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Poverty Status and the Impact of Social Networks on Smallholder Technology Adoption in Rural Ethiopia

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ABSTRACT

Despite the promise of many new farm technologies, technology adoption rates in Ethiopia remain low. This paper studies the impact of social networks on technology adoption through social learning. In addition to geographic networks, intentional relationships are considered. The differential impacts by network type, technology, and asset poverty status are explored. We find evidence that although social learning occurs, it is more consistent for households not in poverty traps than for those that are persistently asset poor. Social learning among rural households is stronger for more complex technologies and is associated with intentional relationships rather than with geographic networks.

Keywords: Africa, Ethiopia, asset poverty, social networks, technology adoption

1. INTRODUCTION

It is widely recognized that the use of appropriate modern technologies could contribute to poverty reduction in rural Africa. The significant role of personal relationships and social learning in technology diffusion is also increasingly acknowledged. *Social learning* refers to learning that occurs within a social context, such as through observation of neighbors, imitation of associates, or modeling by friends.

Much learning emerges from social interaction, which, in turn, creates a potential to design extension systems that capitalize on social learning to leverage their impact on technology diffusion. The efficacy of using extension systems to catalyze social learning, however, requires a nuanced understanding of how different kinds of relationships influence technology use among different rural groups.

Although the effect of social networks in diffusing technology has been identified, only recently have researchers begun distinguishing between social learning and other potential network effects or studying how and when networks facilitate information flows (Munshi 2004; Bandiera and Rasul 2006). For example, little or no research has considered whether social learning is equally effective for poor and nonpoor households alike, or whether some types of networks are more effective in disseminating information than are others. This paper investigates the roles that different kinds of social networks play in household technology adoption in rural Ethiopia and explores the differential effect of networks on technology adoption across households facing different levels of poverty. The paper addresses four questions: (1) Do networks in rural Ethiopia contribute to technology adoption? (2) If networks affect technology adoption, what kinds of networks matter? (3) Can we find evidence of social learning in network effects? (4) Are these network effects the same across households in different forms of poverty and across different technologies?

2. 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 other farmers.[1] Studies further reveal how learning from others and from personal experience provides information that promotes technology use. This paper follows more recent studies to explore network effects and social learning prior to adoption.

Social learning is one of several factors that could link social networks with technology adoption. In addition to the information externality offered by networks, Besley and Case (1994) and Bandiera and Rasul (2006) noted that decisions within groups may be correlated when there are other shared goals for or constraints to the adoption decision. Homogeneity within a group may also cause members to adopt technology at a similar time; however, in this case, the network's size may not necessarily affect adoption. If there were risk sharing in a network or if the technology in question were too expensive for an individual farmer, 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, because fixed costs would be spread over the membership. Meanwhile, group dynamics could also affect the willingness of individuals to engage in new activities, though there is no reason to posit a relationship between network size and probability of adoption based on group dynamics.

With respect to social learning, more members in a network implies that more information flows through it; however, the relationship between membership size and technology adoption varies with network size itself. A larger network might indicate access to more information about a technology and thus might encourage adoption. However, information from personal experience may be costly to acquire, and the experience of others could substitute for it. Hence, a larger network could encourage households to delay adoption and free ride on the experience of other members in the network, as shown in Bardhan and Udry (1999) and Bandiera and Rasul (2006). This adoption-depressing effect may occur when experimenting with new technology is too costly and the expected profit increases with the information received from one's own trials and/or the trials of others in the network. Because the additional information gained from personal trials declines if the larger network provides more free information, a large network could discourage personal trials.

Consider, for example, the introduction of a horticultural crop that requires careful management but that can yield higher profits than the conventional production system. A farmer who does not associate with anyone using this new technology may consider adopting it; however, she will also most likely recognize that she may at first experience losses in income while she is learning the system's technical and market aspects. If she is unwilling to absorb the costs of learning by doing, then she will not adopt. Should someone else in her network adopt the technology instead, that person would experience the costs of learning, while the other members of the network may costlessly learn from observing the adopter. Thus, having one adopter in the network lowers the costs of adoption for others and may accelerate their attempts to use the technology.

The information gained costlessly from observing others will be of lower quality than that gained from one's own experience, due to the heterogeneity in resources and skills across farmers and the incomplete transmission of information. Hence, when only a few people in the network practice the technology, there will be a high value to doing one's own trials and learning by doing. However, the larger the pool of information available from observation, the higher the quality and the lower the difference in quality between learning from others and learning by doing. Thus, at some point, having more people in a network practicing a technology may encourage farmers to learn from others and delay adoption until they are certain of how to practice the new technology themselves. Therefore, it is possible that a larger network of adopters could marginally reduce the probability of adoption in a given period by the non-adopter in the network. Hence, social learning could generate an inverted U relationship between the probability of adoption and the number of adopters in the network.

[1] See Besley and Case (1993), Besley and Case (1994), Foster and Rosenzweig (1995), and Munshi (2004) for more information on the evolution of the social learning model in agriculture.

Because the effect of network size on adoption through social learning is not constant across network sizes, one can test both for an effect of networks on adoption and for social learning as a channel for the effect. Finding an inverse U relationship between the probability of adoption and the number of adopters in a household's information network, as in Bandiera and Rasul (2006), would suggest social learning. Although finding a strictly linear or U relationship would be consistent with social learning, such a result could also be explained by other network effects, such as risk pooling or cost sharing.

Whether or not social learning is the conduit, the effects of networks on adoption could be heterogeneous, depending on the kind of network, the technology in question, and the characteristics of the members. Most previous studies focused on geographic proximity to define networks in which adoption choices may be correlated. However, the geographic explanation assumes that neighbors willingly share information or that farmers observe their neighbors' input use and output, at no cost to themselves. Yet discussions with farmers across Ethiopia reveal that this assumption may not hold. With land allocated by government and then passed on from generation to generation, farmers have little choice as to who their neighbors are, and they are not always on good terms with each other. Furthermore, various procedures associated with a new technology, such as application rates and timing, may not be easily observable and may instead necessitate more purposeful interaction. This paper thus explores social networks based on characteristics other than physical proximity.

As evidence that adoption networks need not be based on physical proximity, studies such as Slicher Van Bath (1969) revealed that during the English agricultural revolution, it was not uncommon to find fields being cultivated with traditional techniques bordering lands being cultivated by newly introduced crop rotation. More recently, Bandiera and Rasul (2006) found that farmer adoption decisions were correlated to the decisions of friends and family, as well as to people of the same religion; however, these decisions were not correlated to the decisions of those in different religions. Similarly, in their study on technology adoption in Ghana, Conley and Udry (2001) found that farmers tend to have a limited number of incomplete technology information sources that are not necessarily based on geographic proximity. Visits to the study villages in 2007 revealed that extension delivery relied somewhat on the idea that technology could spread from model farmers through networks based on proximity. A more nuanced understanding of the nature and quality of social learning among rural households could contribute to efforts to restructure and improve extension services in Ethiopia and elsewhere.

Even if social networks encourage technology adoption, it is important to understand whether and how their effects differ across households characterized by different poverty forms and dynamics. Previous work (Liverpool and Winter-Nelson 2010) showed that formal credit has little effect on the use of modern technology for persistently asset-poor rural Ethiopians, even though the use of certain technologies, such as fertilizer, contributes to their asset accumulation over time. Exploring whether relaxing information constraints through social learning has a positive effect on the use of these technologies by the persistently poor could indicate the role of social networks in poverty reduction. Furthermore, identification of differential network effects across poverty classes would inform the design of extension and other poverty-reduction strategies in rural Ethiopia.

3. THEORETICAL FRAMEWORK

Social Learning

The effect of social learning is measured using a target input model, in which a farmer adopts a technology and then experiments with input and management techniques over time to improve profits. Adoption only occurs when the expected value of the discounted flow of profits under the new technology exceeds that of the old technology; the greater the initial information concerning the technology, the greater the initial profitability. Information may come from one's own experience or from observing others. The former may be costly, as it involves forgoing a known production system in order to experiment with a new one, while the latter may yield poor-quality information due to heterogeneity and incomplete observation. More initial information lowers the cost of one's own experimentation, making the initial use of the new technology more profitable. Some information from a network may therefore encourage adoption and one's own experimentation. However, if a network is large and likely to supply valuable information, a farmer might choose to delay adoption and benefit from the experience of others. Thus, social learning can lead to an inverse U relationship between the probability of adoption and network size.[2] (Readers not interested in the theoretical justification for this approach may skip to the text following Equation (17).)

