Poverty status and the impact of social networks on smallholder technology adoption in rural Ethiopia

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Abstract:

Despite recent traces of economic growth, Ethiopia remains one of the poorest countries in the world. Though about 80% of its population is engaged in agriculture, agricultural productivity remains low and extremely vulnerable to climatic conditions. The adoption and use of modern technologies is generally accepted as a potential vehicle out of poverty for many but adoption rates in the country remain low with the nature of the adoption process largely unstudied (Spielman et al, 2007). This paper studies the impact of social networks in the technology adoption process in rural Ethiopia. In addition to geographic networks, it considers the role played by other networks with more purposeful interactions such as a household's friends. We also explore the differential impacts of social networks by network type, technology and the asset poverty status of households.

Key word: social networks, poverty, technology adoption, Ethiopia

JEL classifications: O31 O33 Q12, Q13

Introduction

The longstanding effort to understand the persistence of poverty has exposed the complexity of its underlying structure and dynamics. While there is now a general consensus on the failure of canonical growth models to satisfactorily explain persistent chronic poverty, more complete models remain in development. Recent efforts have identified the role of various exclusionary mechanisms which prevent some households from escaping poverty and explain the divergent poverty outcomes obtained by different groups. The struggle to understand why certain households or groups are excluded from economic growth remains an active area of research. The role of social networks in shaping consumption, production and exchange behavior is one area of current debate (Barrett, 2005).

Relationships are important to the adoption and dissemination of modern technologies in agrarian economies, and particularly in rural Ethiopia. Despite the general view that adoption and use of modern technologies (like irrigation for producing high value cash crops) could serve as a vehicle out of poverty for many, adoption rates in Ethiopia remain low (Spielman et al, 2007). Farmer adoption of modern techniques and innovation may be inhibited by lack of sufficient credit to acquire inputs and make necessary investments or due to limited access to input and output markets. Yet another potential deterrent to the adoption of new techniques is inadequate information on their practice. A common solution to this constraint has been the expansion of extension services, whose form and efficacy can depend on the nature of social learning as well formal instruction. While the effect of social networks in reducing the information constraint has been shown to exist, it is only recently that researchers have begun to study more how this effect occurs and to distinguish between effects after adoption and those causing adoption. (Munshi, 2004, Bandiera and Rasul, 2006). Furthermore, very little research has been done to see if and how these network effects differ across households characterized by different forms and levels of poverty. In this light, this paper contributes to this research twofold: first by investigating the roles that social networks in household technology adoption in rural Ethiopia, and second by exploring the differential effect of networks across households at different levels of poverty and thus their potential to help households grow out of poverty. This study attempts to answer the following four questions: First, do networks contribute to technology adoption? Second, if networks affect technology adoption, what kinds of networks matter? Third, can we find evidence of social learning in network effects and fourth, are these network effects the same across households in different forms of poverty.

Social Learning and Technology Adoption

The theory of social learning in technology adoption looks at how information intentionally or unintentionally made available to a farmer as a result of decisions of other farmers affects technology use. The fact that social networks affect technology diffusion has been studied widely. However only recently have researchers begun to study more how this effect occurs and to distinguish between effects after adoption and those causing adoption. Besley and Case (1994) present an early model of information externalities in the adoption and diffusion of improved cotton cultivars in the semi arid tropics. Foster and Rosenzweig (1995) further develop this model in a study of high yielding varieties (HYVs) of wheat and rice in India during the Green Revolution. Munshi (2004) extends the analysis of Foster and Rosenzweig to show how social learning differs across heterogeneous populations. These studies distinguish between the effects of learning by doing and learning from others. They show how information constraints limit technology adoption and how own and neighbor experiences reduce this constraint.

This research follows more recent studies to explore network effects and social learning prior to adoption. While several reasons for a positive relationship between an individual's network and their probability of adopting a new technology exist, social learning theories indicate that the direction of this relationship between network size and adoption is ambiguous. A larger network might indicate access to more information about a technology from the network and thus encourage adoption. However, information from personal experience may be costly to acquire and the experience of others can substitute it. Hence, a larger network could encourage households to delay adoption and free ride on the experience of members of their network. (Bardhan and Udry, 1999 ;Bandiera and Rasul,2006)[1]. Furthermore, the effects of social networks could be heterogeneous depending on the kind of network as well as on the characteristics of farmers such as how informed they are generally and with respect to the technology.

Most previous studies focus on geographic proximity as the causal explanation for correlated adoption choices within social networks. The geographic explanation assumes all farmers have unhindered access to the necessary information on the use of the new technology when it is used in their area. Thus, either neighbors willingly share information or farmers costlessly observe each other's input use and output. Brief discussions with rural farmers across Ethiopia reveal that this assumption is not necessarily true. With land allocated by government and passed on from generation to generation, farmers have little choice as to who their neighbors are and are not always on the best terms with them. Furthermore various procedures associated with a new technology such as quantity and application time of various inputs as well as timing of various management activities may not be casually observable but necessitate more purposeful interaction.

Social networks based on characteristics other than physical proximity might be worth exploring in the bid to understand how information constraints could be reduced in rural Ethiopia. As evidence that adoption networks need not be based on physical proximity, studies like Slicher von Bath (1963) reveal that during the English agricultural revolution, it was not uncommon to see fields being cultivated with very old traditional techniques sharing boundaries with lands cultivated by newly introduced crop rotation. More recently, Bandiera

[1] This occurs because expected profit is increasing in both the information received from own trials as well as from trials from others in the network. Furthermore, the additional information gained from personal trials declines, the larger the network available for the farmer to learn from. This will be discussed further in the theoreticaframework .

and Rasul (2006) find that farmer adoption decisions were correlated to the decisions of friends and family as well as those of the same religion but not for those in different religions. Similarly, in their study on technology adoption in Ghana, Conley and Udry (2001) find that farmers tend to have a limited number of incomplete technology information sources not necessarily based on geographic proximity. As far as we are aware, no such study has been conducted in rural Ethiopia. Given the importance of information in technology adoption and the numerous efforts to restructure and improve extension services in Ethiopia, it is important to understand the nature and quality of social learning among rural households.

Beyond the information externality offered by networks, there are other possible reasons why adoption choices could be related within various groups. As mentioned, but not fully explored, by Bandiera and Rasul (2006), decisions within groups could be correlated if there are other shared goals for, or constraints to the adoption decision, such as economies of scale in commercialization of a commodity. For example, if there is risk sharing within networks or if the technology in question is too expensive for an individual farmer to buy and operate, one might expect a high degree of correlation of adoption among group members. Similarly, group effects and dynamics could reduce the willingness of individual farmers to engage in new activities.

