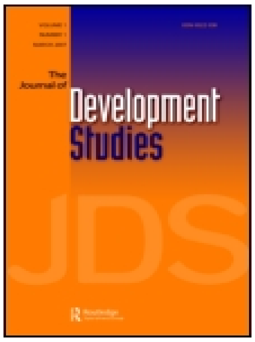

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Social Learning and Farm Technology in Ethiopia: Impacts by Technology, Network Type, and Poverty Status

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ABSTRACT *Improved farm technologies in Ethiopia display high levels of promise and low rates of adoption. This article studies the impact of social networks on technology adoption focusing on social learning through networks based on physical proximity and those based on intentional relationships. Impacts by network type, technology, and asset poverty status are explored. Social learning is more evident for households not in persistent poverty, for more complex technologies, and within networks based on intentional relationships rather than proximity. Results indicate that technology diffusion in Ethiopia is likely to be enhanced if extension can target intentional networks, rather than spatial clusters.*

Introduction

Most observers agree that appropriate modern technologies could contribute to poverty reduction in rural Africa (von Braun et al., 2008). The significant role of personal relationships and social learning in technology diffusion is also increasingly acknowledged (Conley and Udry, 2010; Bandiera and Rasul, 2006; Munshi, 2004). Social learning refers to learning that occurs within a social context, such as through observation of neighbours, imitation of associates, or modelling by friends. Recognition of social learning invites the chance to design extension systems that leverage social networks to promote technology diffusion. Using extension systems to catalyse social learning and other network effects, however, requires a nuanced understanding of how different kinds of relationships influence technology use.

An effect of social networks on technology diffusion has been well established in the literature, but the specific role of social learning as opposed to other network effects is less well researched (Munshi 2004; Bandiera and Rasul 2006; Conley and Udry, 2010; Maertens, 2010). Furthermore, little or no research has considered whether social learning is equally effective for poor and non-poor households and, with the exceptions of Van den Broek and Dercon (2011) and Bandiera and Rasul (2006), few studies have considered whether some types of networks are more effective in disseminating information than others. Studies like Dercon et al. (2006) have looked at the possible expansion of the functions of existing local institutions (largely funeral insurance) for

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other development activities but the role of such networks in disseminating information remains largely unexplored.

This article investigates the roles that different kinds of social networks play in adoption of diverse technologies by Ethiopian farm households facing different levels of poverty. The article addresses three questions: (1) Do networks in rural Ethiopia contribute to technology adoption? (2) Is there evidence of social learning in network effects? And (3) How does the effectiveness of social learning vary with type of network, type of technology and poverty status of households? Social learning requires precise knowledge of the behaviour of network members, which may be more available in some networks than in others. Thus, this article considers networks of proximity and networks of voluntary association and examines whether persistently poor households experience different network impacts than other households.

Ethiopia ranks 157 out of 169 in the Human Development Index with life expectancy of 56 years compared to the worldwide average of 69 years and a GNI per capita (PPP) of $991 compared to $2050 for sub-Saharan Africa (UN, 2010). The majority of Ethiopians are engaged in agriculture with over 84 per centof the population being rural. More than three-quarters (77.8%) of the population lives on less than $2 a day and 45 per cent of Ethiopians live below the national poverty line (IMF, 2006; Ethiopian Economic Association, 2005). Since the 1990s, the Government of Ethiopia has pursued an Agriculture Development Led Industrialisation (ADLI) strategy. This strategy emphasises extension and rural finance to promote intensification of food production through the use of improved seed, fertiliser and other inputs (Byerlee et al., 2007). High prevalence of poverty, low agricultural productivity and the government's desire to promote technology adoption through improved extension make Ethiopia an appropriate site for study of how social networks affect agricultural technology adoption among poor farmers.

Conceptual Framework: Social Networks, Social Learning, and Technology Adoption

Research on social learning and technology adoption considers how technology use by one farmer is affected by information made available by the decisions of others (Besley and Case, 1993; Besley and Case, 1994; Foster and Rosenzweig, 1995; and Munshi, 2004). This section explains how networks and social learning could affect farmer behaviour regarding adoption. It distinguishes between social learning and other network effects and makes the case for potentially different social learning effects by network type, poverty status and technology type.

While there are many ways in which social networks might affect adoption of a new technology, specific observed relationships between network size and adoption are more plausibly explained by social learning than by other mechanisms. Apart from social learning, adoption decisions within a network may be correlated due to uniformity of goals or constraints among members (Besley and Case, 1994; Bandiera and Rasul, 2006). If homogeneity within a group causes members to adopt technology at a similar time, the network's size is unlikely to affect adoption. Alternatively, faced with a fixed cost or risk, collective action could lower the cost per member and lead to a correlated adoption within the group. Under these circumstances, larger networks would be more likely to facilitate adoption than would smaller ones. Similarly, social influence based on a desire to conform to common norms would make adoption increasingly likely as the size of the network of adopters grows.

Adoption probabilities that increase consistently with the size of the adopter network suggest social influence, among other possible explanations. Adoption probabilities that peak and then fall with increase in network size are more consistent with social learning than other network effects (Bardhan and Udry, 1999; Bandiera and Rasul, 2006). The 'inverted U' relationship between network size and adoption can emerge if the returns to a new technology rise with increased knowledge about the method and if people can learn either from their own experience or from the experience of others. In this case, increases in network size initially indicate access to more information about a technology and thus encourage adoption. However, since information from personal experience may be costly to acquire, and the experience of others could substitute for it, a larger network of adopters could encourage households to delay adoption and free ride on the experience of other members. This adoption-delaying effect can emerge because the additional information gained from personal trials declines when the larger network provides more information. Thus a large network could discourage personal trials, delaying adoption. An inverse U relationship between the number of adopters in a network and personal adoption is more easily explained by social learning than by other network effects and can be used as evidence of learning as a network mechanism at play. Claims of identification of social learning are tempered by recognition that social learning could exist without generating the inverse U and that other explanations for such a pattern could be posited.

