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Neighbours and Extension Agents in Ethiopia

Who Matters More for Technology Diffusion?

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Abstract

The increased adoption of fertiliser and improved seeds are key to raising land productivity in Ethiopian agriculture. However, as in much of sub-Saharan Africa, the adoption and diffusion of such technologies has been slow. We use data from Ethiopia between 1999-2009 to examine the role of learning from extension agents versus neighbours for both improved seeds and fertiliser. We use the structure of spatial networks of farmers and panel data to identify these influences and find that while the initial impact of extension agents was high, the effect wore off , in contrast to learning from neighbours.

Keywords: social networks, social learning, technology adoption.

JEL codes: C31 Q16

Raising agricultural productivity is seen as vital to economic growth in sub-Saharan Africa. Consequently, there has been enormous interest in replicating the Asian green revolution. Thus, the focus has been on new technologies, particularly the adoption and diffusion of improved seed varieties and the increased use of fertliser, supported by investments in effective extension services. Understanding how new technologies spread and how effective extension services are in this process remain important questions. In this paper, we use longitudinal household data from rural Ethiopia to study the adoption of improved seed and fertiliser between 1999 and 2009, contrasting the role of learning from extension agents with that from neigbhours. The longitudinal nature of the data allows us to control for the endogeneity in the placement of extension services; in parallel, we exploit recent techniques in the empirics of social networks (Bramoulle et al., 2009 (9)) to use the spatial distribution of farmers within villages to identify the impacts of neighbours on adoption. We find that the adoption of fertiliser and especially of improved seeds is slow; that learning from adopting neighbours is mainly responsible for the spread of these technologies throughout this period, and that extension agents had a significant impact

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on adoption in 1999, but by 2004 and later by 2009, their role was almost irrelevant for the adoption process despite a vast increase in extension agents throughout rural Ethiopia.

The Ethiopian government has placed agricultural growth at the centre of its growth strategy. It has put forward ambitious targets to increase the use of chemical fertiliser and improved seeds in its recent development plans such as PASDEP (Plan for Accelerated and Sustainable Development to End Poverty) and the Growth and Transformation Plan (Government of Ethiopia, 2004; Government of Ethiopia, 2010), and spends close to 1% of GDP on extension services. However, as in much of sub-Saharan Africa, adoption of such technologies has been slow. Current levels of improved seed use in Ethiopia are around 5% of cropped area with cereals, which is double the area compared to 1997/98, but is undoubtedly low. It is only for maize that adoption has increased substantially with a fourfold increase to about 20% , but this is still well below target (Central Statistical Authority (CSA) data, 1998, 2003 and 2008). Fertiliser is applied to only about 39% of the total land area cropped with cereals, an increase from 32% in 1997/98 but below levels attained in 2001/02 (CSA data, 1998, 2003 and 2008). Fertiliser use is about 25 kg per hectare of arable land (Gollin, 2011(28)), although on fertilised land, application rates are close to 100kg per hectare or the recommended average application rate (CSA 2008). The key issue appears to be to get more farmers to use chemical fertiliser and improved seeds since diffusion is slow.

Low adoption is not unique to Ethiopia and the literature offers many reasons for low take up of new technologies (Feder et al., 1985 (24); Doss et al. 2003, (18)). For Ethiopia in particular, there has been much discussion of constraints on adoption of new technologies. The supply of seed faces serious difficulties (Dercon et al., 2009(14); Davis et al., 2010 (12)), while fertiliser use faces heterogeneity in profits (Alemayehu et al., 2009, (1); see also Suri, 2011(40) for Kenya). Related to this are the high risks involved in taking up relatively expensive new technologies without insurance against harvest shortfalls (Dercon and Christiaensen, 2011(15)). Alternative explanations such as lack of access to appropriate financial instruments (Duflo et al., 2011(19)) seem unlikely in this case given the widespread availability of credit at least until 2009 (Dercon and Christiaensen, 2011(15)); after 2009, this problem may be become salient again as the supply of formal (government) credit has disappeared.