The target input model developed here follows that of Bardhan and Udry (1999) and of Bandiera and Rasul (2006).[3] It assumes that farmers use Bayesian updating to learn about the parameters of a new technology. Although farmers are aware of the underlying production technology, they are unaware of one parameter—the target input level. The model posits that farmer i's output in time t; q_{it} , declines in the square of the distance between the input used; k_{it} and the unknown target input use level for farmer i; (χ_{it}). This can formally be expressed as:

$$q_{it} = 1 - (k_{it} - \chi_{it})^2 . \tag{1}$$

After selecting an input level (k_{it}) and seeing the yield, a farmer updates beliefs about χ_{it} . Each time the farmer chooses a level of k_{it} and observes a yield (q_{it}) is a trial that provides information about the distribution of χ_{it} . Thus, farmers learn by doing. Because of farmer- and time-specific effects, the optimal target for farmer i fluctuates around χ^* such that

$$\chi_{it} = \chi^* + \varepsilon_{it} , \tag{2}$$

where ε_{it} refers to these transitory farmer-specific shocks to the optimal target input χ^* . The error is assumed to be independently and identically distributed normal with E(ε_{it}) = 0 and V(ε_{it}) = $\sigma^2{}_u$.

At any time t , farmer i believes $\chi^* \sim N(\chi^*_{it}, \sigma^2{}_{\chi it})$. The model assumes that $\sigma^2{}_u$ is known and that the input is costless, so that the farmer's profit is price (normalized to 1) multiplied by q_{it} .

Because $E_t(\varepsilon_{it}) = 0$, farmer i uses the expected optimal target level as the new level of inputs in order to maximize expected profit. Thus, $k_{it} = E_t(\chi_{it})$, and the expected output is

[2] 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, one could find that an additional observation introduced noise without providing new information.

[3] The target input model is a long-standing model developed by Prescott (1972), Wilson (1975), and Jovanovic and Nyarko (1994) and applied to learning in agriculture by Foster and Rosenzweig (1995).

$$\mathrm{E}_t(q_{it}) = 1 - \mathrm{E}_t[k_{it} - \mathrm{E}_t(\chi_{it})]^2 = 1 - \sigma^2_{\chi it} - \sigma^2_{u}\ , \tag{3}$$

showing that the expected output increases with lower levels of uncertainty about target input χ_{it}.

With regard to learning by doing, in each period, farmer i engages in a trial with a certain level of input k_{it}, sees the output, and then modifies his or her belief about the target input level. At time t, the variance of farmer i's belief about χ^* is $\sigma_{\chi it}{}^2$. After observing the target input for the previous period (χ_{it-1}), the farmer updates their belief about the variance of χ^*, applying Bayes's rule. As shown by Bardhan and Udry (1999), the posterior belief thus becomes

$$\sigma^2_{\chi t+1} = \frac{1}{\dfrac{1}{\sigma^2_{\chi it}} + \dfrac{1}{\sigma^2_{u}}}. \tag{4}$$

If we define the precision of information generated by a farmer's own trial as $\dfrac{1}{\sigma^2_u} = \rho_o$ and $\rho_{io} = \dfrac{1}{\sigma^2_{\chi i0}}$ as the precision of farmer i's initial belief about the variance of χ^*, we can show by substitution that

$$\sigma^2_{\chi it+1} = \frac{1}{\rho_{io} + I_t \rho_o} \tag{5}$$

where I_t is the number of trials that farmer i has had with the new technology between periods 0 and t. Substituting (5) into (3), we can express current expected profits as

$$\mathrm{E}_t(q_{it}) = 1 - \frac{1}{\rho_{io} + I_{t-1}\rho_o} - \sigma^2_u\,. \tag{6}$$

From equation (6), we can see that output (and profit) increases with the number of trials—that is,

$$\frac{\partial E(q_{it})}{\partial I_{t-1}} = \frac{\rho_o}{(\rho_{io} + I_{t-1}\rho_o)^2} > 0. \tag{7}$$

Now, consider the case in which farmer i can improve her estimate of the target input by learning from the trials of other farmers. If we define the network of farmers as $n(i)$ and assume that farmers in this network share information with others at no extra cost, then after each period, farmer i updates her belief about the target input with information from previous trials and with information from trials of other network members $j \neq i$. This means that at time t, when farmer i has had I_{t-1} trials and the network has had $n(i)_{t-1}$ trials, then the posterior belief about the variance of χ^* will be

$$\sigma^2_{\chi it} = \frac{1}{\rho_{io} + I_{t-1}\rho_o + n(i)_{t-1}\rho_o}\ , \tag{8}$$

with expected output now

$$\mathrm{E}_t[q_{it}, n(i)_{t-1}] = 1 - \frac{1}{\rho_{io} + I_{t-1}\rho_o + n(i)_{t-1}\rho_o} - \sigma^2_u \tag{9}$$

and with output increasing with the number of trials of the network:[4]

$$\frac{\partial E[q_{it}, n(i)_{t-1}]}{\partial n(i)_{t-1}} = \frac{\rho_o}{(\rho_{io} + I_{t-1}\rho_o + n(i)_{t-1}\rho_o)^2} > 0 \quad (10)$$

The Technology Adoption Decision

Given some traditional technology (traditional crop or variety) with a known return of q_T, a farmer is faced with the decision of whether to adopt a new technology. Let the adoption of new technology by farmer *i* in time *t* be a dichotomous variable (a_{it}), such that $a_{it} = 1$ if adoption occurs; 0 otherwise. If learning takes place, farmer *i*'s adoption depends on the adoption decision of others in the network. The value of future profits to farmer *i* from period *t* to *T* is

$$V_t[I_{t-1}, n(i)_{t-1}] = \max_{a_{it}\in\{0,1\}} E_t \sum_{s=t}^{T} \delta^{s-t} \{(1-a_{is})q_T + a_{is} q_s [I_{s-1}, n(i)_{s-1}]\} \quad (11)$$

$$= \max_{a_{it}\in\{0,1\}} (1-a_{it})q_T + a_{it} E_t q_t [I_{t-1}, n(i)_{t-1}] + \delta V_{t+1}[I_t, n(i)_t], \quad (12)$$

where $I_{s-1} = \sum_{t=0}^{s} a_{is}$ is the total number of trials that farmer *i* has conducted, up to and including period *s*; $n(i)_{s-1}$ refers to the number of trials that farmer *i*'s network has had over the same period; and δ is the discount rate.

From equations (11) and (12), we can see that technology adoption by farmer *i* depends not only on her expectation of current profits but also on the future expected profitability of adoption. Expected profits increase with the number of trials of the new technology. Thus, the number of trials positively affects expected profit, which determines technology adoption. Because expected profits increase with the number of trials, the technology adoption must be an absorbing state. Applying this approach implies an assumption that the new technologies considered are generally superior to the traditional crops, on average, once appropriate complementary inputs and practices are also adopted. The actual spread of the crop varieties in question over the past five years supports this assumption in this application.

Equations (11) and (12) allow for the possibility that adoption in time *t* might occur, even if the technology were less profitable than the traditional practice in that period. If the loss in current expected profits were less than the discounted gain in future profitability from the additional trial of the new technology, then the technology would be adopted in time *t*, even if the current profitability were less than the traditional variety. The adoption despite the absence of immediate profitability obtains if equation (13a) holds:

$$q_T - Eq(t, n(i)_t) \leq \delta[V_{t+1}(t+1), n(i)_t - V_{t+1}(t), n(i)_t]; \quad (13a)$$

that is, if

$$[V_{t+1}(t+1), n(i)_t - V_{t+1}(t), n(i)_t] \geq 0, \quad (13b)$$

holds, where $[V_{t+1}(t+1) - V_{t+1}(t)]$ refers to the difference between value functions if adoption were to occur in time *t* + 1 after farmer *i* has had *s* trials and value functions estimated in time *t* + 1 when farmer *i*

[4] It can be inferred, under this assumption, that the larger the network size, the larger the number of trials available for farmer *i* from the network.

has had only $s-1$ trials. Expanding from (13b) yields (14), which is positive, reflecting the increase in expected profits due to the information gained from experimenting in time t:

$$[V_{t+1}(t+1),n(i)_t - V_{t+1}(t),n(i)_t] = \sum_{s=t+1}^{T}\delta^s(q(s)-q(s-1))$$

$$= \sum_{s=t+1}^{T}\delta^s\left(\frac{1}{\rho_{io}+(s-1)\rho_0+n(i)_t\rho_0} - \frac{1}{\rho_{i0}+s\rho_0+n(i)_t\rho_0}\right) > 0 \qquad (14)$$