This analysis models social learning using the target input approach developed in Prescott (1972) and Wilson (1975) and applied to agriculture in Foster and Rosenzweig (1995). In this model a farmer adopts a technology and then experiments with inputs and management over time to improve profits. The more information a farmer has at adoption, the closer actual input levels will be to the optimal (target) input level, and the higher will be initial profits. As described more fully in Online Appendix A, adoption occurs when the expected value of the discounted flow of profits over some finite time horizon associated with immediate adoption exceeds that from deferring adoption and maintaining the old technology for another period. By delaying a farmer can observe others and gain information which will raise initial profits at the eventual time of adoption, but given the finite time horizon, delay in adopting a profitable technology will reduce the number of periods over which the technology is used and depress the value of future profits.

Information from one's own experience of adopting may be costly, as it involves forgoing a known production system to experiment with a new one. Meanwhile, observing others who have adopted may yield poor-quality information and implies fewer total periods using the improved technology. The information gained from observing others will be less useful than that gained from one's own experience due to the heterogeneity in resources and skills across farmers and incomplete transmission of information. If only a few people in the network practice the technology there will be a high value to learning by doing rather than learning by watching. The larger the pool of information available through observation, the smaller will be the difference in quality between learning from others and learning by doing. While some exposure to the technology from a network provides information to promote immediate adoption, at some point having more people in a network practising a technology could encourage farmers to learn from others and delay their own adoption. This tension allows the inverse U relationship between the probability of adoption and network size.[1] Finding an inverse U relationship between the probability of adoption and the number of adopters in a household's network, as in Bandiera and Rasul (2006), would suggest social learning. Although finding a strictly positive relationship would also be consistent with social learning, such a result could be explained by other network effects.

The impact of social networks on adoption could vary with the type of network, the type of technology, or characteristics of the member. With few exceptions (Conley and Udry, 2001; Conley and Udry, 2010; Bandiera and Rasul, 2006; Van den Broeck and Dercon, 2011) previous studies focus on geographic proximity to define networks. Networks of proximity can only contribute to social learning if neighbours willingly share information or if farmers easily observe their neighbours' input use and output. Because land in Ethiopia is allocated by the government and then passed on from generation to generation, farmers have little choice as to who their neighbours are and may not be on good terms with them. Furthermore, various procedures associated with a new technology, such as application rates and timing, may not be easily observable and may instead require more purposeful interaction to learn. This article thus explores social networks based on voluntary association as well as those defined by proximity.

Social learning effects might differ across technologies, depending on the amount of new learning necessary and on the perceived applicability of the experiences of others. Munshi (2004) found that network effects were stronger for those technologies whose application was more uniform. One would expect technologies whose application is relatively robust to diverse farm-specific conditions to be more readily spread through social learning. Social learning is also expected to have more impact on diffusion of complex technologies for which information is likely to be a limiting factor, rather than less novel techniques (Hogset and Barrett, 2010). Consequently, this analysis examines the effect of network size on a range of farm technologies.

Concerning the features of the network and the households, poverty status may correspond to lower quality information available through networks and lower responsiveness to information from networks. In addition to being information constrained, poor farmers are likely to exhibit greater risk aversion and face more severe financial constraints, and are therefore less likely to adopt a technology when provided with information. Thus, households below some poverty threshold could be expected to be less responsive to network information than other households. Regardless of their responsiveness to information, persistently poor households may have networks with weaker mechanisms for transmitting information. If poor people are relatively isolated even from other members of their own network, then their networks will be less effective conduits for learning than others. Since the poor may be unable to apply information from networks or may be in information-poor networks, the following empirical analysis seeks to measure separate network effects for poor and non-poor households.

Social Learning and Technology Adoption in Harresawe and Korodegaga

After focus-group meetings in 15 Peasant Associations (PAs) for which Ethiopian Rural Household Survey (ERHS) data are available, the PAs of Harresawe and Korodegaga were identified as having recent experience with the introduction of new agricultural technologies.[2] In both these PAs, technical innovations involve use of irrigation, adoption of improved cereal varieties, and use of chemical fertilisers. In this respect observations of Harressawe and Korodegaga are consistent with recent studies that indicate the high potential of improved cereals and small-scale irrigation to address food security and increase smallholder incomes in Ethiopia (Tucker and Yirgu, 2010; Awulachew et al., 2005; Byerlee et al., 2007). In addition to focus group discussions, data for this analysis are from surveys conducted in 2007 with 172 households in Harressawe and Korodegaga. To add longitudinal depth to the study, households were selected that had been covered in previous rounds of the ERHS conducted in 1994 (twice), 1995, 1997, 1999, and 2004.

Harresawe is in the Tigray region of Northern Ethiopia (CSAE, 1996b). Located in a drought prone area, farmers in this PA produce barley in unreliable rain-fed systems and have been food insecure for the last decade. Over 85 per cent of the households in Harresawe's district (*woreda*) required food assistance during the 2002 drought. Discussion with key informants in the PA revealed that various NGO and government efforts have focused on irrigation development. In 1994, collaborating NGOs constructed a dam in Harrasawe which was handed over to the government to manage. This dam became operational in 1997 and was reported to have enabled numerous farmers to improve their livelihoods. In 2007 community leaders reported that about 41 per cent of the land in Harresawe was irrigated. Key informants in the village indicated that there was still room for irrigation expansion. Furthermore, over 60 per cent of respondents who did not engage in irrigation cited factors such as limited knowledge about irrigation or funds for complementary inputs such as pumps as the reason for not adopting. Less than 40 per cent mentioned lack of access to the dam or other water sources. Most households interviewed had plots of land less than 2 km from the dam whether or not they practised irrigation. Irrigation was initially applied to barley, but since 2004–2005 irrigated fields have been converted to newly introduced vegetable and pulse production. Discussions with the resident agricultural extension agents and farmers indicated that while irrigation was familiar to most households, growing field peas and vegetables under irrigation was new. These innovations were considered beneficial as field peas and vegetables commanded high prices and because irrigating these crops enabled multiple cropping cycles per year. However, achieving multiple crop cycles and accessing markets presented management challenges for smallholders.