Other plausible suspects are imperfect information about the returns to a new technology and the consequent importance of learning. Conley and Udry (2010)(11) examine this problem in Ghana where farmers learn from the experiences of others and the flows of information depend on the structure of social networks. In this paper, we explore whether imperfect information about the returns to modern technology contributes to low adoption rates in Ethiopia. We contrast the role of the adoption in the neighbourhood with own adoption of improved seeds and fertiliser, and contrast this with an alternative way of transmitting information to farmers via extension agents. Survey data from the 1999 round of the Ethiopian Rural Household Survey suggest that most information on fertiliser and seeds came from these two sources: about half for fertiliser and two-thirds for seed, got the information from extension agents, and the rest from talking to friends or neighbours or, to a lesser extent, from observing early adopters. In the analysis below we explore whether actual adoption can be traced back to either of these two main sources.

Extension programmes may be an effective way to transmit information about modern inputs and encourage adoption. Across sub-Saharan Africa, the evidence of the effectiveness of the extension system is varied and disputed (Evenson, 1997 (23); Bindlish and Evenson, 1997 (6); Gautam and Anderson, 2000 (25)). In 1995, a first large expansion of the extension programme took place as part of the PADETES/NAEIP programme, aiming to reach about 9 million farmers, using the adapted T&V (Training and Visit) model. Bonger et al (8) (2004) and EEA/EPRI (20) (2006) have suggested that these extension programmes have been a mixed success. In last five years, a large expansion of the extension programme has taken place, increasing the number of extension workers (locally called "development agents") threefold by 2008, and adapting the T&V system further to reach larger number of farmers. The most recent expansion of the services have yet to be evaluated, although Davis et al. (2010) (12) provide a careful review of the current functioning, identifying a series of weaknesses. Nevertheless, at present the extension system, measured in terms of the number of extension workers per farmer, is among the most intensive systems, with 600 farmers to a development agent at present, thus similar to China; in contrast, Tanzania has four times and India eight times as many farmers per extension worker (Davis et al., 2010 (12)).

We use data from a longitudinal survey of farm households, the Ethiopian Rural Household Survey, using data over three rounds covering a decade (1999, 2004 and 2009), and 15 farmers' communities across the country. Using the same data set, but without the latest round, Dercon et al. (2010) (17) showed that access to extension agents can be linked to 7% higher consumption growth, although, this is simply a reduced form relationship and cannot be established as causal. Furthermore, the last observation on extension agents in their data is from 1999 and hence their attribution of effect dates from that period. Here we examine the role of extension agents in the later period, between 1999 and 2009, their impact on adoption of improved seeds and fertiliser, and contrast that to learning from neighbours as a route to adoption. We use longitudinal data combined with a spatial identification strategy for network effects to identify the effects of extension and social learning. While there is a substantial literature on technology adoption, the literature on the separate impacts of information transmitted via extension agents and neighbours is thin, in part because of the difficulties of identification and this is in part where we hope to make a contribution[1].

We find evidence of the role of social learning throughout the period: learning from neighbours is strongly significant, and stable throughout the period: an increase of one standard deviation in average adoption of improved seeds by neighbours (corresponding to local diffusion rates increasing by 22%) raising the probability of own adoption by 11% points. Learning from adoption

[1]Barrett and Moser(2006)(4) study rice intensification in Madagascar using recall data to reconstruct adoption over time, and allow for extension and local adoption to influence this decision. However, they are unable to control for placement of agents or the endogeneity of learning in networks.

ceases to be relevant after 1999, and despite further vast investment in extension by government in subsequent years, especially since 2004, we cannot find any return. Given low adoption, especially for seeds, this may suggest that there is a problem with the nature of extension in recent years. However, it is also consistent with a view that after an early boost from extension, adoption will largely by via social learning. Social learning in this setting appears to be mainly about farmers identifying for themselves from own and neighbours' experience whether it is profitable to do so. If adoption is not rising further in this period, this suggests that other constraints may be binding. For seeds, supply may be crucial, while for fertilizer, the profitability of using it may be limited at current prices and given limited seed supply and quality.

In the next section, we outline the econometric approach taken. This is followed by a summary of the data and results.