Thus this paper studies the effect of a household's network of neighbors and friends on their technology adoption decisions with a view to distinguishing between social learning and other peer effects. Finding an inverse "u" relationship between the probability of adoption and the number of adopters in a households-information network as in Bandiera and Rasul (2006) will reveal social learning and thus the potential for using certain groups as a vehicle to disseminate information of new technologies. While finding a strictly linear or “u” relationship could indicate the presence of social learning, such a result could also be explained by other network effects. For example, a “u” shape might indicate a threshold effect where a smaller network with shared risks reduces incentive to adopt but as this risk sharing group gets larger, the high cost of failure is mitigated, thus encouraging adoption. A linear relation shop could suggest benefits of pooling resources to reduce unit costs. Thus, findings may suggest whether networks have an impact and whether that impact is through social learning. Furthermore, identification of differential network effects across poverty classes will also inform the planning and design of extension as well as other poverty reduction strategies in rural Ethiopia.

Even if social networks encourage technology adoption, it is important to understand if and how their effects differ across households characterized by different poverty forms and dynamics. Previous work has indicated that reducing formal credit constraints tends to have no effect on the use of modern technology for the persistently asset poor though the use of certain technologies, like fertilizer, assists in their ability to accumulate assets over time (Liverpool and Winter-Nelson, 2009). Thus exploring whether reducing information constraints through social learning has a positive effect on the use of these technologies by persistently poor could indicate its role as a potential vehicle out of persistent poverty.

Theoretical Framework

Social Learning

Social learning is often measured using a target input model or a profitability model. The target input model lays emphasis on the farmer’s problem of deciphering the optimal management of a new technology. This approach contrasts with other models of social learning like Besley and Case (1993;1994) and Ellison and Fudenberg (1993) which focus on the problem of determining the true profitability of a new technology from personal and network experience. This study adopts the target input model to focus on the role that networks play in learning when new crops or technologies are introduced and the evidence of learning about the best use of inputs from others (Foster and Rosenzweig,1995). Secondly, it can be shown that unlike in the case of uncertain but exogenous profits, the profitability of any new technology grows over time as knowledge accumulates. Thus, as pointed out by Foster and Rosenzweig (1995), we can test for learning externalities directly by looking at productivity. Increasing profitability with increased knowledge accumulation implies that technology adoption is an absorbing state. The above assumption appears more appropriate in our context than the assumption of complete learning about the technology needed for identification as made by Besley and Case (1994, page 17). Also, ultimately, the reduced forms that emerge from both theoretic models capture farmers learning by doing and learning from others.

The target input model[2] developed here follows that of Bardhan and Udry (1999) as well as Bandiera and Rasul(2006). It assumes that farmers use Bayesian updating to learn about the parameters of a new technology. While farmers are aware of the underlying production technology, they are unaware of one parameter, i.e the target input level.

The target input model assumes that farmers output in time t; q_{it}, declines in the square of the distance between the input used k_{it}, and the unknown input target, c_{it}

[2] The target input model is a longstanding model which has been developed by Prescott(1972), Wilson (1975), Jovanovic and Nyarko(1994) and applied with regards to learning in agriculture by Foster and Rosenzwig(1995).

$q_{it} = 1 - (k_{it} - c_{it})^2$ (1.1)

Though the target input level c_{it} is not known at time t, after the farmer has selected his input level k_{it} and sees his yield, he updates his belief about what the target input is. Each time the farmer makes a selection of k_{it} and gets a particular yield is a trial after which he is provided more information about the distribution of c_{it}. Thus farmers learn by doing. Because of farmer and time specific effects, the optimal target for farmer i fluctuates around c^* is defined as:

$$c_{it} = c^* + e_{it} \qquad (1.2)$$

Where e_{it} refers to these transitory farmer specific shocks to the optimal target input c^*. The error is assumed to be independently and identically distributed normal with E(e_{it}) =0 and V(e_{it}) =$s^2{}_u$.

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

Since $E_t(e_{it})$ =0, to maximize his expected profit, farmer i uses his expected optimal target level as his new level of inputs. Thus, k_{it} =E(c_{it})= c_t^* and expected output is

$$E_t(q_{it}) = 1 - E_t\,[\,k_{it} - E_t(c_{it})]^2 = 1 - s^2{}_{cit} - s^2{}_u \qquad (1.3)$$

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

With regard to learning by doing, in each period, farmer i engages in a trial with a certain level of target input k_{it}, sees the output after which he modifies his belief about the target input level. At time t, the variance of farmer i's belief about c^* is s_{cit}^{2}. After observing the target input for the previous period, c_{it-1}, the farmer updates his belief about the variance of c^* applying Bayes's rule and as shown by Bardhan and Udry (1999), his posterior belief becomes:

$$s^{2}{}_{ct+1} = \frac{1}{\dfrac{1}{s^{2}{}_{cit}} + \dfrac{1}{s^{2}{}_{u}}} \tag{1.4}$$

If we define the precision of information generated by a farmers own trial as $\dfrac{1}{s^{2}{}_{u}}$ = r_o and $r_{io} = \dfrac{1}{s^{2}{}_{ci0}}$ as the precision of farmer i's initial belief about the variance of c^*, we can show by substitution that

$$s^{2}{}_{cit+1} = \frac{1}{r_{io} + I_t r_o} \tag{1.5}$$

Where I_t is the number of trials farmer i has had with the new technology on his own farm between periods 0 and t. Substituting (1.5) into (1.3) we can express current expected profits[3] as:

$$\mathrm{E}_t(q_{it}) = 1 - \frac{1}{r_{io} + I_{t-1} r_o} - s^{2}{}_{u} \tag{1.6}$$

From equation (1.6), we can see that output increases with the number of trials, i.e.

$$\frac{\partial E(q_{it})}{\partial I_{t-1}}) = 1 - \frac{r_o}{(r_{io} + I_{t-1} r_o)^2} > 0 \tag{1.7}$$

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3 We actually have $\mathrm{E}_t(q_{it+1}) = 1 - \dfrac{1}{r_{io} + I_t r_o} - s^{2}{}_{u}$ which when put in current terms gives us (1.6)

Now, consider the case where a farmer can improve his estimate of the target input by learning from the trials of other farmers. If we define the network of farmers who share information as $n(i)$ and assume that farmers in this network costlessly share information, then after each period, farmer i updates his belief about the target input with not only information from his previous trials, but also from those of other network members $j \neq i$. This means that at time t where farmer i has had I_{t-1} trials and the network $n(i)_{t-1}$ trials, his posterior belief about the variance of c^* will be

$$s^2_{cit} = \frac{1}{r_{io} + I_{t-1} r_o + n(i)_{t-1} r_o} \tag{1.8}$$

with expected output now being

$$E_t[q_{it}, n(i)_{t-1}] = 1 - \frac{1}{r_{io} + I_{t-1} r_o + n(i)_{t-1} r_o} - s^2_u \tag{1.9}$$

with output also increasing with the number of trials of the network.[4]

$$\frac{\partial E[q_{it}, n(i)_{t-1}]}{\partial n(i)_{t-1}}) = 1 - \frac{r_o}{(r_{io} + I_{t-1} r_o + n(i)_{t-1} r_o)^2} > 0 \tag{1.10}$$