As in Harrasawe, recent innovations in Korodegaga relate to irrigation of high value crops. Located in Oromiya region within 500 metres of the Awash River, residents of Korodegaga have long been exposed to some form of irrigation (CSAE, 1996a). However, focus group meetings and discussions with development agents (extension agents) revealed that it was only since 2004 that improved seeds for maize and vegetables were made available to local farmers. In 2006 development agents were assigned to the PA with the charge of assisting farmers in the production of the new crops and varieties using irrigation based on diversions of surface water or shallow wells. In Korodegaga average distance to surface water was not significantly different between those practicing irrigation and those who did not. As in Harrasawe residents consider management of these new crops and their marketing to be challenges to their adoption. As shown in Table 1, about 15 per cent of households in both PAs have adopted irrigation.

Like irrigation, use of modern varieties is becoming increasingly common in these areas. According to ERHS data, only about 10 per cent of households in the study PAs used improved crop varieties in 1999. By 2007, 70 per cent of households in Korodegaga and 20 per cent in Harasawe planted improved varieties. Use of chemical fertiliser in Ethiopia has risen and fallen with changes in input and output prices. ERHS data show a maximum of 60 per cent and 40 per cent of households in Korodegaga and Harresawe used fertiliser between 1994 and 2004; use rates in 2007 were within this range (Table 1).

This study considers three agricultural technologies: irrigated production of vegetables or pulses; use of improved varieties of maize or barley; and use of chemical fertilisers. Since both improved varieties of cereals and irrigated pulse and vegetable production are new innovations, one would expect more scope for social learning in these technologies. The greatest potential for social learning is in irrigated pulses and vegetables production since this technique requires the most pronounced changes in production and marketing practices and because homogenous (irrigated) growing conditions imply that relatively high-quality information can come from other people's trials. Improved cereal production, often administered through standard packages of seed and associated inputs, does not imply as radical a break from traditional cereal production and different farmers may be operating under very different conditions. Hence, social learning may be less relevant for improved cereals than for irrigated pulses and vegetables. Because most farmers have been familiar with chemical fertiliser for some time, social learning is not expected to affect use of this technology, though other network effects may exist. For irrigation of pulses and vegetables, the analysis includes only households that had not adopted irrigation prior to 2004. In 2007, 92 per cent of households using irrigation were engaged in irrigating vegetables, pulses, or oil seed. Various network effects are expected to drive a positive relationship between network size and the probability of adoption over some ranges of network sizes for all technologies. Observation of an inverse U relationship between probability of adoption and network size will be taken as evidence of social learning in particular.

Table 1. Technology use across study sites (2007)

	Harresawe	Korodegaga	Total
Irrigation adoption rates	0.21	0.11	0.15
	(0.41)	(0.31)	(0.36)
Improved seeds adoption rates	0.20	0.70	0.48
	(0.41)	(0.43)	(0.50)
Fertiliser adoption rates	0.41	0.56	0.44
	(0.50)	(0.50)	(0.50)

Source: Calculated from authors' survey of the ERHS households. Standard deviation in parentheses.

Empirical Model of Technology Adoption

Based on the target input model, the decision to adopt a technology at any point in time will depend to some extent on the size of the network of adopters with which a farmer is associated. This relationship can be measured empirically through estimation of

$$(TA_{ik}) = (\alpha_A) + (\lambda_A Z_i) + f[n(i)] + (\psi_A V_i) + (E_{ik}) \quad i = (1, \ldots, N),$$

where TA_{ik} is the adoption of technology k by household i. Z_i refers to a vector of exogenous variables capturing household i's characteristics, including household size, sex of household head, age of household head, highest years of education in the household, distance from the farm to the nearest market and nearest paved road (in kilometres), amount of land controlled by household (in hectares), value of household nonproductive assets (mostly jewellry), and household size. V_i is a dummy variable to account for unobserved variations across PAs that could affect a household's technology use decision.

The social network effect is captured through $n(\ )$. The networks considered are defined by purposive social interaction (friends) and by geographic proximity (neighbours). Based on discussions with farmers prior to the structured survey, neighbours were defined as those who live and/or farm in close proximity to farmers and whose activities are easily visible to respondents in the course of their normal daily activities but with whom respondents do not necessarily have frequent social interaction. Friends, on the other hand, were defined as those on whom farmers visit, call on during celebrations, and consult or rely on in times of trouble. For households that had adopted the technology, $n(\ )$ represents the number of farmers in the network that had already adopted the technology before the respondent did so. For households that had not adopted the technology at the time of the survey, $n(\ )$ is the current number of adopters in the farmer's social network. As in Bandiera and Rasul (2006), the network variable used here is the respondents' reported number of adopters from their total network who had adopted prior to their own adoption. These networks of adopters range in size from 0 to 40 (mean = 5 friends, 3 neighbours) for irrigated vegetables and pulses and extend to over 60 for improved cereals (mean = 6 friends, 6 neighbours). The full friends and neighbours network sizes are not known and networks cannot be mapped from our data.

As emphasised in Hogset and Barrett (2010), a bias in the reported values of $n(\ )$ could emerge if adopters are more (or less) likely to know the prevalence of adoption among members of their network than non-adopters. This bias seems unlikely to be substantial in this application. Because the technologies involve changes in crop or crop variety that are highly visible, farmers living in close proximity will automatically be aware of adoption in the spatial network. If farmers are unaware of the adoption of technology by a member of their network of friends, the network is manifestly weak and so the measure will appropriately exclude the unobserved adopter from the measured network size. Furthermore, since the crops and varieties in question were introduced within a short time (1–2 years) of data collection and the networks are small (see Tables 3(a)–3(c)), bias emerging from misreporting is likely to be modest. We mitigate remaining bias by accounting for particular farmer characteristics (like age and education) which could affect their ability to properly identify their network sizes.