Social Learning: an empirical approach

The fact that returns to the adoption of particular technologies are higher than average returns with traditional techniques does not guarantee adoption. It may be that returns are heterogenous - soil and other conditions might be more favourable in some areas than in others. It is not easy for farmers to distinguish returns that accrue to the new technique versus returns to scale, or other inputs simultaneously used. One farmer's profitable technique might be another's ruin. In these circumstances, acquiring knowledge from extension workers, or observing one's neighbours' production choices, or experimentation on a small scale could shift out the production frontier over time. Foster and Rosenzweig (1995)(27) examine the adoption of high-yielding varieties in India during the Green Revolution. They find that imperfect knowledge about the management of the new seeds was a significant barrier to adoption; this barrier diminished as farmers increased their use of the new seed and watched their neighbours' experience with HYVs. Conley and Udry (2001, 2010)(11) (10) examine pineapple cultivation in Ghana. They find that farmers do learn (about optimal input use: in particular, the use of fertiliser) from their neighbours in social networks. They confirm this further by examining the impact of networks where the technology is simple and well known: in that case, they find that social learning has no impact, suggesting that optimal input use is not obvious, leading to returns from social learning. Extension agents are an obvious potential source of learning about technologies too, but returns to extension are strongly disputed. For example, their role was emphasised in the Green Revolution in Asia (see Ruttan (1977) and the references therein (37)) and more recently in Kenya and Burkina Faso (see Bindlish and Evenson,1997 (6) and Evenson et al., 1998(22)). However, Gautam and Anderson (2000), for example, (25) conclude that early studies overstated the impact of extension and pinning down its impact involves difficult issues of attribution and identification; they concluded that the data for Kenya simply do not suggest a discernible impact. They suggest that panel data are required to allow more accurate identification.

Agriculture in Ethiopia also offers a setting in which returns to new technologies are difficult to ascertain, and where yields are highly variable, even within villages (see Getachew, 2011 (26)). A recent study of model farmers and their neighbours found large differences which are not readily attributable to observable factors. The evolution of land fertility offers one of the factors which farmers find hard to handle. For example, in 1999, a third of farmers in the ERHS found that yields are stable, but 58% reported declining yields while 10% reported increasing yields. With limited experience of modern inputs and changing land fertility, information about new technologies is hard to be sure about, and could make learning about new technologies difficult and adoption a slow process.

In this context, and in line with the other evidence quoted above, adoption may well be affected both by the extent of local diffusion (so that farmers can observe the success and failings of others) as well as direct measures to boost information about inputs, via extension. Both present serious problems in pinning down their benefits using observational data. The main difficulty in obtaining the impact of peers on one's own decision to adopt new seed or use fertiliser is that peer decisions are contemporaneous and perhaps just correlated rather than influential in affecting own adoption. We discuss in greater detail the technical problem of identification of peer effects and the method we use to construct suitable instruments for the influence (or adoption decisions) of one's neighbours below. In this paper, the role of neighbours of the farmers as a potentially relevant peer group is explored, constructing spatial neighbourhoods using a number of alternative definitions of close neighbours. But in brief, our main estimates use spatial neighbours, within a kilometre from the household [2], using the approach by Bramoulle et al. (2009) (9).[3] . We also offer estimates based on alternative assumptions about the relevant peer group from whom a farmer might learn: the first, using the locally-defined hamlet (within the village) and the second, using non-overlapping neighbours from other hamlets who are spatially close. The estimates reported here are robust to alternative definitions. Below, we discuss the technical problem of identification of these peer effects and the method we use in constructing suitable instruments for the influence (or adoption decisions) of one's peers.

Identification in social networks

The fundamental identification problem, in estimation of peer effects, termed the *reflection problem* by Manski (1993)(32), makes it clear that within a linear-in-means model, identification of peer effects depends on the functional relationship in the population between the variables characterizing peer groups and those directly affecting group outcomes. Manski lists three effects that need to be distinguished in the analysis of peer effects. First, Endogenous effects: These

[2] We use the distance of 1 km because it is approximately the mean distance to the plots owned by the household. Distances to plots are not available - but the time taken to plots are available and based on this, we construct a mean distance.