Although (14) is positive, it is decreasing in $n(i)$. If information from personal trials and the trials of others are substituted, then as more other farmers use the new technology, less additional information will be gained by the individual farmer's own experimenting. Thus, if many of farmer i's neighbors or friends have characteristics that would lead them to adopt a new technology early, it might be in farmer i's best interest to refrain from experimenting and to instead benefit from the information from their experiments (Bardhan and Udry 1999). These opposing effects can be seen by taking the derivative of equation (15) with respect to network size, which reflects the necessary condition for a farmer to adopt the new technology (crop) in time t, based on (13).

$$E_t q_t[t,n(i)_t] + \delta[V_{t+1}(t+1,n(i)_t)] \geq q_T + \delta[V_{t+1}(t),n(i)_t]. \qquad (15)$$

Taking the derivative with respect to $n(i_t)$ yields

$$\frac{\partial E_t q_t[t,n(i)_t]}{\partial n(i)_t} + \delta\frac{\partial\{V_{t+1}[t+1,n(i)_t] - V_{t+1}[(t),n(i)_t]}{\partial n(i)_t} \geq 0 . \qquad (16a)$$

Given that we are dealing with a discrete scenario,

$$[V_{t+1}(t+1),n(i)_t - V_{t+1}(t),n(i)_t] \approx \frac{\partial V}{\partial I}$$

$$= \sum_{s=t+1}^{T}\delta^s\left(1-\frac{1}{\rho_{i0}+s\rho_0+n(i)_t\rho_0}-\sigma_u^2\right) - \left(1-\frac{1}{\rho_{i0}+(s-1)\rho_0+n(i)_t\rho_0}-\sigma_u^2\right) \qquad (16b)$$

$$= \sum_{s=t+1}^{T}\delta^s\left(\frac{1}{\rho_{io}+(s-1)\rho_0+n(i)_t\rho_0} - \frac{1}{\rho_{i0}+s\rho_0+n(i)_t\rho_0}\right) > 0 .$$

Its derivative with respect to $n(i_t)$ can be expressed as

$$\frac{\partial V}{\partial I\partial n(i)_t} = \delta\frac{\partial\{V_{t+1}[t+1,n(i)_t] - V_{t+1}[(t),n(i)_t]}{\partial n(i)_t} \qquad (16c)$$

$$= \frac{(\rho_{io}+(s-1)\rho_0+n(i)_t\rho)*0-(1)*\rho_0}{(\rho_{io}+(s-1)\rho_0+n(i)_t\rho_0)^2} - \frac{(\rho_{io}+s\rho_0+n(i)_t\rho)*0-(1)*\rho_0}{(\rho_{io}+s\rho_0+n(i)_t\rho_0)^2}$$

$$= \frac{-\rho_0}{(\rho_{io}+(s-1)\rho_0+n(i)_t\rho_0)^2} - \frac{-\rho_0}{(\rho_{io}+s\rho_0+n(i)_t\rho_0)^2}$$

$$= \frac{-\rho_0}{(\rho_{io}+(s-1)\rho_0+n(i)_t\rho_0)^2} + \frac{\rho_0}{(\rho_{io}+s\rho_0+n(i)_t\rho_0)^2}$$

$$= \frac{\rho_0}{(\rho_{io} + s\rho_0 + n(i)_t \rho_0)^2} - \frac{\rho_0}{(\rho_{io} + (s-1)\rho_0 + n(i)_t \rho_0)^2} \leq 0 \approx \frac{\partial V}{\partial I \partial n(i)_t}.$$

And substituting this into equation (16), we get

$$\frac{\partial E_t q_t[t, n(i)_t]}{\partial n(i)_t} + \delta \frac{\partial \{V_{t+1}[t+1, n(i)_t] - V_{t+1}[(t), n(i)_t]}{\partial n(i)_t}$$

$$= \frac{\partial E_t q_t[t, n(i)_t]}{\partial n(i)_t} + \delta \sum_{s=t+1}^{T} \delta^s \frac{\rho_0}{(\rho_{io} + s\rho_0 + n(i)_t \rho_0)^2} - \frac{\rho_0}{(\rho_{io} + (s-1)\rho_0 + n(i)_t \rho_0)^2},$$

where, when $\frac{\partial E_t q_t[t, n(i)_t]}{\partial n(i)_t}$ is replaced by its value,

$$\frac{\partial E[q_{it}, n(i)_{t-1}]}{\partial n(i)_t} = \frac{\rho_o}{(\rho_{io} + n(i)_t \rho_o)^2}$$

gives

$$\frac{\partial E_t q_t[t, n(i)_t]}{\partial n(i)_t} + \delta \frac{\partial \{V_{t+1}[t+1, n(i)_t] - V_{t+1}[(t), n(i)_t]}{\partial n(i)_t}$$

$$= \frac{\rho_o}{(\rho_{io} + n(i)_t \rho_o)^2} + \delta \sum_{s=t+1}^{T} \delta^s \frac{\rho_0}{(\rho_{io} + s\rho_0 + n(i)_t \rho_0)^2} - \frac{\rho_0}{(\rho_{io} + (s-1)\rho_0 + n(i)_t \rho_0)^2} \quad (17)$$

The first term in equation (17) indicates the positive effect of learning from the network, though it is decreasing in $n(i)_t$. However, the marginal value of a personal trial is decreasing in the size of the network (meaning $\frac{\partial V}{\partial I \partial n(i)_t} \leq 0$), which means that the gain in future profitability due to an additional trial is decreasing in the size of the network. Intuitively, because information from personal trials and one's own network are substitutes, a larger network of adopters lowers the value of additional information from a personal trial and creates an incentive for a farmer to strategically delay adoption. This means that the net gains from adoption in time *t* can be an increasing or decreasing function of the number of adopters in a farmer's network. Furthermore, from equation (17), the more accurate a farmer's personal information is, the less important the additional information from the network will be, and the less sensitive that farmer is to the number of adopters in the network. Because the effect of network size $n(i)$ on adoption is positive but decreasing in the size of the network, tests for a quadratic relationship between adoption and network size can provide evidence of social learning.

This relationship between network size and probability of adoption must be clearly distinguished from the effects of information on profitability. As shown in equation (7), the relationship between information from one's network and profitability is always positive, because more information reduces the uncertainty about the practice of the new technology and hence about the expected profit (equation (3)). However, the effect of information from a farmer's network on her decision to adopt a technology at a particular point (*t*), rather than at any time in the future ($t + x$), is not necessarily strictly positive, due to the substitutive effect of information from her network and from his own personal trial. As shown in equations (16a) and (17), the actual effect of a farmer's network size on her decision to adopt at a particular time *t* could depend on the network size itself.

Drawing from equations (11) and (12) and from the derivative of equation (15), which is expressed in equation (17), we can see that with smaller networks, it is more likely that the positive marginal effect of more information from one's own network outweighs the negative marginal effect of an additional trial. However, in a network with many people, it is likely that the negative marginal effect of an additional trial (due to the presence of a large pool of information from a bigger network) could outweigh the marginal positive effect of having more information in the presence of an already large pool of information from the large network.[5] This could then lead farmers with a large network to delay adoption and to benefit from the experience of others in their network. But this only means that farmer *i* may not adopt in time *t* and instead will adopt at some future period ($t + x$) or never.

Although the direction of the relationship between output and information sources shown in equation (10) should not be different across various technologies and different poverty classes, the effect of the different sources of information, or of additional information from various sources, might be different. With regard to poverty status, in addition to being information constrained, very poor farmers are, on average, more risk averse. Because traditional models of expected utility assume risk neutrality, this study accounts for the potentially different levels of risk aversion by using a household asset variable in a general specification of equation (18) (see Tables 3–8) and a categorical variable that distinguishes households in persistent asset poverty from those that are not in a model specification of equation (18) (see Tables 3, 4, and 6) that distinguishes poverty classes.[6]

For more risk-averse households with limited assets (and, hence, less diversity of investment portfolio), information might have a higher marginal effect on their probability of adoption if it were to significantly reduce their expected output variation. On the other hand, facing a double hurdle (due to risk aversion and lack of information), the relaxed information constraint might have a smaller effect on the probability of the very poor adopting technology. Network effects might differ across technologies, depending on the amount of new learning necessary and on the perceived personal applicability of the experiences of others. Munshi (2004) found that network effects were stronger for those technologies whose use and needed information were less heterogeneous. Finally, the importance of networks might critically depend on the factors that define the networks themselves.