E_{ik} is the error term, capturing unobserved individual and network characteristics that affect household participation. To account for potential endogeneity of networks (particularly the friend's network), we include education, household size, household proximity to markets and household assets. Exogenous variables are interacted with a dummy variable indicating whether or not a household is in asset poverty; those identified as asset poor over a 10-year period prior to the survey are considered to be in persistent poverty. Asset poverty is estimated using the ERHS data for 1994–2004. To account for any bias in the ability of the long-term asset poverty classification to capture current wealth, we also included the value of livestock and non-productive assets like jewellry in the vector of controls.

As explained in Manski (1993), social learning studies must disentangle endogenous, exogenous, and correlated effects. Endogenous effects describe the impact that the adoption decision of a network member has on an individual. Simultaneity emerges as a concern through Manski's reflection problem in which the average behaviour of the group influences the individual, who in turn influences the group. Exogenous effects describe the idea that an individual may be part of a group because of characteristics of the group itself. For example, farmers with an electric pump may wish to group with other farmers who own electric pumps to share information on how to operate and maintain the device. Correlated effects describe the idea that network members may be similar in their choices due to similar individual characteristics or because they face the same local, institutional, or cultural conditions. Failing to control for these three different effects may lead to inference biases, as the analysis is unable to disentangle impacts of social networks from the impacts of local conditions (Matuschke, 2008).

PA dummy variables are used here to account for local, institutional or cultural conditions that could affect farmer adoption of the various technologies. We also include demographic information to control for household level characteristics that could be correlated with adoption. While we conduct several robustness checks to ascertain possible causal effects of networks, we recognise that we may not have completely removed potential sources of bias due to endogeneity of farmer networks and thus our estimation results inform whether the adoption decisions within social networks were correlated.

As in standard latent variable analyses, TA_{it}* represents household *i*'s present value of net gains from participating in agricultural innovation k at time t:

$$TA^*_{ikt} = A[Z_i, V_i f[n(i)]\, E_{ikt}].$$

Although it is not possible to see the net present value ascribed by each household, one can observe their dichotomous decision to use a new technology:

$$TA_{ikt} = 1, \text{ if } TA^*_{ikt} > 0;$$
$$TA_{ikt} = 0, \text{ otherwise.}$$

We assume that $prob(TA_{ikt} = 1) = prob(E_{1i} > -\{f[n(i)] + Z_i + V_i\}) = \mathrm{F}(-\{f[n(i)] + Z_i + V_i\})$, assuming symmetry of the function describing F( ) around zero and exploring various specifications for *f*[ ]. The first model specification includes the squared network effects to test for a quadratic polynomial fit and the U or inverse U shape.

$$P[TA_{ik} = 1] = F[(\alpha_A) + (\lambda_A Z_i) + \theta_1[n(i)] + \theta_2[n(i)^2] + (\psi_A V_i) + (E_{1iv})] \quad (1)$$

A second model explores possible threshold effects in network size. It tests for the differential effect of having a network of (1–4), (5–8), and eight or more members engaged in a particular technology at the time of adoption relative to having no adopters in the network:

$$P[TA_{ik} = 1] = F[(\alpha_A) + (\lambda_A Z_i) + \beta_0[0] + \beta_1[1] + \beta_2[2] + \beta_3[3] + (\psi_A V_i) + (E_{1i})^x], \quad (2)$$

where [0], [1], [2], and [3] reflect different splines. Equations (1) and (2) were estimated using probit, logit, and linear probability models for each of the three technologies. Results were similar across the three methods, and only probit models are reported. Specifications were run with and without interaction terms for poverty status. The poverty status variable is a dummy variable equal to 1 if a household is in persistent poverty. It is interacted with each network variable (friends and neighbours) by multiplying the network size variable by the dummy variable.

Descriptive Data

The analysis begins by using the ERHS dataset (1994–2004) to classify households as persistently asset poor or not. The asset-based approach to poverty measurement classifies as asset poor those households with assets inadequate to generate an income stream supporting consumption above the expenditures poverty line (Carter and Barrett, 2006). An asset poverty line is the asset value that exactly supports consumption at the expenditures poverty line. In this application, an asset index is established as a function of the household's land, livestock, farm implements, other physical assets, and education. The weights on each component of the asset index are based on an estimate of the relationship between assets and consumption, replicating the process described in Liverpool and Winter-Nelson (2010) who also analysed ERHS data. Households with an asset index below the asset poverty line in each survey year are considered to be in persistent poverty. Other households tended to be below the poverty line in some, but not all, survey rounds. Complete data were available for 135 households, 63 of which were identified as in persistent asset poverty.

Descriptive statistics in Table 2 reveal the poverty of most households in this sample. On average, the households cultivate about three hectares of land and have no members with more than five years of education. Fifty-seven per cent of households are headed by men and the average age of household heads is about 50 years. Their assets tend to consist of several head of livestock valued at about 4333 EB.[3] Households in persistent poverty have somewhat smaller livestock holdings, and live further from local markets but closer to paved roads. Adoption rates

Table 2. General descriptive statistics

Variable	Complete sample	In persistent poverty	Not in persistent poverty
Male head (1/0)	0.575	0.587	0.565
	(0.48)	(0.50)	(0.47)
Household livestock	4332.85	4103.60***	4602.255
(Ethiopian birr)	(4609.70)	(4910.34)	(4129.59)
Household nonproductive	390.884	364.613	413.872
assets (Ethiopian birr)	(529.58)	(447.20)	(594.58)
Age of household head (years)	51.002	53.048	48.090
	(13.99)	(12.48)	(17.07)
Distance to closest market	12.952	14.786***	11.347
(km)	(8.07)	(8.14)	(7.70)
Distance to paved road (km)	20.199	15.718**	24.119
	(20.7)	(17.96)	(21.64)
Household parcel size	2.807	2.769	2.849
(hectares)	(2.95)	(3.30)	(2.52)
Household size (number)	5.459	5.762**	5.476
	(2.08)	(2.05)	(3.20)
Most education (years)	5.362	5.123	5.356
	(3.27)	(3.29)	(3.09)
Recent adopters of irrigation	0.155	0.152**	0.159
(0/1)	(0.36)	(0.37)	(0.36)
Recent adopters of improved	0.480	0.441**	0.573
seeds (0/1)	(0.501)	(0.497)	(0.498)
Recent adopters of fertiliser	0.439	0.463	0.434
(0/1)	(0.498)	(0.503)	(0.502)
Number of observations	135	63	72

Source: Calculated from authors' survey of the ERHS households.
Notes: Standard deviation in parentheses. *** means that the average is statistically significantly different across poverty status at 1 per cent, ** means that the average is statistically significantly different across poverty status at 5 per cent and * means that the average is statistically significantly different across poverty status at 10 per cent.

for irrigation and improved seeds are significantly lower for persistently poor households though fertiliser adoption rates are similar for both poverty classes.