[3] Plots are largely clustered and near the house - however, it is possible that in some cases plots might be scattered further afield. However, without GPS locations for plots this variation cannot be controlled for. We make the assumption that farmers exchange information with their immediate neighbours in this exercise.

arise from an individual's behaviour being influenced by the behaviour of his peers. Second, Contextual effects: These represent the propensity of an individual to behave in some way as a function of the exogenous characteristics of his peer group. Third, Correlated effects: These describe circumstances in which individuals in the same group tend to behave similarly because they have similar individual characteristics or face similar institutional arrangements. This means that there are unobservables in a group which may have a direct effect on observed outcomes, i.e., disturbances may be correlated across individuals in a group.

The main challenges, therefore, consist in (1) disentangling *contextual* effects,and *endogenous* effects, and (2) distinguishing between *social* effects, i.e., exogenous and endogenous effects, and *correlated* effects, i.e., household in the same peer group may behave similarly because they are alike or share a common environment. Such correlated effects can also include sorting of households, for example, the endogenous location choice by households.

Lee (2007)(31) was first to show formally that the spatial autoregressive model specification (SAR), widely used in the spatial econometrics literature, can be used to disentangle endogenous and exogenous effects. To account for correlated effects Lee introduced group fixed effects. Lee notes that in a SAR model, identification of endogenous and contextual effects is possible if there is sufficient variation in the size of peer groups within the sample. This is because when group sizes are different, the magnitudes of the social interactions generated in each group will be distinct thus one can obtain some information about the social interaction coefficients from the variations in the interaction patterns of different groups. Bramoulle et. al (2009)(9) (henceforth BDF) propose an encompassing framework in which Manski's mean regression function and Lee's SAR specification arise as special cases. BDF show that endogenous and exogenous effects can be distinguished through a specific network structure, for example the presence of intransitive triads within a network. Intransitive triads describe a structure in which individual i interacts with individual j but not with individual k whereas j and k interact.[4] (The intuition is that individual k , in this example, is a *non-overlapping* neighbour of j, whose characteristics and behaviour can then serve to identify the impact of j on i). BDF account for correlated effects through a local or global within transformation i.e., network fixed effects[5].

The model can be characterised as follows. Denote the set of farmers as i $(i = 1, ..., n)$ and y_i denotes the outcome of farmer i, $\mathbf{x}_i$ is a $1 \times K$ vector of exogenous characteristics. Each farmer has a peer group P_i of size n_i. P_i represents the farmer's local network i.e. direct connections i to other farmers in any given network l. The network l thus consists of all the connections, i.e. both the direct connections and those that are indirect, farmers connected to the farmer only via other farmers. So in the notation below, we will qualify all notation further by l, as in y_{li}. In the

[4]This particular network structure produces exclusion restrictions which achieve identification in the same way as exclusion restrictions achieve identification in a system of simultaneous equations.

[5]In a local transformation the model is written as a deviation from the mean equation of the individual's peers and in a global transformation it is written as a deviation from an individual's network. Note that in the presence of correlated effects, the distance between individuals within the network needs to be ≥ 3. Distance in this context is defined as the shortest directed path between two nodes in a given network.

application, the outcome is the adoption decision concerning the modern input. By assumption farmer i is excluded from P_i, i.e., $i \ni P_i$. Denoting each farmers' network l, we assume that our sample of size l is i.i.d. and from a population of networks with a fixed and known structure. The assumption of a fixed network structure is made on the basis that networks are defined by the location of the farmer's household. We distinguish between three types of effects: a farmer's outcome y_i is affected by (i) the mean outcome of her peer group (endogenous effects), (ii) his own characteristics (correlated effects), and (iii) the mean characteristics of his peer group $\mathbf{x}_l$ (contextual effects):

$$y_{lit} = \beta \frac{\sum_{j \in P_i} y_{ljt}}{n_i} + \gamma x_{lit} + \delta \frac{\sum_{j \in P_i} x_{ljt}}{n_i} + \varepsilon_{li} + \varepsilon_{lt} + u_{lit} \tag{1}$$

Hence, β captures endogenous effects and δ contextual effects. We require strict exogeneity of $\mathbf{x}_l$ with respect to u_{li}. Correlated effects are contained in u_{li}. Note that we make no further assumptions on u_{li}, i.e., we do not require the residuals to be homoscedastic or normally distributed.