The technology adoption decision

Given the existence of some available traditional technology (traditional crop or variety), with a known return of q_T a farmer is faced with the decision to adopt a new technology or not. 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 and 0 otherwise. If learning takes place as suggested in the previous section, farmer i's adoption depends on the adoption

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

decision of others in his network. The value of future streams of profits to farmer i from period "t" to "T" is:

$$\mathrm{V_t}[I_{t-1}, n(i)_{t-1}] = \max_{a_{it}\in\{0,1\}} \mathrm{E_t} \sum_{s=t}^{T} d^{\,s-t}\{1-a_{is})q_T + a_{is}q_s[I_{s-1}, n(i)_{s-1}]\}] \tag{2.1}$$

$$= \max_{a_{it}\in\{0,1\}} (1-a_{it})q_T + a_{it}E_t q_t[I_{t-1}, n(i)_{t-1}] + dV_{t+1}[I_t, n(i)_t]] \tag{2.2}$$

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. and $n(i)_{s-1}$ refers to the number of trials that farmer i's network has had over the same period. d is the discount rate.

From equations 2.1 and 2.2, we can see that technology adoption by farmer *i* depends on his expectation of current profits as well as the future expected profitability of adoption. Expected profits are increasing in the number of trials of the new technology. Thus, the number of trials positively affects expected profit which determines technology adoption. Furthermore, the fact that expected profits increase with the number of trials indicates that technology adoption is an absorbing state. While several studies have revealed examples of innovations that are attempted and abandoned once proven less profitable than alternative technologies, this would tend to occur in places where new technology has not been tested for contextual appropriateness before introduction. Based on information in the survey areas, we feel safe to assume that the new crops and varieties explored in this study have generally proven to be superior to the traditional crops on average once appropriate complementary inputs and practices are also adopted; these being the unknown in this process. Issues of relative profitability will be captured by controls for possible heterogeneity among farmers.

Equations 2.1 and 2.2 allow the possibility that adoption in time "t" might occur even if the technology is less profitable than the traditional practice in that particular period, as long as the benefit in the future from an additional period of personal trial and/or the trials of others in time "t" is sufficiently large. If the loss in current expected profits is less than the discounted gain in future profitability from the additional trial of the new technology, then the technology will be adopted in time "t" even if the current profitability is less than the traditional variety. This result obtains if the right hand side of the following equation:

$$q_T - Eq(t, n(i)_t) \le d[V_{t+1}(t+1), n(i)_t - V_{t+1}(t), n(i)_t] \qquad (2.3)$$

is greater than zero;

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

$$= \sum_{s=t+1}^{T} d^s \left(\frac{1}{r_{io} + (s-1)r_0 + n(i)_t r_0} - \frac{1}{r_{i0} + sr_0 + n(i)_t r_0} \right) > 0 \qquad (2.4)$$

Where $[V_{t+1}(t+1) - V_{t+1}(t)]$ refers to the difference in value functions if adoption occurred in time t+1 when farmer *i* has had *s* trials and value function estimated in time t+1 where farmer has had *s-1* (one less) trials.

The right hand side of equation 2.4 is positive, reflecting the increase in the expected profits due to the information gotten by the farmer from experimenting in time *t*. However, while the entire value on the RHS is positive, it is decreasing in *n(i)*. If information from personal trials and the trials of others are substitutes, then as more other farmers use the new technology, less addition information is gained by the individual farmer's own experimenting. Thus if many of farmer *i*'s neighbors or associates have characteristics that would lead them to adopt a new technology early, it might be in i's best interest to refrain from experimenting until she has seen how others have done with the new technology. (Udry and Bardhan, 1999). These opposing effects can be seen by taking the derivative of 2.5 which reflects the necessary condition for a farmer to adopt the new technology(crop) in time t, based on 2.3.

$$E_t q_t[t, n(i)_t] + d[V_{t+1}(t+1, n(i)_t]) \geq q_T + d[V_{t+1}(t), n(i)_t] \qquad (2.5)$$

which is

$$\frac{\partial E_t q_t[t, n(i)_t]}{\partial n(i)_t} + d\,\frac{\partial\{V_{t+1}[t+1, n(i)_t] - V_{t+1}[(t), n(i)_t]}{\partial n(i)_t} \qquad (2.6)$$

$$= \frac{r_o}{(r_{io} + n(i)_{t-1} r_o)^2} + d\sum_{s=t+1}^{T} d^s \left(\frac{r_0}{[r_{io} + (s-1)r_0 + n(i)_t r_0]^2} - \frac{r_0}{[r_{i0} + sr_0 + n(i)_t r_0]^2} \right) \qquad (2.7)$$

The first term in equation 2.7 indicates the positive effect of learning from the network though it is decreasing in $n(i)_t$. However, given that information from personal trials and one's network are substitutes, the larger a farmers network of adopters, the lower the value of additional information from personal trial is, creating an incentive for the farmer to strategically delay adoption. This can be seen by the negative sign of the second part of equation (2.7). The sign of the overall equation depends on which value dominates and consequently 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. Bandiera and Rasul explain the sign of this relationship as an indication of myopia amongst farmers with the more myopic farmers being less likely to delay strategically (hence positive sign of net gains) and vice versa for the less myopic farmers.

It is also important to note from equation 2.7 that the net gains to adoption in time "t" is also a decreasing function of the accuracy of farmer *i*'s initial information about the technology. The more accurate his own personal information, the less important the additional information from the network will be, and the less sensitive he is likely to be to the number of adopters in his network. Also, given that the effect of network size $n(i)$ on adoption is positive, but decreasing in the size of the network, tests for a non-linear relationship between adoption and network size can provide evidence of social learning.

Empirical Technology Adoption Decision Model

We have shown via the social learning model that farmers learn from their experience as well as the experience of others in their networks. This information increases the profitability of the technology. The more trials (and consequently information) farmer i has had access to (from the number of adopters in his network) at time t, the more profitable technology i is to him. We have also shown that adoption of a new technology for any farmer is a function of the value of current and future streams of profits (given adoption) for that farmer. Given that profitability is an increasing function of information and that information from one's own trial and the trials of his network are substitutes, we have shown that while the direction of the association is not certain, the decision to adopt a technology at any point in time will depend to some extent on the size of his network. The relationships can be measured empirically through estimation of:

$$(TA_{ikv})_x = (a_A)_x + (l_A Z_{iv})_x + f[n(i)]_x + (y_A V_i)_x + (E1_{iv})_x \qquad i=(1\ldots N);$$

where $TA_{ikv}{}^x$ is the adoption of technology k by household *i* where household i belongs to poverty status class *x*. Z_{iv} refers to a vector of exogenous variables capturing household *i*'s demographic characteristics, as well as other factors that affect a household's decision to adopt a particular technology. This includes, household size, sex of household head, age of household head, highest years of education in the household, distance to the nearest market, size of land cultivated by household(in hectares),value of household implements, 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_{ivt} is the error term capturing unobserved individual and network characteristics which affect household participation. In the model, the social network variable is measured as the reported number of adopters among the farmer's social network, at the time of adoption. The networks explored are friends and neighbors. Various specification for *f[n( )]* are explored. The main ones are a quadratic function to test for the direction of the relationship between network size and probability of adoption. The other two approaches are the use of splines to explore possible threshold effects in the size of various networks and non parametric estimations to confirm the results of other specifications.

