam, 263–285.

Coleman, J., Katz, E., Mentzel, H., 1957. The diffusion of an innovation among physicians. Sociometry 20(4), 253–270.

Conley, T.G., Udry, C.R., 2001. Social learning through networks: The adoption of new agricultural technologies in Ghana. Am. J. Agric. Econ. 83(3), 668–673.

Dasgupta, S., 1989. Diffusion of Agricultural Innovations in Village India. Wiley Eastern Limited, New Delhi, India.

Davis, K., 2008. Extension in sub-Saharan Africa: Overview and assessment of past and current models and future prospects. Paper presented at the 24th Annual Conference of the Association for International Agriculture and Extension Education: "Global Entrepreneurship: The Role of International Agricultural and Extension Education," EARTH University, Costa Rica, March 10–15.

De Weerdt, J., 2005. Risk sharing and endogenous network formation. In: Dercon, S. (Ed.), Insurance against Poverty. Oxford University Press, Oxford, 197–246.

Dong, D., Saha, A., 1998. He came, he saw, (and) he waited: An empirical analysis of inertia in technology adoption. Appl. Econ. 30, 893–905.

Feder, G., Just, R.E., Zilberman, D., 1984. Adoption of agricultural innovations in developing countries: A survey. Econ. Devel. Cult. Change 33(2), 255–298.

Feder, G., O'Mara, G.T., 1981. Farm size and the diffusion of green revolution technology. Econ. Devel. Cult. Change 30(1), 59–76.

Feder, G., Savastano, S., 2006. The role of opinion leaders in the diffusion of new knowledge: The case of integrated pest management. World Devel. 34(7), 1287–1300.

Fertiliser Association of India, 2004. Fertiliser Statistics 2002–2003. Fertiliser Association, New Delhi, India.

Foster, A.D., Rosenzweig, M.R., 1995. Learning by doing and learning from others: Human capital and technical change in agriculture. J. Polit. Economy 103(61), 1176–1209.

Gautam, R.C., 2003. Growing Pearl Millet in India. Kitab Mahal, Allahabad, India.

Ghadim, A.K.A., Pannell, D.J., Burton, M.P., 2005. Risk, uncertainty, and learning in adoption of a crop innovation. Agric. Econ. 33, 1–9.

Government of Maharashtra, 2005. Economic Survey of Maharashtra 2004 – 2005. Government of Maharashtra, Mumbai, India.

Granovetter, M.S., 1973. The strength of weak ties. Am. J. Sociology 78(6), 1360–1380.

Granovetter, M.S., 2005. The impact of social structure on economic outcomes. J. Econ. Perspect. 19(1), 33–50.

Grosh, M., Glewwe, P. (Eds.), 2000. Designing Household Survey Questionnaires for Developing Countries: Lessons from 15 years of the Living Standards Measurement Study. World Bank, Washington, DC.

Gujral, H.K., 1999. Critical Factors Influencing the Adoption of Improved Pearl Millet Cultivars in Maharashtra, India. Unpublished manuscript. ICRISAT. Pantancheru, India.

Hogset, H., 2005. Social networks and technology adoption. Paper presented at the American Agricultural Economics Association Annual Meeting. Providence, Rhode Island, July 24–27.

Hogset, H., Barrett, C.B., 2007. Imperfect Social Learning among Kenyan Smallholders. Discussion paper. Cornell University. Department of Applied Economics and Management, Ithaca, NY.

ICRISAT, 1999. Typology Construction and Economic Policy Analysis for Sustainable Rainfed Agriculture. ICRISAT, Patancheru, India.

Isham, J., 2002. The effect of social capital on fertilizer adoption: Evidence from rural Tanzania. J. African Econ. 11(1), 39–60.

Manski, C.F., 1993. Identification of endogenous social effects: The reflection problem. Rev. Econ. Stud. 60, 531–542.

Manski, C.F., 2000. Economic analysis of social interactions. J. Econ. Perspect. 14(3), 115–136.

Matuschke, I., Mishra, R.R., Qaim, M., 2007. Adoption and impact of hybrid wheat in India. World Devel. 35(8), 1422–1435.

Matuschke, I., Qaim, M., 2008. Seed market privatisation and farmers' access to crop technologies: The case of hybrid pearl millet adoption in India. J. Agric. Econ. 59(3), 498–515.

Maxwell, S., 2004. Farming and the poor: Seven new challenges. ODI Opinions, July.

Miguel, E., Kremer, M., 2003. Networks, social learning and technology adoption: The case of deworming drugs in Kenya. Poverty Action Lab Project. Available at http://www.povertyactionlab.com/projects/project.php?pid=36.

National Sample Survey Organisation, 2005. Situation Assessment Survey of Farmers: Access to Modern Technology for Farming. Report no. 499(59/33/2). Government of India, New Delhi, India.

Neill, S.P., Lee, D.R., 2001. Explaining the adoption and disadoption of sustainable agriculture: The case of cover crops in northern Honduras. Econ. Devel. Cult. Change 49(4), 793–820.

Pomp, M., Burger, K., 1995. Innovation and imitation: Adoption of cocoa by Indonesian smallholders. World Devel. 23(3), 423–431.

Rogers, E.M., 2003. Diffusion of Innovations. Free Press, New York.

Santos, P., Barrett, C.B., 2004. Interest and Identity in Network Formation and Activation: Who do Smallholders Seek out for Information in Rural Ghana? Unpublished manuscript. Paper presented at the American Agricultural Economics Association Annual Meeting, Denver, Colorado, August 1–4.

Self, S., Grabowski, R., 2007. Economic development and the role of agricultural technology. Agric. Econ. 36, 395–404.

Udry, C.R., Conley, T.G., 2005. Social networks in Ghana. In: Barrett, C.B. (Ed.), The Social Economics of Poverty; on Identities, Communities, Groups, and Networks. Routledge, Oxon, 244–267.

Zehr, B., 2001. Emerging biovision: Hybrid wheat. In: M.S. Swaminathan Research Foundation. (Ed.), MSSRF-FAO Expert Consultation on Science for Sustainable Food Security, Nutritional Adequacy, and Poverty Alleviation in the Asia-Pacific Region. Swaminathan Research Foundation, Chennai, India, 226–230.