Turning to the estimation of Equation (1), we first construct the neighbour matrix (alternatively interpreted as a peer interaction matrix), W, which is interacted with the outcome variable and exogenous peer characteristics to form spatial lags, where the lags refer to indirect spatial neighbours. We define W using a 'K Nearest neighbours' (KNN) characterization. KNN is a distance-based definition of neighbours where 'K' refers to the number of neighbours of a farmer at a specific location. Distances are computed by the Euclidean distance between GPS locations of households. Therefore, under this approach, the set of 'neighbours' for household i includes the K households characterized by the shortest distance to household i within each village. In the first instance, we set $K = 5$, although we restrict this set by only considering those within a maximum distance threshold of one kilometre; in other words, of those households living within one kilometre, we pick the five nearest. One of the key reasons for doing so is that the new model of extension since 2009 does something very similar - it targets a model farmer and constructs as-patial network of the 5 nearest neighbours around him who are then monitored and targeted via the model farmer. This method, using a 1 km. radius seems sensible empirically as well, since in practice, only 1 percent of neighbours were dropped as they lived too far. Using this method, we drop all such households that are not a nearest neighbour to any other household in the sample.[6] (Note that alternative definitions of K are possible, even desirable and we discuss these in the next section - however, for the sake of simplicity we confine ourselves to the 5 nearest neighbours here). Depending on the number of nearest neighbours used in our definition of W, this leads us to drop a small number of households which causes slight variations in the sample size across specifications. Yet, under the assumption that households are a random sample of the underlying population, dropping such 'island' households does not bias our results. We row normalize W so that Wy_i represents the average outcome of the agent's peer group excluding herself i.e. it is the

[6] In fact, for such 'island' households, column sums of the spatial weight matrix W are zero.

same as $\frac{\sum_{j \in P_i} y_{lj}}{n_i}$.

Equation (1) can be now written in structural form as:

$$y_l = \beta W y_l + \gamma x_l + \delta W x_l + u_l \tag{2}$$

where $W y_l$ represent the endogenous peer effect and $W x_l$ represents the contextual effects. Note, that in the above case we allow for intra-group variations in social interactions which are asymmetric in general since farmers are attached in varying ways to their peers (as opposed to those studies that use the entire reference group such as a village, which assume that individuals within a the peer group are all fully connected and have the same level of social interactions; variation in social interaction in this case are brought about only due to across group variation). Therefore the nonlinearity introduced by these asymmetric interactions provide necessary conditions for identification. This is because our chosen peer interaction structure (W) induces variation in the magnitude of social interactions such that each farmer has a unique and different set of peers/neighbours. Moreover the variation in the number of indirect neighbours that results due to this assymetry of connections allows us to use the non-overlapping neighbours to identify the parameters.

The reduced form of Equation (1) is given by;

$$y_l = (I - \beta W)^{-1}(\gamma I + \delta W)x_l + (I - \beta W)^{-1} u_l \tag{3}$$

If we omitted the endogenous effects from Equation (2), i.e., $W y_l$, the model could be estimated using OLS under the assumption that all covariates are independent of the error term, i.e., strictly exogenous. However, OLS is biased and inconsistent in the presence of a spatial autoregressive lag (Anselin, 1988)(2). Denoting the variance-covariance matrix of ϵ_l as ψ_{ϵ_l}, it is easy to see that,

$$E[(W y_l) u_l^{'}] = W(I - \beta W)^{-1} \psi_{u_l} \neq 0 \tag{4}$$

Anselin (1988) suggested a Maximum Likelihood (ML) estimator to address the endogeneity problem. To avoid computation accuracy problems in the ML approach noted by Prucha and Kelejian (1999)(36), Kelejian and Prucha (1997, 1998)(35) suggested a spatial two-stage least squares estimator (S2SLS). They suggest using a set of instrument matrices to instrument for $W y_l$.

From Equation (4), we can see that, ideally the set of instruments contains linearly independent columns of $[W^2 x_l, W^3 x_l, W^4 x_l \ldots]$. The use of such instruments is possible when the matrices,

I, W and W^2 are linearly independent. This is easily violated when groups are all of similar size and everyone within a group is connected to everyone else. In this case I, W and W^2 are linearly dependent and $W = W^2$. W^2 cannot be then used as an instrument.