As in the traditional latent variable analysis, $TA_{ivt}*$ represents the household's present value of net gains from participating in agricultural innovation at time *t*.

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

While we cannot see the net present value ascribed by each household, we do observe their dichotomous decision to use a modern technology or not.

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

$TA_{ikvt} = 0$ 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 where we explore various specifications for f[ ].

As discussed earlier, social networks are expected to have an effect on technology adoption, but the nature of this relationship is not immediately obvious. Thus in the first model specification, we include the squared network effects as another variable to test for a quadratic polynomial fit and the “u” or “inverse u” shape.

$$P\ [TA_{ikv} = 1]^{x} = F[(a_A)^{x} + (\lambda_A Z_{iv})^{x} + ?_1[n(i)]^{x} + ?_2[n(i)^2]^{x} + (\psi_A V_i)^{x} + (E1_{iv})^{x}]$$

Then we also explore possible threshold effect in network size testing the differential effect of having a network size of (1-4),(5-8) and 8+ members in the network engaged in a particular technology at the time of adoption relative to having no one in the network using the technology.

$$P\ [TA_{ikv} = 1]^{x} = (a_A)^{x} + (l_A Z_{iv})^{x} + ß_0[0] + ß_1[1] + ß_2[2] + ß_3[3] + (y_A V_i)^{x} + (E1_{iv})^{x}$$

Where [0], [1], [2] and [3] reflect different splines

Data

This study uses a subset of the Ethiopia Rural Household Survey (ERHS) dataset and 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 longstanding data collection effort by Oxford University, the University of Addis Ababa, and the International Food Policy Research Institute (IFPRI).

It started in 1989, when a survey team visited seven peasant associations in Central and Southern Ethiopia. In 1994, the survey expanded to 15 peasant associations (PAs) across four regions, yielding a sample of 1477 households. Additional rounds were conducted in late 1994, 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. Supplemental household surveys were also administered in 2 out of the 15 PAs. These 2 villages, Haresawe and Korodegaga, were selected based on local information and community level surveys that indicated that innovative technologies had been introduced in these regions. Data on adoption of improved technologies including improved varieties of various cereals and irrigated vegetables were collected from 186 households in these two PAs. Demographic information as well as information on their assets, access to various institutions, social networks and the prevalence of technology adoption within these networks were also collected. Other data are based on the previously collected data from the 6 rounds of the survey conducted between 1994 and 2004.

The 2 main technologies explored here are improved cereals and irrigated vegetables and pulses. While these technologies are not brand new, discussions with farmers and development agents indicated that there has been a recent emphasis on the production of high value crops such as fruits and vegetables as well as other marketable crops like pulses and improved cereals. As a control for new technologies, we explore the social network effects in a relatively old technology (chemical fertilizer) on recent adopters. Social learning is not expected to affect adoption of this older technology. In Harresawe, the farmers and the development agent cited 2004/2005 as the period of major shift in the village 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, we restricted the analysis to households who had adopted irrigation since 2004.[5] Ninety two percent (92%) of these households were engaged in irrigating fruits, vegetables, pulses or oil seed in 2007.

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. This analysis begins by using the complete ERHS dataset to classify households by their asset poverty status. The asset based approach to poverty measurement classifies as asset poor asset those households whose assets are inadequate to generate an income stream supporting consumption above the expenditures poverty line (Carter and Barrett, 2006). An asset poverty line is defined as 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 appendix A. Households whose asset index was below the asset poverty line in each survey year are classified as "always asset poor". "Never asset poor" households are those whose asset index was above the poverty line each year, and households whose status changed between years 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 who were persistently asset poor (considered to be in a poverty trap) and those who were not.

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

Tables 1(a) to 1(c) describe network sizes for adopters and not adopters across networks and across poverty classes for the technologies considered. The results show that on average, adopters of improved seed had more friends who had previously adopted than had not adopted. However, the mean number of neighbors who had adopted earlier is higher for non adopters than for adopters. With regard to poverty status, adopters in poverty traps had fewer adopters in their network than persistently poor non adopters. In contrast those adopters who were not in a poverty trap had more adopters among their friends, but fewer among their neighbors than non-poor non-adopters. Compared to those in poverty, the non-poor have more adopters in their networks of friends but not in their networks of neighbors. For neighbors, we find larger number of adopters in the network of non adopters compared to adopters across both poverty categories, though the difference in means is much higher amongst those not in a poverty trap. This suggests that learning from networks may not be defined by space but rather by other interests.

With regards to irrigated crop we find a higher mean of adopters in both the friend and neighbor network among adopters rather than non-adopters though the difference in mean adopters is higher within the friend network than in the neighbor network. While the mean adopters in the network of non-adopters is similar across poverty status, adopters of irrigated crops amongst households in a poverty trap are significantly higher than those not in a poverty trap; 8 vs 5. Fertilizer, like irrigated crops reveals more adopters in the network of adopters compared to non-adopters. Thus tables 1a – 1c appear to indicate the presence of some sort of network effects, possibly different across network types and poverty status.

The descriptive statistics in table 2 reveal the relatively poor nature of our sample. Households tend to cultivate about 2 hectares of land, be headed by middle aged men of about 50 years old and have on average someone with a maximum of about 5 years of education. Their assets tend to comprise of 1 or 2 head of livestock valued at about 400EB[6] with households in poverty trap tending to have lower assets, more people engaged in full time farming and less accessibility to markets.

Estimation Results:

Improved Cereals

Given the binary nature of the adoption variable, we explore probit, logit and linear probability models. In the case of recently adopted improved varieties of cereals, we find evidence of social learning that varies by network type. As can be seen from table 3 below, 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. While 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 tends to have an insignificant effect on the odds of adoption. We also find that younger households and households cultivating larger landholdings are more likely to adopt the improved seed. The closer the household is to a paved road, the more likely they are to adopt. We differentiate between the closest market used (usually the local peasant association market) and access to other markets which is an indicator of more commercialization opportunities.