Table 3a shows the mean number of adopters of irrigated vegetables and pulses in the networks of adopters and non-adopters, divided by poverty status. The descriptive data show that adopters of irrigation had more neighbours and friends who had adopted previously than did non-adopters. In contrast, Table 3b indicates that while adopters and non-adopters of improved cereal varieties had similar number of adopters among their friends, non-adopters had a larger network of neighbour adopters than did adopters. Among the persistently poor households, adopters had fewer friends who had adopted previously than did the non-adopters. Finally, for fertiliser the adopters consistently had more adopters in their social networks than did the non-adopters. Thus, Tables 3a–3c indicate different network effects across network types, technology, and poverty status.

Table 3a. Mean number of network members already using technology: irrigated crops (2007)

	Complete sample			In persistent poverty		Not in persistent poverty	
	Total	Adopters	Nonadopters	Adopters	Nonadopters	Adopters	Nonadopters
Friends	4.706	6.612	2.251	8.136	2.346	5.276	2.409
	(7.747)	(9.505)	(3.290)	(11.121)	(2.629)	(7.559)	(3.761)
Neighbours	2.997	3.926	1.845	4.459	1.683	3.450	2.115
	(3.975)	(4.455)	(2.925)	(4.893)	(2.262)	(4.028)	(3.346)
N	135	21	114	10	53	11	61

Source: Calculated from authors' survey of the ERHS households.
Note: Standard deviation in parenthesis.

Table 3b. Mean number of network members already using technology: improved cereals (2007)

	Complete sample			In persistent poverty		Not in persistent poverty	
	Total	Adopters	Nonadopters	Adopters	Nonadopters	Adopters	Nonadopters
Friends	5.69	5.57	5.78	4.69	7.64	6.66	4.58
	(13.46)	(11.45)	(15.10)	(7.95)	(14.37)	(14.70)	(15.64)
Neighbours	6.28	3.115	9.112	3.42	13.93	2.79	5.98
	(15.00)	(19.83)	(4.78)	(5.52)	(28.23)	(10.83)	(10.84)
N	135	71	64	28	35	43	29

Source: Calculated from authors' survey of the ERHS households.
Note: Standard deviation in parentheses.

Table 3c. Mean number of network members already using technology: fertilizer (2007)

	Complete sample			In persistent poverty		Not in persistent poverty	
	Total	Adopters	Nonadopters	Adopters	Nonadopters	Adopters	Nonadopters
Friends	5.665	7.25	4.188	6.967	3.906	7.551	4.757
	(7.32)	(9.13)	(4.68)	(9.97)	(3.52)	(8.29)	(7.55)
Neighbors	6.83	8.201	5.548	7.532	6.974	8.668	4.384
	(10.9)	(9.14)	(6.75)	(9.75)	(18.15)	(7.69)	(5.37)
N	130	63	67	35	30	28	37

Source: Calculated from authors' survey of the ERHS households.
Note: Standard deviation in parentheses.

Results

Considering recent adoption of irrigated vegetables and pulses, results in Table 4 yield evidence of social learning among networks of friends. The coefficient on the network of friends who had previously adopted is positive and significant in the level value and negative and significant in the squared form, describing the inverse U relationship. The estimated coefficients imply that the probability of adoption increases as the number of adopters among friends rises to seven and falls when more than seven friends have adopted. The peak in the inverse U relationship thus emerges at a network size that is observed in the data. Indeed, using the observed data and the estimated coefficients, simulating an additional friend in the adopter network reduces the probability of adoption for 12.64 per cent of the households. Adding three adopters to the friends networks reduces the probability of adoption in 30 per cent of the households.[4] This pattern suggests a network effect that is consistent with social learning among friends.

In contrast, no neighbour network effect is found, indicating that network effects are more prevalent within groups of intentional interaction than in those based on proximity alone. To account for the possibility that some neighbours could be friends, specifications in which each network type was alternately excluded were run. They yielded similar results in terms of the signs and significance of the network coefficients.[5] Other factors that appear to affect adoption of irrigated vegetables and pulses are access to a paved road, household wealth captured by

Table 4. Social network effects on the adoption of irrigated pulses or vegetables, estimation by poverty status: probit model

	Not distinguishing poverty status		Distinguishing poverty status	
Irrigated crops	Coefficient	P > z	Coefficient	P > z
Male head (1/0)	0.0100	0.980	0.1746	0.698
Household livestock	0.0001**	0.043	0.0001**	0.004
Household nonproductive assets	0.0006**	0.019	0.0007**	0.034
Visited by an extension agent in the last year	0.2341	0.524	−0.0306	0.939
Age of household head (years)	0.0127	0.305	0.0150	0.312
Distance to closest market (km)	0.0172	0.574	0.0305	0.375
Distance to paved road (km)	−0.0222**	0.040	−0.0255**	0.029
Household parcel size	−0.3711**	0.011	−0.6434**	0.001
Household size	0.0706	0.450	0.0897	0.355
Most education (years)	0.0120	0.827	−0.0433	0.494
Friend adopters (number)	0.3786**	0.007	0.5915**	0.001
Friend adopters squared	−0.0275**	0.030	−0.0603**	0.002
Neighbour adopters (number)	0.0786	0.557	0.5298	0.150
Neighbour adopters squared	−0.0042	0.632	0.0118	0.832
In persistent poverty			0.3787	0.495
Friends*Not in persistent poverty			−0.3223	0.230
Friends squared*Not in persistent pov.			0.0466**	0.095
Neighbours*Not in persistent poverty			−0.6140	0.113
Neighbours squared*Not in persistent pov.			−0.0066	0.905
Steep land (1/0)	−0.2825	0.386	−0.2172	0.569
Poor quality soil (1/0)	−0.8579	0.152	−0.9953	0.149
Harresawe	1.9397**	0.002	3.3280***	0.000
Constant	−3.3635**	0.001	−4.5769***	0.000
Number of observations	135		135	
Prob > chi^2	0.0000		0.0000	
Pseudo R^2	0.3027		0.4317	