In the case of (spatial) networks as here, identification is achieved if the network is characterized by a small degree of intransitivity e.g., farmer i is connected to farmer j and farmer j is connected to farmer k, but farmer i and farmer k are *not* connected. This produces a directed network topology which achieves identification of peer effects as shown by BDF. The networks-based intuition of this strategy is straightforward: $W^2 x_l$ is an identifying instrument for $W y_l$, since x_{kl} affects y_{jl} (since they are connected and interact with each other) but x_{kl} can only affect y_{il} indirectly, through its effect on y_{jl}. In our particular case, the relevant instruments are then $W^2 x_l$, *an* $n \times 1$ vector of weighted averages of adoption of the neighours of neighbours of each farmer in the village. By definition, these neighbours of neigbours are part of the overall network, but not overlapping with the direct peer group, whose effects is being identified.

While this will identify the endogenous effects, there is still an issue of correlated effects and of selection effects. Correlated effects occur when individuals within a peer group behave similarly due to the common environment that they face. Selection effects arise when an individual chooses his own peer/reference group; this causes a bias in the peer interaction effect due to the presence of unobservables that both influence the choice of peer group and the outcome. This is the case when group formation is endogenous, for example, when popular students interact primarily with other popular students or, and relevant for our case, when households sort themselves into a locality of their choice. In this paper, following Blume and Durlauf (2006)(7), we employ a first-differenced specification to address the issue of correlated and selection effects.

We employ differences between the two available rounds of data to account for unobservables that are constant over time. Accounting for such unobservables appears to be important in light of a large body of work suggesting that peer effect estimates are biased due to the presence of unobserved household characteristics (e.g., Evans, Oates, and Schwab, 1992)(21). The period-difference will therefore eliminate this unobserved household/f/farmer fixed effect that could bias the peer interaction effect.

We are interested in explaining the change in adoption achieved by households between t and $t-1$. We write the change in a farmer's adoption take-up as a function of the change in a farmer's own characteristics whilst allowing for peer effects by incorporating spatial lag terms of the dependent variable. Hence, we rewrite Equation (1) as

$$\triangle y_{li} = \beta \frac{\sum_{j \in P_i} \triangle y_{lj}}{n_i} + \gamma \triangle x_{li} + \delta \frac{\sum_{j \in P_i} \triangle x_{lj}}{n_i} + \triangle u_{li} \tag{5}$$

where $\triangle y_{li} = y_{li,t} - y_{li,t-1}$ denotes the difference in adoption levels between periods t and

$t-1$ for household i in network l. $\frac{\sum_{j \in P_i} \triangle y_{lj}}{n_i}$ denotes the spatial autoregressive term and $\triangle x_{li} = x_{li,t} - x_{li,t-1}$ denotes the change in farmer i's own characteristics while $\frac{\sum_{j \in P_i} \triangle x_{lj,t}}{n_i}$ denotes the change in household i's peers' characteristics between t and $t-1$. This can be easily seen in terms of the network specification,

$$\triangle y_l = \beta W \triangle y_l + \gamma \triangle x_l + \delta W \triangle x_l + \triangle u_l \tag{6}$$

However, while we are able to difference out all the household and village level fixed effects that are constant over time, correlated effects will still continue to persist if there are common environment related time-varying unobservables that effect both the farmers as well as their neighbour's outcomes. In the context of adoption, prices for inputs and outputs are an obvious example. We address this issue by including village fixed effects in our first differenced specification.

$$\triangle y_l = \beta W \triangle y_l + \gamma \triangle x_l + \delta W \triangle x_l + \theta p_l + \triangle u_l \tag{7}$$

where p_l denotes indicators for the village that each household belongs to.

Further empirical issues

The identification of neighbours' adoption decisions is obtained here by using the non-overlapping sets of neighbours - or neighbours of neighbours, who can be thought of as affecting the decisions of spatial neighbours directly - but not the household's own decision, beyond the effect they have on the spatial neighbours. First difference estimation allows us to control further for correlated and selection effects; additional village fixed effects will capture all possible supply side issues that affect the farmers as well as their neighbours. One empirical task will be to explore whether the adoption of neighbours of neighbours predicts the adoption of the neighbours - thereby testing the strength of the instrument. Testing the exclusion restriction is of course not directly possible; however it would appear reasonable in a spatial setting in which observing neighbours' plots matters for observing returns that one's own decision to adopt is only influenced by the neighbours of neighbours via one's direct neighbours.