Next we test to see if this behavior differs by poverty status. Results (shown in table 4) indicate that evidence of social learning still exists but varies across both network and poverty status. While the effect of friends continues to exhibit the inverse "u" relationship for

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[6] One US dollar is equivalent to about 11 Ethiopian Birr (EB). The PPP conversion factor is approximately 0.25.

the households not in the poverty trap, the effect is not statistically different from zero for those households in a poverty trap. This indicates that there are differential social learning effects not only across network types but also across poverty levels. It appears that while the level variable for the number of neighbors who have adopted has no effect on the odds of adoption for all households, the squared term is positive for the households in a poverty trap, though only significant beyond 10% in the logit estimation. This difference across poverty levels may reflect different kinds of networks or efficacy of networks by poverty class. Where network members are less knowledgeable or information transfer is less efficient, a larger number of informants is needed for adequate information to trigger adoption and the promise of gaining information from the network is less likely to deter own experimentation. Poor households may be more likely to be in such networks. Alternatively, the different results by poverty class could also indicate other network effects such as economies of scale if indeed these are crops for commercialization. Since the neighbor effect is not statistically significantly different across poverty status, such an explanation might be feasible for households likely to commercialize

Irrigated fruits, vegetables and pulses

Next we explore the same model for irrigation of pulses and vegetables. Considering the adoption procedure for recent adopters (from 2004), again we find that network effects for friends who had previously adopted exhibits the inverse u relationship but this is not evident for neighbors who have already adopted. Considering the separate effects of the various networks only the effect of friends is significant, still exhibiting the inverse u relationship indicating social learning. Coefficient values suggest increasing probability of adoption up to about 10 friends, and then reversal in the effect. To validate these results, we attempt non-parametric estimation of the effects of these networks. Figures 1 and 2 show that while the friends network seems to exhibit the inverse u relationship, the neighbor network effect appears to be more of an increasing function of the network size. While there are some network effects of neighbors, social learning is more evident in networks where there is more intentional interaction. Other factors that appear to affect adoption of irrigated crops are access to commercialization opportunities, households wealth captured by non productive assets including jewelry and other household items.

Again we test for a differential effect of the friend's network across poverty class. From table 6, we find that households with more non productive assets, better access to external markets and larger cultivated land size are more likely to adopt irrigated crops. We find that though a network effect of friends is present, it does not clearly reveal the inverse u relationship and does not appear to be statistically significantly different across poverty classes[7]. However, the small sample size may be responsible for low levels of statistical significance.

Thus we further explore any difference across poverty status by a non parametric estimation. The non parametric estimates in figures 3 and 4 confirm that there are similar effects of a household's network of friends who had previously adopted irrigated crops on their probability of adoption across households in different poverty categories. The results reveal an inverse u relationship between network size and probability of adoption, that may have been obscured in the parametric estimation due to the small sample size.

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[7] Given our small sample size Just to confirm these results, we explore more parsimonious specifications such as dropping the non productive asset measure given that this might be correlated with poverty status. This does not change the results Furthermore the correlation coefficient between various variables indicates that we do not have a problem with multicollinearity.

Given the weakness of the results in table 6, we test for a threshold effect on the friends' network by introducing splines. Table 7 shows the marginal effects of various factors on the adoption of irrigated crops[8]. The results reveal that compared to households who have no friends who have adopted irrigated crops, households with between 1 and 4 friends who had adopted have a 40% higher probability of adopting irrigated crops. For those with between 5 and 8 friends are about 67% more likely to adopt the technology and while having more than 8 friends using a technology are less likely than those with 5 and 8 to adopt, they are 62% more likely than those who have no friends using a technology. This further indicates that the relationship between the size of the friend network and probability of adoption is shaped as an inverse u. A test on the equality of coefficient reveals that the coefficient on 1-4 friend adopters is statistically significantly different from having 5-8 members at 1%, and while 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.

Fertilizer

Next we explore the results for fertilizer. Since fertilizer is an old technology, we do not expect to find strong evidence of social learning, but network effects could still exist. We explore the factors likely to determine fertilizer adoption among households who have adopted fertilizer since 2004. We find that households who had recently begun to grow pulses and oil seed, improved seeds and vegetables were more likely to be recent adopters of fertilizer use. Wealthier households and households with more educated members were also more likely to be recent fertilizer adopters. When the size of different networks was

[8] As expected, the logit and probit results are consistently the same across this analysis. However, we decided to use the marginal effects here to ease the interpretation of the network effect of the spline results.

considered separately, we find evidence of network effects among friends only. The results in columns 5-7 in table 8 show that there appears to be a strictly increasing relationship between number of adopters in a households group of friends who had previously been using fertilizer and their likelihood of adopting fertilizer use for recent fertilizer adopters. This seems to indicate some network effects exist, but not necessarily social learning. Increasing returns to the number of adopters of fertilizer use might be indicate economies of scale effects of a household's network. Given that the use of fertilizer is strongly associated with commercial crop production, it makes sense that scale effects in coordinating input procurement and output sale might be present.

Finally we explore the differential effect across poverty classes. The main conclusions from table 9 is that social network effects though weaker still appear to exhibit increasing returns to scale, but only for those households who are not in a poverty trap. For those in a poverty trap, it appears that social network effects are not statistically significantly different from zero. We find evidence of some network effect exclusion for the persistently poor households though we cannot identify the mechanism through which this exclusion occurs. This is worrisome if those households in a poverty trap are not able to take advantage of network effects such as coordination in the procurement of inputs or marketing of outputs necessary for their adoption of yield enhancing technologies. However, this highlights possible differences between the type of networks that households in a poverty trap use compared to those not in poverty trap as well as their reasons for the use of fertilizer. If these poor households are using fertilizer to increase production to improve productivity and not necessarily for commercialization, it might make sense that network effects supporting commercialization opportunities might not be necessary. However, if there are input procurement benefits to network members, this lack of significance implies that the poorest households are excluded from such opportunities with more severe consequences.

Conclusions:

This paper explored the role of social networks on adoption of new technologies in rural Ethiopia. It found evidence of social learning, though this differs across network types and with poverty status. For modern technologies most recently introduced into the villages studied (improved cereals), we find evidence of social learning, that operates through the network of friends among households not in a poverty trap. We find that networks of neighbors who have adopted is only significant for households in a poverty trap and even there, it is only at very large network sizes that the neighbor network is positively associated with adoption of improved seed

For recently adopted irrigated vegetables, pulses and oil seeds, we still find evidence of social learning and encouragingly this is not statistically significantly different across poverty class. However, again we find evidence that social learning occurs across networks for which there is more purposeful interaction rather than that provided by geographical proximity. For a well known technology, fertilizer, we find evidence of network effects but not social learning. Again we find that network effects differ by poverty status, with networks unfortunately not affecting fertilizer adoption for the poorest households.

The finding that social learning effects are available in rural Ethiopia is and that they emerge through purposeful interaction rather than proximity is significant for extension planning. Technology diffusion is likely to be enhanced if extension can reach more networks of interest. This implies a need to target intentional groups of rural people rather than spatial clusters. Identifying such groups presents a challenge to extension services.