Source: Calculated from authors' survey of the ERHS households.
Note: *, **, *** imply significant at 10 per cent, 5 per cent and 1 per cent respectively.
All models are estimated with robust standard errors.

livestock and nonproductive assets including jewellry, and other household items. Households with larger parcels of land were less likely to adopt irrigation, which could reflect greater pressure to intensify in households with less land, or greater capacity to do so in households with more labour per hectare, among other possible factors.

To ensure that the results indicated more than just diminishing returns to additional friends in ones network, we plot the marginal impact of an additional friend on the predicted probability of adoption using a nonparametric kernel regression. The results shown in Figure 1 confirm the inverse U relationship between adoption and the number of friends who have adopted. Compared to the parametric estimate, the point at which an additional friend among adopters reduces the probability of adoption occurs slightly higher (10 friends), but still within the range of observed network sizes.

In the specification that distinguishes poverty classes, wealthier households, those with better access to external markets, and those controlling smaller land parcels are more likely to adopt irrigated crops (Table 4). Evidence of social learning from networks of friends (as demonstrated by the inverse U) remains and is not statistically significantly different across poverty classes.[6] To supplement the results in table 4, the regression reported in table 5 applies splines for networks of different sizes. The results reveal that households with between 1 and 4 friends who adopted have a 77 per cent higher probability of adopting irrigated crops than households with no adopters among their friends. Those with between 5 and 8 adopters among their friends are more than twice as likely to adopt the technology. Although those households with more than 8 friends using the technology are less likely to adopt than are those with between 5 and 8 friends, the former are still more than twice as likely to adopt as those who have no friends using a technology. A Wald test on the equality of the coefficient reveals that the coefficient on 1–4 friend adopters is statistically significantly different from having 5–8 friend adopters. However, we fail to reject that having 1–4 is statistically significantly different from having more than 8 members, confirming that the relationship between the size of the friend network and the probability of adoption is shaped as an inverse U, with a peak that is in the range of observed network sizes.

Considering improved varieties of cereals, Table 6 shows that younger households and households who had been visited by extension agents are more likely to adopt. Results indicate network effects that vary by network type. In the specification without poverty class interactions,

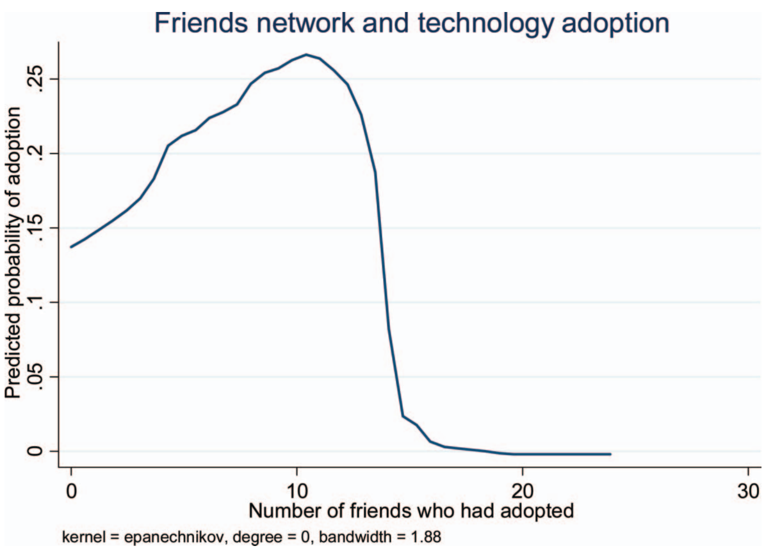

Figure 1. The relationship between the size of a farmer's network and probability of adopting irrigated vegetables.

Source: Generated by authors in the statistical software package STATA

Table 5. Social network (friend adopters) effects by splines on the adoption of irrigated crops

Irrigated crops	Coefficient	P > z
Male head (1/0)	0.0692	0.862
Household livestock	0.0001**	0.028
Household nonproductive assets	0.0006**	0.016
Visited by an extension agent in the last year	0.3225	0.374
Age of household head (years)	0.0173	0.166
Distance to closest market (km)	0.0059	0.856
Distance to paved road (km)	−0.0245**	0.021
Household parcel size	−0.3329**	0.012
Household size	0.0419	0.642
Most education (years)	0.0184	0.734
1–4 adopters among friends	0.8229*	0.057
5–8 adopters among friends	1.2565**	0.005
More than 8 adopters among friends	1.2287**	0.011
Steep land (1/0)	−0.2614	0.416
Poor quality soil (1/0)	−0.7342	0.188
Harresawe	1.8950**	0.003
Constant	−3.5445**	0.002
Number of observations	135	
Prob > chi^2	0.000	
Pseudo R^2	0.278	

Source: Calculated from authors' survey of the ERHS households.
Notes: *, **, *** imply significant at 10 per cent, 5 per cent and 1 per cent respectively.
Test of joint significance of splines – H0: 1–4 adopters = 5–8 adopters = More than 8 adopters = 0. Results: Chi2(3) = 10.16 Prob > chi2 = 0.017. Conclusion: Reject null.
All models are estimated with robust standard errors.

the probability of adopting improved seeds exhibits diminishing marginal effects with respect to the number of friends who had previously used improved seed, but the small coefficient on the quadratic term implies that increasing the number of adopters in the friends network continues to increase the probability of adoption for networks of over 300. Thus the inverse U is not exhibited within a network size that would be evidence of social learning. Distinguishing poverty classes leads to a somewhat more pronounced quadratic effect among the non-poor households but the size of friends network is increasing in the quadratic term.[7] Results imply a social network effect among friends that differs by poverty status and cannot be attributed to any particular network mechanism.