A key issue is identifying the appropriate peer group. Above, one possible definition was introduced: we use the five nearest neighbours provided they live within 1 km. of the farmer. Neighbourhoods are not particularly small, and geographical distance is bound to matter for the extent to which farmers can observe returns to new inputs. One potential problem is that plots may be scattered, as our spatial approach would then not be correct. However, in the villages studied, this does not appear to be at all common.[7]

Nevertheless, alternative definitions of neighbourhoods are possible, and are explored as well. Expanding the relevant neighbourhood via the distance criterion quickly hits the boundaries of localities. As an alternative, we test the robustness of this identification mechanism to using the self-reported neighbourhood as the space of near neighbours. In particular, in the survey, households are asked to identify the hamlet they live in, and locally recognised definitions are used, leading to a handful of localities within each village.[8] As neighbourhoods within villages are far larger - and involve households within an average radius of about 2-4 kilometres, this robustness test is relevant and addresses possible criticisms that 1 km. restriction is misleading.

Identification then has to be done differently. In particular, consider the relevant peer reference group as all households belonging to the same hamlet in a village. As noted by BDF, peer effects are still identified since households interact in village based groups of different sizes. The peer/neighbourhood interaction matrix, W, has block diagonal elements of varying sizes. This brings about variation in reduced-form coefficients across communities of different size that ensures identification. This alternative definition captures both peer and neighbourhood effects. This implies, that the reduced form is given by;

$$y_l = (I - \beta W)^{-1}(\gamma I)x_l + (I - \beta W)^{-1}\epsilon_l \tag{8}$$

First difference estimation is still possible and relevant; as are village fixed effects, to deal with

correlated and selection effects. As will be shown below, the results remain remarkably similar. We also examine a variant of this identification as follows: two farmers A and B might reside in adjoining hamlets and hence be (spatially) close to each other even if in different hamlets, while a(non-overlapping) neighbour C might reside in the same hamlet as B but be quite far away (say over 1 km away) from either of them. In this case, we can use farmer C to identify the effect of farmer B on farmer A. This is therefore the third method we employ. We find that the results from these alternative methods are remarkably similar - the results reported below are strongly robust to the alternative estimates.

While this discussion handles the identification of social learning, in this paper we aim to contrast it with the impact of extension visits as well. The use of farm household fixed effects allows us to tackle another relevant problem related to identification: that extension services are not just offered randomly to farmers, but that they may be offered to specific farmers for a reason. To the extent that farmers offered services or more visits are better (or worse) farmers, and to the extent that these factors are unobservable, by controlling for the fixed effect (by using first differences), this placement problem can be controlled for. Extension visits may still be dictated by supply

[7] This may be reflecting that after 1976, land reform had ensured that all land is owned by the state and allocated by the peasant association, including with views on improving productivity by reducing scattering of plots.

[8] As will be explained below in the data section, 'villages' as used here refers to Peasant Associations, the lowest administrative unit in the country.

side factors, but the inclusion of village fixed effects (dummies) in the first-difference equation will capture trends in the village-level placement of extension as well.[9] All estimations include (time-varying) controls as well for other farmer characteristics, such as wealth and educational levels of the household. Finally, even though data on adoption are not available at the plot level, we have information on (self-reported) quality of plots, controlling further for a possible source of targeting by extension workers and demand for modern inputs.

In the results below, results are shown for the basic 'five (or fewer) neighbours within 1 km' definition of peer groups[10]. We report the IV cross-section results, as well as the IV first-difference results. For further robustness, we also estimate all equations accounting lagged adoption by the farmer and lagged adoption by the peer group.

Data and Descriptives

The data are from the Ethiopian Rural Household Survey, and in particular its rounds 5, 6 and 7, i.e. 1999, 2004 and 2009. These rounds are particularly suitable as they have details on extension and modern input adoption, with improved seeds for crops such as wheat and maize only becoming more systematically available since around 2000. This survey that has been running since 1994, covering 19 Peasant Associations across the four main regions. Details of the survey are in Dercon et al. (2009)(17), who also show that the survey is broadly representative for the diversity of the main crop farming systems in the country. They also show that attrition has been low, and especially in more recent rounds, it has been restricted to about 1-2 percent per year. Here, we focus on those farmers involved in cereal production.