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[5] Following the law of diminishing marginal product and with information as an input to the production function, we expect the marginal value of information at high levels of information to be lower than at low levels.

[6] This classification is based on the long-term asset poverty status estimated econometrically. See appendix and Adato, Carter, and May (2006) for more details on this approach.

4. EMPIRICAL TECHNOLOGY ADOPTION DECISION MODEL

The social learning model shows that farmers can learn from their experience and from the experience of others in their networks. Because profitability is an increasing function of information and that information from one's own trial and the trials of others are substitutes, the decision to adopt a technology at any point in time will depend to some extent on the size of the network of adopters. This relationship can be measured empirically through estimation of

$$(TA_{ik}) = (\alpha_A) + (\lambda_A Z_i) + f[n(i)] + (\psi_A V_i) + (E1_i) \quad i = (1, \ldots, N),$$

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 demographic and other characteristics, including household size, sex of household head, age of household head, highest years of education in the household, distance to the nearest market (in kilometers), size of land cultivated by household (in hectares), value of household implements, and number of household members engaged in full-time agricultural activities. V_i is a dummy to account for unobserved variations across villages that could affect a household's technology use decision; $n(\,)$ captures the social network effects; and E_{it} is the error term, capturing unobserved individual and network characteristics that affect household participation. For poverty distinctions, 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 are considered to be in a poverty trap. The social network variable is measured as the self-reported number of adopters among the farmer's social network at the time of adoption. The networks considered are defined by purposive social interaction (friends) and by geographic proximity (neighbors). Various specifications for $f[n(\,)]$ are explored, with the main one being a quadratic function to test for the form of the relationship between network size and probability of adoption; it is used to identify social learning. The other two approaches are the use of splines to explore possible threshold effects in the size of various networks and the use of nonparametric estimations to confirm the results of other specifications.

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

$$TA_{it}^* = A[Z_{it}, V_i\, f[n(i)]\, E_{it}].$$

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

$TA_{ikvt} = 1$, if $TA_{ikvt}^* > 0$;

$TA_{ikvt} = 0$, otherwise.

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

$$P[TA_{ik} = 1] = F[(\alpha_A) + (\lambda_A Z_i) + \theta_1[n(i)] + \theta_2[n(i)^2] + (\psi_A V_i) + (E_{1iv})] \tag{18}$$

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 8+ members engaged in a particular technology (improved seed) at the time of adoption relative to having no adopters in the network:

$$P[TA_{ik} = 1] = F[(\alpha_A) + (\lambda_A Z_i) + \beta_0[0] + \beta_1[1] + \beta_2[2] + \beta_3[3] + (\psi_A V_i) + (E_{1i})^x], \tag{19}$$

where [0], [1], [2], and [3] reflect different splines.

5. DATA

This study uses a subset of the Ethiopia Rural Household Survey (ERHS) dataset, as well as additional data collected from two ERHS villages. The ERHS dataset contains detailed information on consumption expenditure, assets, and agricultural activities of rural Ethiopian households and is the product of a long-standing data collection effort by Oxford University, the University of Addis Ababa, and the International Food Policy Research Institute (IFPRI). Since 1994, the survey has covered 1,477 households in 15 peasant associations (PAs) across four regions. Survey rounds were conducted in 1994 (twice), 1995, 1997, 1999, and 2004.

During 2007, supplementary community-level surveys were administered in all 15 PAs to identify recent changes in the villages, particularly between 2004 and 2007. Based on this community-level information, two PAs—Harresawe and Korodegaga—were identified as having recent experience with rapidly spreading new technologies. Household surveys in these two PAs in 2007 gathered data on the adoption of improved technologies, including improved varieties of various cereals and irrigated vegetables, from 172 households that were part of the ERHS sample. Demographic information, as well as information on assets, access to various institutions, social networks, and the prevalence of technology adoption within these networks, was also collected. This analysis uses data from the 2007 household surveys to estimate the technology adoption decision models; it uses the six rounds of the ERHS conducted between 1994 and 2004 to develop the asset poverty status variable.[7]

This analysis considers two relatively new technologies and one older technology. The two new technologies are use of improved cereals and use of irrigation for vegetables and pulses. Although these technologies themselves are not completely novel, discussions with farmers and development agents indicated that there had been a recent emphasis on the production of high-value crops, such as fruits and vegetables, as well as on other marketable crops, such as pulses and improved cereals. *Improved cereals* refers to improved varieties of barley and maize, which resident development agents (extension agents) and farmers identified as being introduced in recent years. It is possible that networks shared retained seeds, which would imply social provision of inputs and information; cost reduction through input sharing would strengthen the expected positive effect of network size on adoption but is unlikely to explain the inverted U shape used to identify social learning.

The older technology, chemical fertilizer, has been used in the areas for longer and is thus included as a control. Because most farmers have been familiar with chemical fertilizer for some time, social learning is not expected to affect adoption of this technology. In Harresawe, farmers and the local development agent cited 2004–2005 as the period of major shift in terms of increased focus on field pea production and 2004 as a year for increased vegetable production. For irrigation of pulses, fruits, and vegetables, the analysis includes only households that had not adopted irrigation prior to 2004.[8] In 2007, 92 percent of households using irrigation were engaged in irrigating fruits, vegetables, pulses, or oil seed.

A priori, a social learning effect may be most likely for irrigated pulses and vegetables, because the management intensity implies a substantial need for information and because homogenous (irrigated) growing conditions imply that relatively high-quality information can come from other people's trials. Improved cereal production, often administered via 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 useful for improved cereals than for irrigated pulses and vegetables. Finally, social learning is least likely to be significant for chemical fertilizer. Nonetheless, adoption of all of these technologies could be supported through other network affects, such as pooled costs of transactions.

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[7] This asset index is discussed fully in the appendix. As stated in the text, households that remained in poverty status for every survey round of the 10-year period are considered to be in a poverty trap, while those that were asset nonpoor in at least one survey round between 1994 and 2004 are considered to not be in a poverty trap.

[8] Certain aspects of irrigation, such as personal digging of wells, setting up of water-harvesting ponds, and setting up of small-scale drip irrigation, have recently been introduced on a wider scale.

This study explicitly distinguishes among households by their asset poverty status to discern differential effects of social networks on the probability of farmers adopting technology. The analysis begins by using the complete ERHS dataset to classify households according to their asset poverty status. 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, as described in the appendix. Households with an asset index below the asset poverty line in each survey year are classified as "always asset poor." "Never asset poor" households are those with an asset index above the poverty line each year. Households whose status changed from year to year are classified as "transitory asset poor." Because very few households in the two villages were in the never asset poor category, the analysis distinguishes only between households that were persistently asset poor (considered to be in a poverty trap) and those that were not.

Table 1a shows the mean number of adopters of irrigated vegetables and pulses in the networks of adopters and nonadopters of irrigation, divided by poverty status. The descriptive data show that adopters of irrigation had more neighbors and friends who had adopted previously than did nonadopters. In contrast, Table 1b indicates that adopters of improved cereal varieties had fewer adopters among their neighbors and more adopters among their friends than did the nonadopters. Among the asset-poor households (poverty trap), adopters had fewer friends who had adopted previously than did the nonadopters. Finally, for fertilizer, adopters consistently had more adopters in their social networks than did the nonadopters. Thus, Tables 1a–1c indicate the presence of some sort of network effects, although they may be different across network types, technology, and poverty status.

Table 1a. Mean number of network members already using technology: Irrigated crops

	Complete Sample			**Poverty Trap**		**Not in a Poverty Trap**	
	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)
Neighbors	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		171					

Source: Calculated by the authors from ERHS.

Table 1b. Mean number of network members already using technology: Improved cereals

	Complete Sample			**Poverty Trap**		**Not in a Poverty Trap**	
	Total	*Adopters*	*Nonadopters*	*Adopters*	*Nonadopters*	*Adopters*	*Nonadopters*
Friends	4.959	5.662	4.195	4.348	7.467	6.949	2.295
	(10.30)	(11.02)	(9.47)	(7.25)	(13.95)	(14.45)	(4.74)
Neighbors	5.263	3.135	7.573	3.000	6.929	2.769	5.933
	(12.60)	(4.63)	(7.24)	(4.99)	(14.44)	(3.48)	(10.64)
N	171						

Source: Calculated by the authors from ERHS.