Neighbour networks yielded no evidence of social learning or any other positive network effect. Indeed, after accounting for the network of friends that had adopted improved seed, the neighbour network variable has a negative effect on adoption. Estimating the regression without the friend variables yields statistically insignificant coefficients on neighbours and neighbours squared of 0.047 ($P > Z = 0.511$) and −0.003 ($P > Z = 0.233$).[8] These results indicate that there are differential network effects not only across network types but also across poverty levels.

Robustness Checks

Fertiliser Use

To help distinguish social learning effects from other network-based determinants of adoption, the econometric model is applied to the use of a well-known technology – chemical fertiliser. While one would not expect to find social learning for this technology, other network effects could still exist. For example, network effects through reduced cost of procurement might be observed through adoption that is monotonically increasing in network size. Table 7 shows that

Table 6. Social network effects on the adoption of improved cereals, estimation by poverty status: probit estimation^{++}

	Not distinguishing poverty status		Distinguishing poverty status	
Improved cereals	Coefficient	P > z	Coefficient	P > z
Male head (1/0)	0.0508	0.876	0.1767	0.586
Household livestock	0.0000	0.655	0.0000	0.647
Household nonproductive assets	−0.0002	0.601	−0.0002	0.569
Visited by an extension agent in the last year	0.9600***	0.005	1.0286***	0.002
Age of household head (years)	−0.0196*	0.074	−0.0265***	0.028
Distance to closest market (km)	−0.0287	0.267	−0.0238	0.402
Distance to paved road (km)	−0.0045	0.690	−0.0068	0.584
Household parcel size	−0.0008	0.984	−0.0059	0.886
Household size	0.0032	0.971	0.0245	0.779
Most education (years)	−0.0016	0.973	−0.0119	0.800
Friend adopters (number)	0.0667**	0.036	−0.1932	0.136
Friend adopters squared	−0.0001**	0.036	0.0099**	0.039
Neighbour adopters (number)	−0.0824**	0.040	0.0844	0.311
Neighbour adopters squared	−0.0002	0.724	−0.0046**	0.018
In persistent poverty			−0.0959	0.789
Friends*Not in persistent poverty			0.2517*	0.096
Friends squared*Not in persistent poverty			−0.0101**	0.043
Neighbours*Not in persistent poverty			−0.1791	0.206
Neighbours squared*Not in persistent poverty			0.0045	0.578
Steep land (1/0)	0.3648	0.199	0.4548	0.118
Poor quality soil (1/0)	−0.3131	0.345	−0.4457	0.213
Harresawe	−2.1851***	0.000	−2.2530***	0.000
Constant	2.0539**	0.015	2.3548***	0.008
Number of observations	135		135	
Prob > chi^2	0.000		0.0000	
Pseudo R^2	0.401		0.4330	

Source: Calculated from authors' survey of the ERHS households.
Note: *, **, *** imply significant at 10 per cent, 5 per cent and 1 per cent respectively.

wealth (livestock) and education were important factors encouraging the adoption of chemical fertiliser. Evidence of network effects emerges among friends only, where a small and strictly increasing relationship between the number of adopters and the likelihood of adoption implies a network effect that is not necessarily social learning. With a $chi^2(2) = 5.41$ and Prob $> chi^2 = 0.06$, we reject the null of the joint hypothesis test of significance of the base and squared interaction term between poverty status and friend adopters. Whether or not poverty classes are considered, the effect of the friends-network is small and monotonically increasing. Neighbour effects are absent and there appears to be no evidence of social learning for fertiliser adoption, supporting the interpretation of results for irrigation of vegetables and pulses as suggesting social learning.

Social Learning vs. Spurious Effects

As in other studies on network effects, unobserved household characteristics could drive the association between network size and probability of adoption. While Manski (1993) clearly raised possible problems in identifying social network effects,[9] Brock and Durlauf (2000) showed that this identification problem is intrinsically linked to linearity, such that nonlinear social effects that are properly specified can still identify endogenous network effects. In addition to the nonlinearity argument proposed by Brock and Durlauf (2000) and used by Bandiera and Rasul

Table 7. Social network effects on the adoption of fertiliser use

Fertiliser	Coefficient	P > z	Coefficient	P > z
Male head (1/0)	0.3314	0.356	0.6380**	0.046
Household livestock	0.0027**	0.004	0.0002	0.250
Household nonproductive assets	0.0003	0.315	0.0003	0.231
Visited by an extension agent in the last year	0.1474	0.620	0.1319	0.635
Age of household head (years)	−0.0170	0.119	−0.0152	0.133
Distance to closest market (km)	0.0049	0.851	0.0177	0.413
Distance to paved road (km)	0.0092	0.470	−0.0137	0.211
Household parcel size	−0.2221**	0.019	−0.1666**	0.009
Household size	0.0640	0.469	0.0269	0.753
Most education (years)	0.0941**	0.050	0.100**	0.045
Friend adopters (number)	0.0388	0.087	0.0228	0.662
Friend adopters squared	0.0008**	0.005	0.0021**	0.018
Neighbour adopters (number)	0.0228	0.518	0.0002	0.995
Neighbour adopters squared	0.0002	0.414	0.0008	0.102
In persistent poverty	–	–	−0.6712	0.135
Friends*Not in persistent poverty	–	–	0.1015	0.244
Friends squared*Not in persistent pov.	–	–	−0.0005**	0.026
Neighbours*Not in persistent poverty	–	–	0.0454	0.434
Neighbours squared*Not in persistent pov.	–	–	−0.0007	0.201
Steep land (1/0)	0.1233	0.664	−0.0487	0.862
Poor quality soil (1/0)	−0.2924	0.417	−0.2600	0.502
Harresawe	−0.7981	0.145	0.4144	0.466
Constant	−0.9689	0.285	−0.6105	0.498
Number of observations	130		130	
Prob > chi^2	0.0000		0.0000	
Pseudo R^2	0.2401		0.2713	

Source: Calculated from authors' survey of the ERHS households.
Note: *, **, *** imply significant at 10 per cent, 5 per cent and 1 per cent respectively.