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 member of the family or other shock like health related adversities. Though *Iddir* arrangements are informal, they are well coordinated and organized with long life spans and relatively high levels of trust amongst members. This organization already plays multiple roles in the rural environment, and might be a conduit for social learning that extension services could employ. Our preliminary results indicate the presence of social learning effects in *Iddirs* but due to multicollinearity between the *Iddir* network adopters variable and friends network, we focus on the friends in this paper

Tables and Figures:

Table 1a. Mean number of network members already using improved seed by network type for recent adopters of improved seed

Network type	Complete Sample			Poverty Trap		Not in a Poverty Trap	
	Total	***Adopters***	***Non Adopters***	***Adopters***	***Non Adopters***	***Adopters***	***Non Adopters***
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
	(12.56)	(4.63)	(7.24)	(4.99)	(14.44)	(3.48)	(10.64)
Observations	171	89	82	76		84	

(Standard deviation in parenthesis)

Table 1b. Mean number of network members already practicing irrigation by network type for recent adopters of irrigated crops

Network type	Complete Sample			Poverty Trap		NonPoverty Trap	
	Total	***Adopters***	***Non Adopters***	***Adopters***	***Non Adopters***	***Adopters***	***Non Adopters***
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)
Observations	167	94	73	27	47	36	45

(Standard deviation in parenthesis)

Table 1c. Mean number of network members already using fertilizer by network type for recent adopters of fertilizer

Network type	Complete Sample			Poverty Trap		NonPoverty Trap	
	Total	***Recent Adopters***	***Non Adopters***	***Recent Adopters***	***Non Adopters***	***Recent Adopters***	***Non Adopters***
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)
Observations	172	58	92	25	34	30	42

(Standard deviation in parenthesis)

Table 2. Descriptive statistics

Descriptive Statistics			
Variable	**Complete Sample**	**Poverty Trap**	**Non Poverty Trap**
MaleHead(1/0)	0.581	0.539	0.553
	(0.49)	*(0.50)*	*(0.50)*
Household Livestock(Ethiopian Birr)	462.89	403.05	410.36
	(461.86)	*(302.17)*	*(491.03)*
Household Non Productive assets (Ethiopian birr)	406.65	363.255	411.60
	(526.07)	*(419.27)*	*(559.99)*
Agehead (years)	49.700	50.565	48.09
	(13.99)	*(12.45)*	*(17.07)*
Distance to closest market(Km)	4.471	14.88	11.87
	(3.66)	*(7.96)*	*(8.04)*
Distance to paved road(km)	13.179	5.090	3.94
	(8.06)	*(4.23)*	*(3.05)*
Household Land Cultivated (hectares)	2.053	2.947	2.814
	(2.74)	*(2.05)*	*(3.15)*
Fulltime 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

(Standard deviation in parenthesis)

Table 3: Social Network effect on the adoption of improved cereals

	Logit estimation results		Probit estimation results		
Improved seed	***Odds Ratio***	***P>z***	***Coefficient***	***Marginal Effect***	***P>z***
MaleHead(1/0)	0.956	0.933	-0.034	-0.0113	0.910
Household Livestock	0.999	0.286	0.000	0.0000	0.293
Household NonProductive assets	0.999	0.902	0.000	0.0000	0.884
Agehead (years)	0.967*	0.082	-0.019*	-0.0062	0.078
Distance to closest market(Km)	0.9858	0.758	-0.009	-0.0030	0.717
Distance to paved road(km)	1.0054	0.737	0.003	0.0009	0.763
Household Land Cultivated	1.099*	0.104	0.059	0.0198	0.110
Fulltime Farm Labor (Number)	0.9709	0.880	-0.019	-0.0064	0.868
Most Education(years)	1.0172	0.811	0.006	0.0021	0.869
Friend Network size	1.0984**	0.028	0.051**	0.0170	0.024
Friend Network size Squared	0.9980**	0.030	-0.001**	-0.0001	0.031
Neighbor network size	0.9398	0.576	-0.031	-0.0104	0.648
Neighbor network size squared	0.9983	0.673	-0.001	-0.0004	0.671
Harresawe	0.0411***	0.000	-1.883***	0.579	0.000
Number of Observations	150		150		
Prob > chi2	0.0000		0.0000		
Pseudo R2	0.3598		0.3588		

*=significant at 10% **=significant at 5% ***significant at1%

Table 4. Social Network effects estimation by poverty status

	Logit estimation Results		Probit estimation		results
NewCereal	***Odds Ratio***	***P>z***	***Coefficient***	***Marginal effects***	***P>z***
MaleHead(1/0)	1.0472	0.936	0.0137	0.0011	0.963
Household Livestock	0.9999	0.486	-0.0001	0.0000	0.512
Household NonProductive assets	0.9998	0.770	-0.0001	0.0000	0.745
Agehead (years)	0.9628*	0.077	-0.0220*	-0.0018	0.049
Distance to closest market(Km)	0.9906	0.868	-0.0086	-0.0007	0.758
Distance to paved road(km)	0.9973	0.892	-0.0029	-0.0002	0.794
Household Land Cultivated	1.1203	0.159	0.0664	0.0055	0.115
Fulltime Farm Labor (Number)	0.9594	0.845	-0.0271	-0.0022	0.822
Most Education(years)	0.9974	0.972	-0.0057	-0.0005	0.886
Not in a poverty trap	0.9433	0.923	-0.0559	-0.0046	0.866
Friends*PovTrap	0.7172	0.144	-0.1907	-0.0157	0.130
Friends*PovertyTrapSquared	1.015*	0.082	0.0088*	0.0007	0.083
Friends*NonPovertyTrap	1.538*	0.102	0.2456*	0.0202	0.078
Friends*NonPovertyTrapSquared	0.985*	0.079	-0.009*	-0.0007	0.078
Nighbors*PovertyTrap	1.2046	0.197	0.1099	0.0090	0.284
Neighbors*PovertyTrapSquared	1.000**	0.036	0.1403	0.0004	0.130
Neighbors*Non PovertyTrap	0.7766	0.337	-0.0046	-0.0115	0.350
Neighbors*NonPovertyTrapSquared	1.0031	0.782	0.0018	0.0002	0.774
Harresawe	0.050***	0.001	-1.7623***	-0.1810	0.000
Number of Observations	138		138		
Prob > chi2	0.0000		0.0000		
Pseudo R2	0.379		0.3793		

*=significant at 10% **=significant at 5% ***significant at1%

Table 5: Social Network effect on the adoption of irrigated crops

	Logit estimation Results		Probit estimation results		
Irrigated crop	***Odds Ratio***	***P>z***	***Coefficient***	***Marginal effects***	***P>z***
MaleHead(1/0)	0.472	0.418	-0.530	-0.147	0.295
Household Livestock	1.000	0.163	0.000	0.000	0.202
Household NonProductive assets	1.002***	0.004	0.001***	0.000	0.005
Agehead (years)	1.021	0.417	0.015	0.004	0.309
Distance to closest market(Km)	1.038	0.632	0.026	0.007	0.497
Distance to paved road(km)	0.929***	0.006	-0.036***	-0.010	0.001
Household Land Cultivated	1.461***	0.000	0.215***	0.060	0.000
Fulltime Farm Labor (Number)	1.773	0.157	0.259	0.072	0.214
Most Education(years)	1.124	0.363	0.039	0.011	0.498
Friend Network size	2.718***.	0.011	0.578***	0.160	0.002
Friend Network size Squared	0.924**	0.015	-0.046***	-0.013	0.006
Neighbor network size	1.289	0.298	0.149	0.041	0.275
Neighbor network size squared	0.990	0.433	-0.006	-0.002	0.466
P1	55.78***	0.007	2.3113***	0.466	0.001
Number of Observations	85		85.000		
Prob > chi2	0.03		0.000		
Pseudo R2	0.3625		0.3548		