Table 1c. Mean number of network members already using technology: Fertilizer

		Complete Sample		Poverty Trap		Not in a Poverty Trap	
	Total	*Adopters*	*Nonadopters*	*Adopters*	*Nonadopters*	*Adopters*	*Nonadopters*
Friends	6.013	7.846	4.981	7.586	5.091	8.080	4.467
	(7.182)	(9.789)	(5.403)	(11.364)	(4.689)	(8.563)	(5.344)
Neighbors	5.737	6.286	4.334	7.856	5.544	5.561	4.966
	(8.177)	(9.143)	(6.754)	(10.877)	(6.052)	(3.528)	(6.059)
N	171						

Source: Calculated by the authors from ERHS.
Note: Standard deviation is expressed in parentheses. Network size refers to the number of people in the network who had adopted before the household in question or who had adopted for nonadopters.

The descriptive statistics in Table 2 reveal the poverty of most households in this sample. On average, the households cultivate about 2 hectares of land, are headed by men of about 50 years in age, and have no members with more than five years of education. Their assets tend to consist of one or two head of livestock valued at about 400 EB,[9] with households in a poverty trap tending to have fewer assets, more people engaged in full-time farming, and less accessibility to markets.

Table 2 Descriptive statistics

Variable	**Complete Sample**	**Poverty Trap**	**Not in a Poverty Trap**
Male head (1/0)	0.581	0.539	0.553
	(0.49)	*(0.50)*	*(0.50)*
Household livestock (Ethiopian birr)	462.890	403.050	410.360
	(461.86)	*(302.17)*	*(491.03)*
Household nonproductive assets (Ethiopian birr)	406.650	363.255	411.600
	(526.07)	*(419.27)*	*(559.99)*
Age of household head (years)	49.700	50.565	48.090
	(13.99)	*(12.45)*	*(17.07)*
Distance to closest market (km)	4.471	5.090	3.940
	(3.66)	*(7.96)*	*(8.04)*
Distance to paved road (km)	13.179	14.880	11.870
	(8.06)	*(4.23)*	*(3.05)*
Household land cultivated (hectares)	2.053	2.947	2.814
	(2.74)	*(2.05)*	*(3.15)*
Full-time farm labor (number)	2.064	2.237	1.917
	(1.14)	*(1.15)*	*(1.10)*
Most education (years)	5.102	5.123	5.356
	(3.19)	*(3.29)*	*(3.09)*
Number of observations	160	76	84

Source: Calculated by the authors from ERHS.
Note: Standard deviation is expressed in parentheses.

[9] One U.S. dollar is equivalent to about 11 Ethiopian birr. The PPP conversion factor is approximately 0.25.

6. ESTIMATION RESULTS

Equation (18) was 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.[10]

Improved Cereals

For improved varieties of cereals, results indicate social learning that varies by network type. In the specification without poverty class interactions, the probability of adopting improved seeds exhibits the inverse U relationship with respect to the number of friends who had previously adopted improved seed use (see Table 3). Although the marginal effects on the level term are positive and significant, the marginal effects on the squared term are negative and significant. On the other hand, the neighbor network has an insignificant effect on adoption. Younger households and households cultivating larger landholdings are more likely to adopt the improved seed.

Table 3. Social network effects on the adoption of improved cereals, estimation by poverty status: Probit estimation[++]

	Not Distinguishing Poverty Status			Distinguishing Poverty Status		
Improved Cereals	*Coeff.*	*Marg. Effects*	*P > z*	*Coeff.*	*Marg. Effects*	*P > z*
Male head (1/0)	–0.0340	–0.0113	0.9100	0.0140	0.0010	0.9630
Household livestock	0.0000	0.0000	0.2930	–0.0001	0.0000	0.5120
Household nonproductive assets	0.0000	0.0000	0.8840	–0.0001	0.0000	0.7450
Age of household head (years)	–0.0190*	–0.0062	0.0780	–0.0220*	–0.0018	0.0490
Distance to closest market (km)	–0.0090	–0.0030	0.7170	–0.0086	–0.0007	0.7580
Distance to paved road (km)	0.0030	0.0009	0.7630	–0.0029	–0.0002	0.7940
Household land cultivated	0.0590	0.0198	0.1100	0.0664	0.0055	0.1150
Full-time farm labor (number)	–0.0190	–0.0064	0.8680	–0.0271	–0.0022	0.8220
Most education (years)	0.0060	0.0021	0.8690	–0.0057	–0.0005	0.8860
Friend network size	0.0510**	0.0170	0.0240	0.2456*	0.0202	0.0780
Friend network size, squared	–0.0010**	–0.0001	0.0310	–0.0090*	–0.0007	0.0780
Neighbor network size	–0.0310	–0.0104	0.6480	–0.0046	–0.0115	0.3500
Neighbor network size, squared	–0.0010	–0.0004	0.6710	0.0018	0.0002	0.7740
Poverty trap				–0.0559	–0.0046	0.8660
Friends * PovertyTrap				–0.1907	–0.0157	0.1300
FriendsSquared * PovertyTrap				0.0088*	0.0007	0.0830
Neighbors * PovertyTrap				0.1099	0.0090	0.2840
NeighborsSquared * PovertyTrap				0.1403	0.0004	0.1300
Harresawe	–1.883***	0.5790	0.0000	–1.7600***	–0.1810	0.0000
Number of observations		150		138		
Prob > chi^2		0.000		0.0000		
Pseudo R^2		0.358		0.3793		

Source: Calculated by the authors from ERHS.
Note: * means significant at 10%. ** means significant at 5%. *** means significant at 1%. Coeff. means coefficient, and ++ means that in these estimations, specifications that controlled for land quality and participation in extension were explored and the conclusions remained as above.

[10] The poverty status variable (which is a dummy variable = 1 if a household is in a poverty trap; otherwise, 0) is interacted with each network variable (friends and neighbors) by multiplying the network size variable by the dummy variable.

The specification that includes poverty classes indicates that social learning may vary across both network type and poverty status. Although the effect of friends continues to exhibit the inverse U relationship for the households not in a poverty trap, the effect is monotonically increasing in network size for those households in a poverty trap. This result indicates that there are differential social learning effects not only across network types but also across poverty levels. This difference across poverty levels may reflect either different kinds of networks or efficacy of networks by poverty class. Where network members are less knowledgeable or information transfer less efficient, a greater number of informants is needed for adequate information to trigger adoption; in addition, the promise of gaining information from the network is less likely to deter a farmer's own experimentation. Poor households may be more likely to be in such networks. Alternatively, the different results by poverty class could indicate other network effects, such as economies of scale if, indeed, these are crops for commercialization. Because the neighbor effect is not statistically significantly different across poverty status, such an explanation might be plausible for households likely to commercialize.

Irrigated Fruits, Vegetables, and Pulses

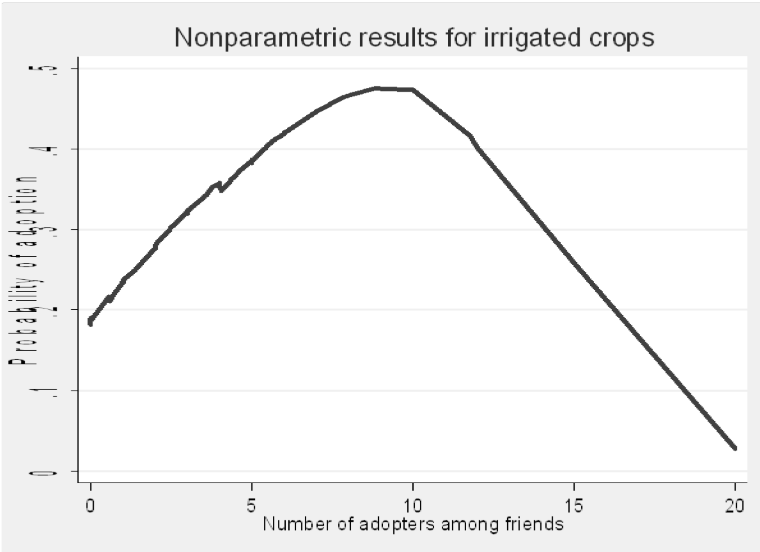
Considering adoption by recent potential adopters (those who had not adopted before 2004), Table 4 shows that the network effects for friends who had previously adopted exhibits the inverse U relationship, suggesting social learning, but this is not evident for neighbors. Coefficient values suggest an increasing probability of adoption for up to about 10 friends; after that, the reverse is true. To validate these results, a nonparametric estimation is reported in Figures 1 and 2. Although the friend network seems to exhibit the inverse U relationship, the neighbor network effect appears to be an increasing function of the network size. While there are some network effects of neighbors, social learning is more evident in networks with more intentional interaction. Other factors that appear to affect adoption of irrigated crops are access to commercialization opportunities (distinct from the local peasant association market), household wealth captured by nonproductive assets (including jewelry), and other household items.