(2006), the finding here that the inverse U relationship persists is further evidence against mimicry or the contextual effects discussed in Manski (1993).

Bandiera and Rasul (2006) considered a case in which an inverse U relationship could be spuriously driven by an unobserved household characteristic (ability) that is positively and linearly associated with network size but nonlinearly associated with the probability of adoption. For example, if low-ability and very-high-ability farmers have lower probabilities of adopting due to capacity constraints and alternative options, respectively, these two effects together could drive an inverse U relationship. To check for this possibility, we exclude households considered to be high ability from the sample and then test for the inverse U relationship. The first group that is dropped are those households in the highest quartile of cereal productivity (measured as yield per hectare of land) and the second group to be dropped are those households in the highest quartile of pulse productivity. As can be seen in Table 8, the inverse U relationship persists in the irrigation regressions even when these groups are dropped from the estimation. The peak remains at about seven friends who have adopted, after which adoption probabilities begin to decline.

Conclusions

This article examined evidence of social network effects on the adoption of diverse agricultural technologies across households in a range of poverty conditions. Observed network effects varied by technology, type of network and poverty status of households suggesting different social mechanisms in different contexts. The results provide evidence consistent with social network effects through social learning for complex, novel technologies (for example, irrigation of

Table 8. Social network effects for irrigated crops after dropping households considered to be high ability

	Dropping high ability (a)		Dropping high ability (b)	
Irrigation	Coefficient	P > z	Coefficient	P > z
Male head (1/0)	−0.4420	0.394	−0.6560	0.177
Household livestock	0.0001**	0.011	0.0000	0.340
Visited by an extension agent in the last year	0.6703	0.180	0.5113	0.275
Household nonproductive assets	0.0006**	0.007	0.0006**	0.016
Age of household head (years)	0.0081	0.625	0.0107	0.461
Distance to closest market (km)	0.0202	0.700	0.0167	0.634
Distance to paved road (km)	−0.0467**	0.002	−0.0146	0.275
Household parcel size	−0.3910**	0.014	0.1248*	0.070
Household size	−0.0929	0.489	0.0520	0.660
Most education (years)	0.0397	0.569	−0.0400	0.566
Friend adopters (number)	0.4465**	0.007	0.4274*	0.058
Friend adopters squared	−0.0309**	0.025	−0.0394*	0.058
Neighbour adopters (number)	0.0223	0.876	−0.1601	0.147
Neighbour adopters squared	−0.0035	0.697	0.0109*	0.061
Steep land (1/0)	0.4653	0.289	−0.5202	0.194
Poor quality soil (1/0)	-	-	−0.6837	0.163
Harresawe	3.2659**	0.001	1.1285	0.118
Constant	−3.1171**	0.020	−3.1145**	0.035
Number of observations	88		101	
Prob > chi^2	0.0000		0.0000	
Pseudo R^2	0.4145		0.2660	

Source: Calculated from authors' survey of the ERHS households.
Notes: *, **, *** imply significant at 10 per cent, 5 per cent and 1 per cent respectively.
The high ability dropped here are those in the highest quartile of cereal productivity.
The high ability dropped here are those in the highest quartile of pulse productivity.

vegetables for market sale). For more familiar technologies (improved cereals and chemical fertiliser) there is evidence of social network effects that cannot be clearly associated with social learning as opposed to other social dynamics. Further, results indicate no social learning and generally limited network effects for networks based on proximity alone. In general, the evidence of social learning and other network effects emerges from analysis of networks based on friendships and purposeful interaction.

Finding that social network effects are available in rural Ethiopia and that they are associated with purposeful interaction rather than through proximity is significant for extension planning. Technology diffusion is likely to be enhanced if extension can reach more networks of interest rather than spatial clusters. While extension efforts can make use of any social network mechanism, this research suggests that network mechanisms and impacts vary substantially across technology types. Findings indicate more evidence of social learning in the mechanism for complex technologies like irrigated vegetables and that this mechanism is available to persistently poor households. For cereals and fertiliser, network effects also exist, but they exhibit themselves differently for the poor and non-poor and work through mechanisms that cannot be identified in this analysis. Differences in the marginal effects of network expansion by poverty status and technology warrant consideration in further analysis of social networks and in the development of effective poverty-reduction strategies.

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Notes

1. An inverse U would also emerge if the incremental value of observing another person declined with the number of people observed and if the population being observed were heterogeneous. In this case, an additional observation could introduce more noise than information.
2. A Peasant Association is a group of villages.
3. One US dollar is equivalent to about 11 Ethiopian birr. The PPP (purchasing parity power) conversion factor is approximately 0.25.
4. Thank you to an anonymous referee for suggesting this simulation exercise.
5. Excluding the neighbour variables, the coefficients on friends and friends squared were 0.44 ($P > Z = 0.003$) and -0.032 ($P > Z = 0.026$). Excluding the friend variables the coefficients on neighbours and neighbours squared were 0.126 ($P > Z = 0.21$) and -0.006($P > Z = 0.36$).
6. Given our small sample size, we explored more parsimonious specifications, such as dropping nonproductive assets. This did not change the results. Furthermore, the correlation coefficient between various variables indicated no multicollinearity.
7. With a $Chi^2(2) = 4.24$ and $Prob > chi^2 = 0.10$, we reject the null of the test of joint significance of the level and squared interaction term between poverty status and friend adopter variable for households not in persistent poverty at 10 per cent significance. With a $Chi^2(2) = 2.42$ and $Prob > chi^2 = 0.298$, we fail to reject the null of the same test for the corresponding neighbour adopter variables indicating their joint insignificance.
8. In a specification excluding the neighbours variables the coefficients on friends and friends squared were 0.101($P > Z = 0.06$) and-.001 ($P > Z = 0.29$).
9. The endogenous network effects (like social learning) cannot be separated from exogenous (contextual effects) or correlated unobservable characteristics if the endogenous effects are a linear combination of exogenous and correlated effects (Manski, 2004).

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