*=significant at 10% **=significant at 5% ***significant at1%

Table 6: Social network effects on the adoption of irrigated crops

	Logit estimation Results		Probit estimation results		
Irrigated crop	***Odds Ratio***	***P>z***	***Coefficient***	***Marginal effects***	***P>z***
MaleHead(1/0)	0.4718	0.418	-0.3970	-0.0907	0.417
Household Livestock	1.0001	0.163	0.0001	0.0000	0.116
Household NonProductive assets	1.0016***	0.004	0.0009***	0.0002	0.004
Agehead (years)	1.0209	0.417	0.0131	0.0030	0.346
Distance to closest market(Km)	1.0380	0.632	0.0251	0.0057	0.526
Distance to paved road(km)	0.9293***	0.006	-0.0408***	-0.0093	0.003
Household Land Cultivated	1.4610***	0.000	0.2229***	0.0509	0.000
Fulltime Farm Labor (Number)	1.7728	0.157	0.3441	0.0786	0.127
Most Education(years)	1.1241	0.363	0.0572	0.0131	0.395
Not in a poverty trap	0.2182	0.153	-0.8171	-0.2075	0.154
Friends*PovTrap	2.6162**	0.039	0.5597***	0.1279	0.031
Friends*PovertyTrapSquared	0.9445	0.267	-0.0338	0.0442	0.239
Friends*NonPovertyTrap	1.4984	0.530	0.1935	-0.0077	0.596
Nighbors*PovertyTrap	0.9460	0.457	-0.0282	-0.0064	0.498
P1	103.68***	0.003	2.618***	0.446	0.001
Number of Observations	79		79		
Prob > chi2	0.03		0		
Pseudo R2	0.3625		0.3644		

*=significant at 10% **=significant at 5% ***significant at1%

Table 7: Social network effects by splines on the adoption of irrigated crops

Irrigated Crop	Marginal effects	Robust standard error	P>z
MaleHead(1/0)	-0.139	0.136	0.312
Household Livestock	0.000	0.000	0.182
Household NonProductive assets	0.0002	0.000	0.004
Agehead (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
Fulltime Farm Labor (Number)	0.088	0.048	0.072
Most Education(years)	0.016	0.016	0.327
Having 1-4 adopters	0.404**	0.199	0.033
Having 5-8 adopters	0.674***	0.169	0.001
Having more than 8 adopters	0.625**	0.248	0.034
Harresawe	0.454***	0.137	0.009
Number of Observations	85		
Prob > chi2	0.03		
Pseudo R2	0.3427		

*=significant at 10% **=significant at 5% ***significant at1%

Table 8: Social Network effects on the adoption of fertilizer use

	Friends and Networks				*Friends only*				*Neighbors only*			
Fertilizer	**Odds Ratio**	**P>z**	**Coef.**	**P>z**	**Odds Ratio**	**P>z**	**Coef.**	**P>z**	**Odds Ratio**	**P>z**	**Coef.**	**P>z**
Male Head (1/0)	1.031	0.96	0.032	0.32	1.0993	0.61	0.052	0.87	1.160	0.79	0.075	0.81
HH Livestock	1.000	0.48	0.000	0.48	1.0000	0.00	0.000	0.49	1.000	0.35	0.00	0.36
New Pulse	3.146	0.12	0.714	0.12	3.0132	2.19	0.683	0.13	3.512	0.10	0.78	0.08
New Cereal	7.693	0.00	1.235	0.00	8.4212	5.00	1.286	0.00	9.236	0.00	1.35	0.00
NewVeg	5.914	0.03	1.042	0.03	6.4155	5.29	1.081	0.02	7.349	0.01	1.16	0.01
Other Assets	1.007	0.11	0.004	0.11	1.0006	0.00	0.000	0.12	1.001	0.18	0.0003	0.15
Agehead (years)	1.006	0.73	0.004	0.73	1.0078	0.02	0.005	0.66	1.001	0.78	0.0033	0.74
Distance to closest market (Km)	0.962	0.35	-0.024	0.34	0.9632	0.04	-0.022	0.36	0.961	0.31	-0.0240	0.29
Distance to paved road(km)	0.999	0.98	-0.001	0.98	1.0021	0.02	0.001	0.92	0.997	0.88	-0.0028	0.79
HH Land Cult.	0.966	0.78	-0.010	0.78	0.9545	0.10	-0.024	0.67	0.941	0.54	-0.0346	0.49
Fulltime Farm Labor (Number)	1.179	0.49	0.082	0.49	1.2389	0.28	0.116	0.36	1.136	0.58	0.0635	0.63
Most Educ. (years)	1.201	0.02	0.110	0.02	1.1925	0.09	0.106	0.02	1.196	0.02	0.1091	0.01
Friend Network size	1.027	0.51	0.017	0.50	1.048**	0.03	0.03^{+}	0.13	-	-	-	-
Friend Network size Squared	1.006	0.27	0.004	0.27	1.002**	0.00	0.001 **	0.03	-	-	-	-
Neighbor network size	1.04	0.48	0.022	0.48	-	-	-	-	0.985	0.22	-0.0084	0.25
Neighbor network size squared	0.99	0.71	-0.003	0.71	-	-	-	-	1.001	0.39	0.0005	0.37

P1	1.08	0.94	0.060	0.94	1.1731	1.13	0.090	0.87	1.461	0.66	0.2117	0.66
Number of Obs.	131		131		131		131		131		131	
Prob > chi2	0.000		0.000		0.000		0.000		0.000		0.000	
Pseudo R2	0.236 5		0.239 3		0.2322		0.234 9		0.212 2		0.2144	

*=significant at 10%   **=significant at 5%   ***significant at1%

Table 9: Differential Social Network effects on the adoption of fertilizer by poverty status