Table 4. Social network effects on the adoption of irrigated crops, estimation by poverty status: Probit model

	Not Distinguishing Poverty Status			Distinguishing Poverty Status		
Irrigated Crop	*Coeff.*	*Marg. Effects*	*P > z*	*Coeff.*	*Marg Effects*	*P > z*
Male head (1/0)	–0.530	–0.147	0.295	–0.3970	–0.0907	0.417
Household livestock	0.000	0.000	0.202	0.0001	0.0000	0.116
Household nonproductive assets	0.001***	0.000	0.005	0.0009***	0.0002	0.004
Age of household head (years)	0.015	0.004	0.309	0.0131	0.0030	0.346
Distance to closest market (km)	0.026	0.007	0.497	0.0251	0.0057	0.526
Distance to paved road (km)	–0.036***	–0.010	0.001	–0.0408***	–0.0093	0.003
Household land cultivated	0.215***	0.060	0.000	0.2229***	0.0509	0.000
Full-time farm labor (number)	0.259	0.072	0.214	0.3441	0.0786	0.127
Most education (years)	0.039	0.011	0.498	0.0572	0.0131	0.395
Friend network size	0.578***	0.160	0.002	0.1935	–0.0077	0.596
Friend network size, squared	–0.046***	–0.013	0.006	–0.0282	–0.0064	0.498
Neighbor network size	0.149	0.041	0.275			
Neighbor network size, squared	–0.006	–0.002	0.466			
Not in a poverty trap				–0.8171	–0.2075	0.154
Friends * PovertyTrap				0.5597***	0.1279	0.031
FriendsSquared * PovertyTrap				–0.0338	0.0442	0.239
Harresawe	2.311***	0.466	0.001	2.618***	0.446	0.001
Number of observations	85			79		
Prob > chi^2	0.000			0.00		
Pseudo R^2	0.3548			0.3644		

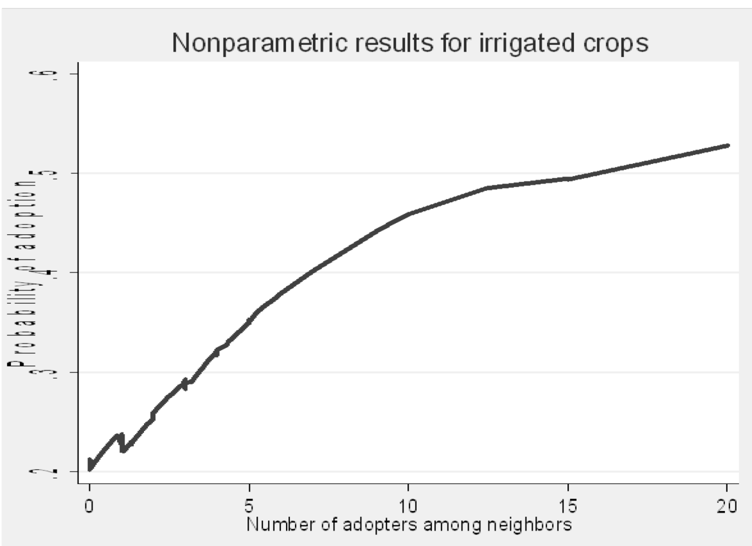
Source: Calculated by authors from ERHS.
Note: * means significant at 10%. ** means significant at 5%. *** means significant at 1%. Coeff. means coefficient, and ++ means that in these estimations, specifications that controlled for land quality and participation in extension were explored and the conclusions remained as above.

Figure 1. Network effect of friends on the probability of adopting irrigated crops using nonparametric estimations



Source: Generated by the authors from ERHS data 2007.

Figure 2. Network effect of neighbors on the probability of adopting irrigated crops using nonparametric estimations



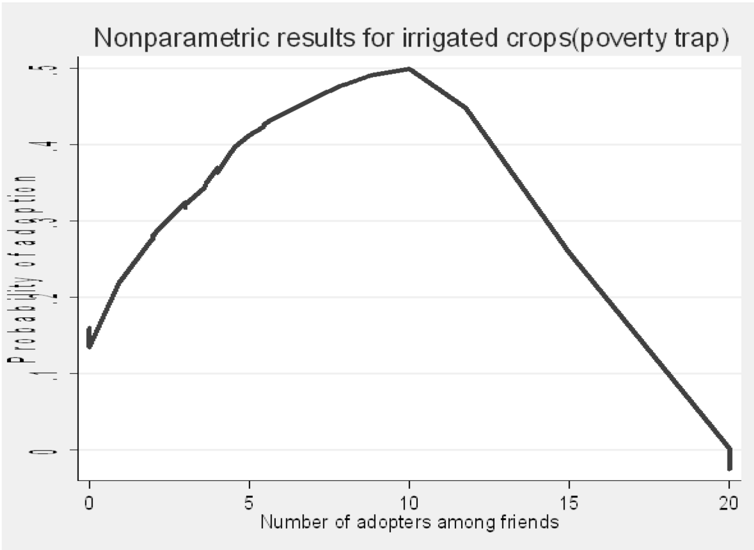
Source: Generated by the authors from ERHS data 2007.

In the specification that distinguishes poverty classes, households with more nonproductive assets, better access to external markets, and larger cultivated land size are more likely to adopt irrigated crops (see Table 4). Although a network effect of friends is present, it does not reveal the inverse U relationship and does not appear to be statistically significantly different across poverty classes.[11] Because the small sample size may be responsible for low levels of statistical significance, nonparametric estimations were conducted. Results of these estimations confirm that households in different poverty categories saw similar effects of a household network of friends that had previously adopted irrigated

[11] Given our small sample size, we explored more parsimonious specifications, such as dropping the nonproductive asset measure, because this might be correlated with poverty status. This did not change the results. Furthermore, the correlation coefficient between various variables indicated no multicollinearity.

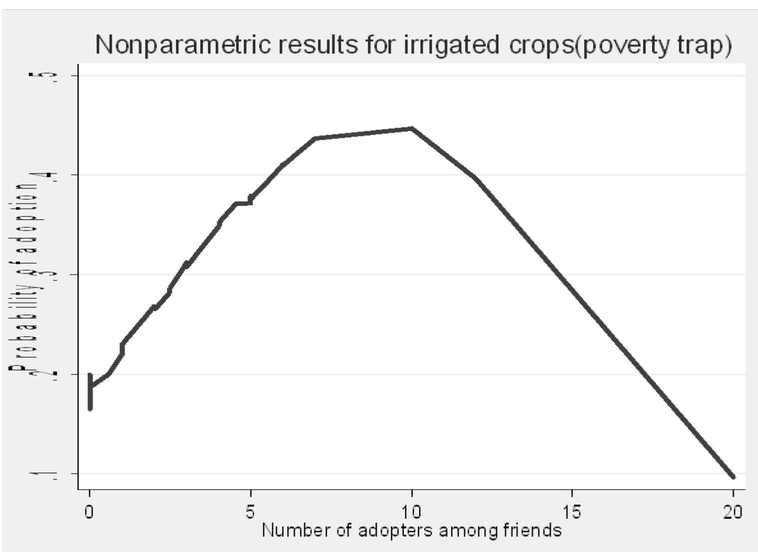
crops on the probability of adoption (see Figures 3 and 4). The results reveal an inverse U relationship between network size and probability of adoption.

Figure 3. Network effects of friends for households in a poverty trap using nonparametric estimations



Source: Generated by the authors from ERHS data 2007.

Figure 4. Network effect of friends for households not in a poverty trap using nonparametric estimations



Source: Generated by the authors from ERHS data 2007.

To supplement the results in Table 4, Table 5 shows the marginal effects of various factors on the adoption of irrigated crops, using splines for networks of different sizes. The results reveal that compared to households with no friends who adopted irrigated crops, households with between 1 and 4 friends who adopted have a 40 percent higher probability of adopting irrigated crops. Those with between 5 and 8 friends who adopted are about 67 percent more likely to adopt the technology. Although those households with more than 8 friends using a technology are less likely to adopt than are those with between 5 and 8 friends, the former are 62 percent more likely than are those who have no friends using a technology. These results further indicate that the relationship between the size of the friend network and the probability of adoption is shaped as an inverse U. A test on the equality of the coefficient reveals that the coefficient on 1–4 friend adopters is statistically significantly different from having 5–8 members (1 percent). Although we fail to reject that having 1–4 is statistically significantly different from having more than 8 members, we also fail to reject that having 5–8 is statistically significantly different from having more than 8 members.

Table 5. Social network effects by splines on the adoption of irrigated crops

Irrigated Crop	Marginal Effects	Robust Standard Error	*P* > *z*
Male head (1/0)	–0.139	0.136	0.312
Household livestock	0.000	0.000	0.182
Household nonproductive assets	0.002***	0.000	0.004
Age of household head (years)	0.0052	0.004	0.186
Distance to closest market (km)	0.004	0.010	0.706
Distance to paved road (km)	–0.010***	0.003	0.001
Household land cultivated	0.059***	0.014	0.000
Full-time farm labor (number)	0.088*	0.048	0.072
Most education (years)	0.016	0.016	0.327
1–4 adopters	0.404**	0.199	0.033
5–8 adopters	0.674***	0.169	0.001
More than 8 adopters	0.625**	0.248	0.034
Harresawe	0.454***	0.137	0.009
Number of observations	85		
Prob > chi^2	0.03		
Pseudo R^2	0.3427		

Source: Calculated by the authors from ERHS.

Note: * means significant at 10%. ** means significant at 5%. *** means significant at 1%.

7. ROBUSTNESS CHECKS

Technology

Irrigated crops and improved varieties are recent technologies introduced in the peasant associations examined. To help distinguish social learning effects from other network-based determinants of adoption, the tests for social learning are applied to the use of an old technology—chemical fertilizer. Because chemical fertilizer is a relatively well-known technology, one would not expect to find strong evidence of social learning, though network effects could still exist. Table 6 shows that households that had recently begun to grow pulses, improved cereals, or vegetables were more likely to be recent adopters of chemical fertilizer. Wealthier households and households with more educated members were also more likely to be recent fertilizer adopters. When the size of different networks is considered separately, evidence of network effects emerges among friends only. Table 6 indicates a strictly increasing relationship between the number of adopters among a household's friends and the likelihood of adopting chemical fertilizer. This relationship indicates that some network effects do exist, though not necessarily social learning. Increasing returns to the number of fertilizer use adopters might indicate economies of scale effects of a household's network, as might emerge through coordinating input procurement and output sale, for example.

Table 6. Social network effects on the adoption of fertilizer use

	Friends and Neighbors		*Friends Only*		*Neighbors Only*			
Fertilizer	**Coeff.**	***P > z***	**Coeff.**	***P > z***	**Coeff.**	***P > z***	**Coeff.**	***P > z***
Male head (1/0)	0.03	0.3	0.05	0.8	0.08	0.8	0.3512	0.314
Household livestock	0.00	0.5	0.00	0.5	0.00	0.4	0.7131	0.122
New pulse	0.71	0.1	0.68	0.1	0.78	0.1	1.3912***	0.000
New cereal	1.24	0.0	1.29	0.0	1.35	0.0	1.4556***	0.0005*
New vegetable	1.04	0.0	1.08	0.0	1.16	0.0	0.0005*	0.079
Other assets	0.00	0.1	0.00	0.1	0.00	0.2	0.0001	0.173
Age head (years)	0.00	0.7	0.01	0.7	0.00	0.7	0.0005	0.962
Distance to closest market (km)	–0.02	0.3	–0.02	0.4	–0.02	0.3	–0.0341	0.169
Distance to paved road (km)	–0.001	0.9	0.001	0.9	–0.01	0.8	–0.0136	0.244
Household land cult.	–0.01	0.7	–0.02	0.7	–0.03	0.5	–0.0239	0.671
Full-time farm labor (number)	0.08	0.4	0.12	0.4	0.06	0.6	0.0559	0.689
Most educ. (years)	0.11	0.0	0.10	0.0	0.11	0.0	0.1346***	0.000
Not in poverty trap							–0.6437	0.167
Friend network size	0.02	0.5	0.03+	0.1	—	—	0.153+	0.130
Friend network size, squared	0.004	0.3	0.001**	0.0	—	—	0.0002*	0.077
Friend * PovTrap								
FriendSquared * PovTrap							0.0677	0.399
Neighbor network size	0.02	0.5	—	—	–0.0084	0.3	–0.0011	0.582
Neighbor network size, squared	–0.003	0.7	—	—	0.00	0.4		
Harresawe	0.06	0.9	0.09	0.87	0.21	0.7	0.9307	0.145
N	131		131		131		121	
Prob > chi^2	0.00		0.00		0.00		0.00	
Pseudo R^2	0.23		0.23		0.21		0.2884	

Source: Calculated by authors from ERHS.
Note: * means significant at 10%. ** means significant at 5%. *** means significant at 1%. Coeff. means coefficient, and ++ means that in these estimations, specifications that controlled for land quality and participation in extension were explored and conclusions remained as above.

Concerning the differential effect across poverty classes, social network effects weakly exhibit increasing returns to scale, but only for those households that are not in a poverty trap (see Table 6). For those households in a poverty trap, social network effects are not statistically significantly different from zero. Although it is worrisome that social networks do not seem to promote fertilizer adoption among the poorest households, the results indicating no evidence of an inverse U relationship in fertilizer adoption support the interpretation of results for irrigation and improved cereals, 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,[12] 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 (2006), finding that the inverse U relationship persists, even after controlling for persistent poverty status and vulnerability, further suggests that we are not dealing with the cases of mimicry or contextual effects discussed in Manski (2004).

For further justification, 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 other financial constraints and alternative options, respectively, these two effects together could drive an inverse U relationship. To check for this, we dropped those households considered to be high ability from the sample and then tested for the inverse U relationship. Households were identified as high ability based on the following:

- Household participation in nonfarm activities, including wage jobs and small-scale enterprises
- Prior household interaction with nongovernmental organizations (NGOs)
- As can be seen in Tables 7 and 8, the inverse U relationship persists when these groups are dropped from the estimation.

Table 7. Social network effects for improved cereals after dropping households considered to be high ability

	Dropping High Ability (a)		**Dropping High Ability (b)**	
Improved Seed	*Coeff.*	*P > z*	*Coeff.*	*P > z*
Male head (1/0)	–0.1130	0.7	–0.0760	0.81
Household livestock	0.0000	0.3	0.0000	0.32
Household nonproductive assets	0.0000	0.7	0.0000	0.67
Age of household head (years)	–0.0220***	0.0	–0.0220**	0.03
Distance to closest market (km)	0.0090	0.7	0.0140	0.54
Distance to paved road (km)	0.0010	0.9	0.0030	0.79
Household land cultivated	0.1040*	0.1	0.0790	0.13
Full-time farm labor (number)	–0.0030	0.9	0.0060	0.96
Most education (years)	0.0020	0.9	–0.0030	0.93
Friends	0.0400***	0.01	0.0440**	0.04
Friends, squared	–0.0006	0.01	–0.0006**	0.05
Number of observations	136		140	
Prob > chi^2	0.000		0.000	
Pseudo R^2	0.3401		0.3521	

Source: Calculated by the authors from ERHS.
Note: * means significant at 10%. ** means significant at 5%. *** means significant at 1%.
(a) Refers to the sample of households with no members engaged in nonfarm enterprises or wage labor.
(b) Refers to the sample of households without past experience with NGOs.