	Logit estimation results		Probit estimation results	
Fertilizer	***Odds Ratio***	***P>z***	***Coefficient***	***P>z***
MaleHead(1/0)	1.8376	0.327	0.3512	0.314
Household Non productive assets	1.0007*	0.101	0.0001	0.173
Household Livestock	1.0001	0.220	0.7131	0.122
NewPulse	2.9235	0.158	1.3912***	0.000
NewCereal	10.876***	0.001	1.4556***	0.001
NewVeg	11.189***	0.003	0.0005*	0.079
Agehead (years)	0.9994	0.974	0.0005	0.962
Distance to closest market(Km)	0.9444	0.193	-0.0341	0.169
Distance to paved road(km)	0.9747	0.234	-0.0136	0.244
Household Land Cultivated	0.9479	0.667	-0.0239	0.671
Fulltime Farm Labor (Number)	1.1046	0.699	0.0559	0.689
Most Education(years)	1.2395***	0.007	0.1346***	0.000
Not in a poverty trap	0.3073	0.177	-0.6437	0.167
Friend Network size*Poverty Trap	1.1288	0.391	0.0677	0.399
Friends network size squared*Poverty Trap	0.997	0.550	-0.0011	0.582
Friend Network size*Not in Poverty Trap	1.314$^+$	0.155	0.153$^+$	0.130
Friends network size squared*Not in Poverty Trap	1.0006*	0.093	0.0002*	0.077
Harresawe	5.809	0.143	0.9307	0.145
Number of Observations	121		121	
Prob > chi2				
Pseudo R2	0.2859		0.2884	

*=significant at 10%   **=significant at 5%   ***significant at1%

Figure 1: Network effect of *friends* on the probability of adopting irrigated crops

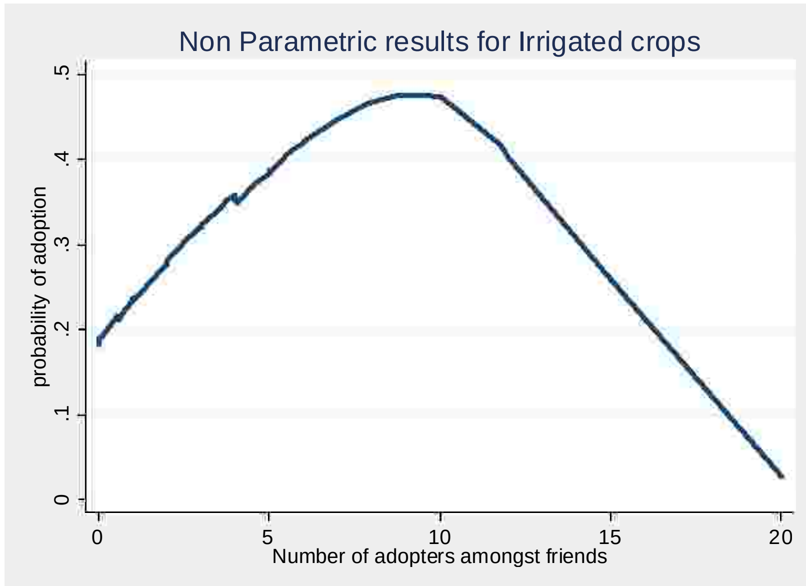


Figure 2: Network effect of *neighbors* on the probability of adopting irrigated crops

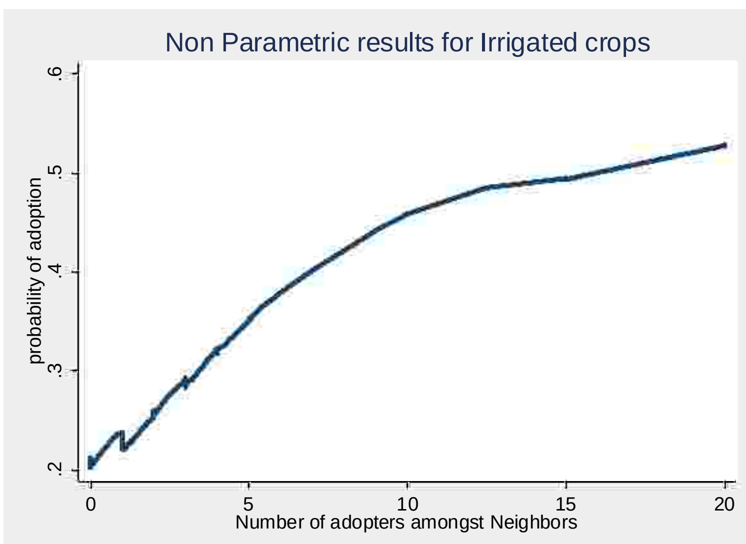


Figure 3: Network effect of *friends* for households in a poverty trap

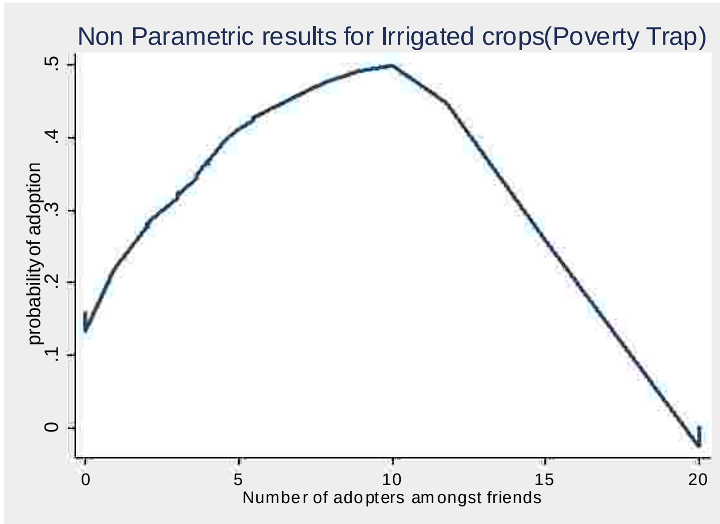
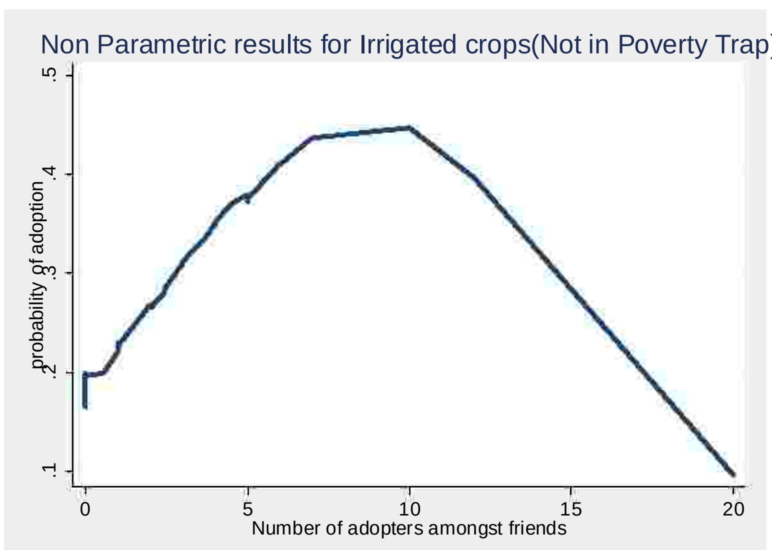


Figure 4: Network effect of *friends* for households *not* in a poverty trap



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