[12] This arises because endogenous network effects (like social learning) cannot be separated from exogenous (contextual effects) or correlated unobservable characteristics because these endogenous effects are not identified because they are a linear combination of exogenous and correlated effects. Manski (2004)

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

	Dropping High Ability (a)		Dropping High Ability (b)	
Irrigated Crops	*Coeff.*	*P > z*	*Coeff.*	*P > z*
Male head (1/0)	–1.254	0.184	0.775	0.29
Household livestock	0.000	0.910	0.000	0.21
Household nonproductive assets	0.006	0.009	0.003	0.01
Age of household head (years)	0.038	0.185	–0.014	0.37
Distance to closest market (km)	0.064	0.299	0.041	0.42
Distance to paved road (km)	–0.072	0.034	–0.043	0.04
Household land cultivated	0.292	0.001	0.151	0.01
Full-time farm labor (number)	0.349	0.426	0.167	0.61
Most education (years)	0.213	0.145	–0.057	0.59
Friends	0.591	0.060	0.609	0.04
Friends, squared	–0.041	0.129	–0.043	0.05
Number of observations	33		54	
Prob > chi^2	0.0270		0.0600	
Pseudo R^2	0.4182		0.3924	

Source: Calculated by the authors from ERHS.
Note: * means significant at 10%. ** means significant at 5%. *** means significant at 1%.
(a) Refers to the sample of households with no members engaged in nonfarm enterprises or wage labor.
(b) Refers to the sample of households without past experience with NGOs.

8. CONCLUSIONS

This paper provides evidence of social network effects on the adoption of diverse agricultural technologies across households in a range of poverty conditions. However, we found that observed network effects varied by technology, poverty status of households, and type of network. The results suggest that although social learning does occur for two new technologies, the effect is more consistent for households that are not in poverty traps than for those that are persistently asset poor. Evidence suggests that social learning among rural households is stronger for more complex technologies (for example, irrigation of vegetables for market sale) and that the nonpoor experience social learning for both irrigation and improved cereal varieties. Results for the more familiar technology (chemical fertilizer) show evidence of a social network effect among the nonpoor, but it is not of social learning. No network effect is identified in the adoption of fertilizer among the poor. Findings imply that although groups are potentially important conduits for dissemination of information to farmers, careful thought needs to be given to the size of groups that could and should be used when new technologies are introduced, particularly when rapid dissemination and adoption are important. Finally, the results indicate no social learning and generally limited network effects for networks based on proximity alone. Rather, the evidence of social learning emerges from an analysis of networks based on friendships.

Finding that social learning effects are available in rural Ethiopia and that they emerge through 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. This finding implies a need to target intentional groups of rural people, rather than spatial clusters. Identifying such groups, however, presents a challenge. One mechanism for targeting groups might be local *iddirs*. *Iddirs* are traditional, community-based insurance schemes to which households periodically contribute a predetermined amount of money to serve as insurance in the event of death of a family member or another shock, such as health-related adversities. Though *iddir* arrangements are informal, they are well coordinated and well organized, with long life spans and relatively high levels of trust among members. *Iddir* organizations already play multiple roles in the rural environment and might be a conduit for social learning that extension services could employ. Some preliminary results indicate the presence of social learning effects in *iddirs*; but however, due to multicollinearity between the *iddir* network adopter variable and the friend network, this paper focused on the networks of friends.

Findings of differential social learning by poverty status imply that the marginal value of information from social networks differs across households with different levels of poverty. Thus, this factor needs to be considered in social network effects studies, as well as in the development of effective poverty-reduction strategies and extension and other information-dissemination strategies in rural areas.

APPENDIX: ASSET POVERTY CLASSIFICATION

The model used to generate weights for the asset poverty index and to estimate the asset poverty line in this paper is similar to that used by Adato, Carter, and May (2006). The model estimates the following relationship:

$$L_{it} = \sum \beta_j (A_{ijt}) + e_{it}, \tag{A1}$$

where L_{it} is the livelihood of household *i* in period *t*; β_j is the coefficient of the current assets owned by household *i* in time *t*; A_{ijt} is the amount of asset *j* owned by household *i* in time *t*; and e_{it} is the time- and household-specific error term. Livelihood is measured as the ratio of current consumption expenditures to an expenditures poverty line representing the cost of a minimum value of food and nonfood consumption goods. The estimates of $\beta_j(A_{ijt})$ are then used to calculate the asset index for a household as

$$\Lambda_{it} = \ddot{L}_{ivt},$$

where Λ_{it} is the asset index, and $\ddot{\beta}_j(A_{ijt})$ is the marginal contribution of assets to livelihood(meaning the asset weight taken from the regression of livelihood on assets). In the linear form, the scaled livelihood variable (L_{it}) has a reference point of 1, such that a household for which $L_{it} = 1$ is exactly on the poverty line, a household with $L_{it} < 1$ is poor, and a household with $L_{it} > 1$ is nonpoor. This estimation uses a double log specification such that the reference point is 0.

To account for time and peasant association level effects, the model was estimated as follows:

$$L_{ivt} = \sum ß_j(A_{ijvt}) + \sum ß_k(A_{ijvt})(A_{ikvt}) + H_{it} + \Psi_v + D_t + \varepsilon_{ivt} \tag{A2}$$

for all assets *j* and *k* in peasant association *v*, where L_{ivt} $\beta_j(A_{ijvt})$ are previously defined and ε_{ivt} is an error term. $\beta_k(A_{ijvt})(A_{ikvt})$ are the coefficients of the squared asset and asset interaction terms; H_{it} is a vector of household demographic characteristics; and Ψ_v and D_t are peasant association and time dummies, respectively, that capture location-specific unobserved and time invariant characteristics, such as seasonal variation or political or economic differences over time.

The asset index for each household is the estimated value of (A2).

Data for estimating (A2) were drawn from the Ethiopia Rural Household Survey (ERHS). The assets used in the estimation were categorized into five groups: land, livestock, farm implements, other physical assets (for example, jewelry and other home furnishings), and education. The asset values were calculated each year; then these values were adjusted yearly by a consumer price index. The livestock variable was divided into draught, dairy, transport, and other livestock. Because the value of livestock and other assets was based on survey responses of uncertain quality, average unit values of all assets were calculated for each peasant association. These averages were then used as the unit value for each livestock type.

After running the necessary specification tests, the two-stage least-squares instrumental variable estimation, proposed by Hausman and Taylor (1981), was used. This procedure uses means and deviation from means as instruments for time-invariant and time-varying endogenous variables. This estimation enabled us to address endogeneity problems caused by unobserved invariant household characteristics that could be related to assets. This technique yields consistent estimates of all desired time-invariant coefficients. The coefficients from the estimation of Equation (A2) were then used to generate the asset index (see Table A.1). Households were considered to be asset poor if their asset index was less than 0; otherwise, they were considered asset nonpoor.

Table A.1. Hausman-Taylor instrumental variable and generalized instrumental variable estimates

	Hausman-Taylor IV		Generalized IV	
	Coefficient	*P > Z*	*Coefficient*	*P > Z*
Landholdings (hectares)	–0.01	0.67	0.03	0.42
Farm tools (values)	0.04	0.05	0.11	0.00
Draught animals (values)	0.09	0.00	0.09	0.00
Dairy animals (values)	0.04	0.04	0.04	0.08
Pack animals (values)	0.10	0.00	0.07	0.02
Other livestock (values)	0.03	0.13	0.05	0.02
Household members	–0.64	0.00	—	—
Adults	—	—	–0.19	0.00
Children	—	—	–0.16	0.00
Elderly	—	—	0.00	0.85
Education	0.00	0.86	–0.01	0.45
Other physical assets	–0.02	0.15	–0.01	0.41
Land * Tools	–0.00	0.01	0.00	0.00
Land * DraughtAnimals	0.00	0.59	0.00	0.15
Tools * Livestock	0.00	0.97	0.00	0.96
Memberships	0.16	0.00	0.15	0.00
Off-farm activities	0.10	0.00	0.13	0.00
Land, squared	0.02	0.00	0.02	0.01
Tools, squared value	0.01	0.02	0.01	0.75
Other livestock, squared value	0.00	0.50	–0.01	0.17
Other physical assets, squared	0.02	0.00	0.01	0.02
Dairy animals, squared value	0.00	0.44	–0.01	0.29
Pack animals, squared value	–0.02	0.00	–0.02	0.05
Draught animals, squared value	–0.03	0.00	–0.03	0.00
Male head	0.08	0.00	0.04	0.37
Age	–0.02	0.07	–0.04	0.01
Nonfarm activities	0.02	0.47	0.04	0.34
Food-for-work program	–0.08	0.04	–0.08	0.09
Constant	0.27	0.01	0.28	0.00
Adjusted R^2	0.36		0.20	

Source: Calculated by the authors from ERHS data 1994–2004.

Note: Dependent variable is household livelihood.

Time and village dummy variables were included but not reported. Continuous variables were transformed into logarithms. Both the generalized instrumental variable (GIV) and the traditional Hausman-Taylor instrumental variable (HTIV) estimators were explored; the HTIV were used in this analysis.

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