Consequently, we investigate the relative importance of different sources transmitting such information, contrasting extension agents with neighbours. Table 1 offers summary evidence on the importance of the different sources of information, obtained from the 1999 round of the Ethiopian Rural Household Survey, concentrating on those households that grow cereals. It suggests that while both neighbours and extension agents are important in transmitting information, extension agents were the primary source of information for both new seed and fertiliser in 1999. In this paper, we explore whether actual adoption of fertiliser and seed can be explained by these factors.

[9]Note that 'villages' here are Peasant Associations (PAs), which is the lowest administrative level, and consists of a few villages or hamlets. All services and markets tend to be at the level of the PAs, including the supply of seeds and fertilizer via the main (and usually only) supply channel, which is the PA.

[10]*Overlap Statistics*: To see how close the neighbours' peer group is to the neighbourhood group we compute distance based summary measures for neighbourhood peer groups. The following statistics are averaged across all villages. The mean distance between any two households in a neighbourhood is 2:04 km with a standard deviation of 1:67 km. The maximum and minimum distance in a neighbourhood are 5:60 km and 0:11 km respectively. To see the extent of overlap, we note that the spatial peer group imposed a cutoff of 1 km. In this case, the average percentage of household pairs within neighbourhoods, with a distance within the 1 km radius is 67%. The average number of neighbours within this definition of neighbourhoods is about 6.

Table 1: Main sources of information for fertiliser/seed

Source of information	Fertiliser	Seed
extension agents (%)	50	68
friends/neighbours (%)	36	17
observed early adopters (%)	14	15
Average number of people discussed adoption with	4	3

Source: ERHS 1999

We use data from a longitudinal survey of farm households, the Ethiopian Rural Household Survey, using data over three rounds covering a decade (1999, 2004 and 2009) to examine the relationship between sources of information and adoption of both improved seed and fertiliser, using the sample of households that do grow cereals from 19 peasant associations across the country. At baseline in 1999, about 18% of farmers used improved seeds and about 62% used fertiliser[11]. Note that these figures are higher than national figures, which is largely explained by the inclusion of some relatively high potential areas. Nevertheless, these adoption rates are still far from complete and there are also substantial differences between villages. As the table above demonstrates, the two most potent sources of information and social learning are extension agents and neighbours. We find that in the initial period both mattered for adoption of new seed - but that the impact of adoption by neighbours is about three times as high, with an increase of one standard deviation in average adoption of improved seeds by neighbours (corresponding to local diffusion rates increasing by 22%) raising the probability of own adoption by 11% points while the impact of raising the number of visits by 1 standard deviation (1.3 more visits) is about 4% points. In 2009, these impacts are relatively similar for improved seeds. However, the impact of extension services by 2009 fell to a return in uptake of modern seeds per visit of only one-tenth of what it was in 1999, as there are far more extension visits in 2009 compared to 1999 (with a mean number of 0.3 in 1999 and a mean of 5.5 visits in 2009), so that one standard deviation corresponds to 9.9 more visits. The impact on adoption of fertiliser is mixed, with a large impact of extension agents in the initial period and a substantial impact of neighbours. By 2009, both wear off, but for diffusion via neighbours, this appears to be a problem of precision of estimation, while for extension, the return per visit collapses to near zero. We also ask if these effects can be robustly identified in impacts over time, focusing on *changes* in technology use. While this allows us to control for time-invariant factors, including the extent to which placement of extension services is driven by concerns about current yield, this analysis is comes with the proviso that identification may not be easy as growth in adoption of both seed and fertiliser has been rather low over the decade. Nevertheless, we find results confirming our earlier results: we find that neighbours seem to matter for adoption of both seed and fertiliser but the effect of extension agents is non-existent. This suggests that our results are robust, pointing evidence of social

[11]A companion piece by Getachew (2011) (26), using these data examines the role of new seeds and fertiliser in yield growth. Cereal yield grew by 21% over the decade (lower than the national average) while input use is far higer than the national average. The paper finds that there is asignificant respoinse of yield to the use of improved seed and fertiliser.

learning rather than any sharp impact of extension workers in this period.

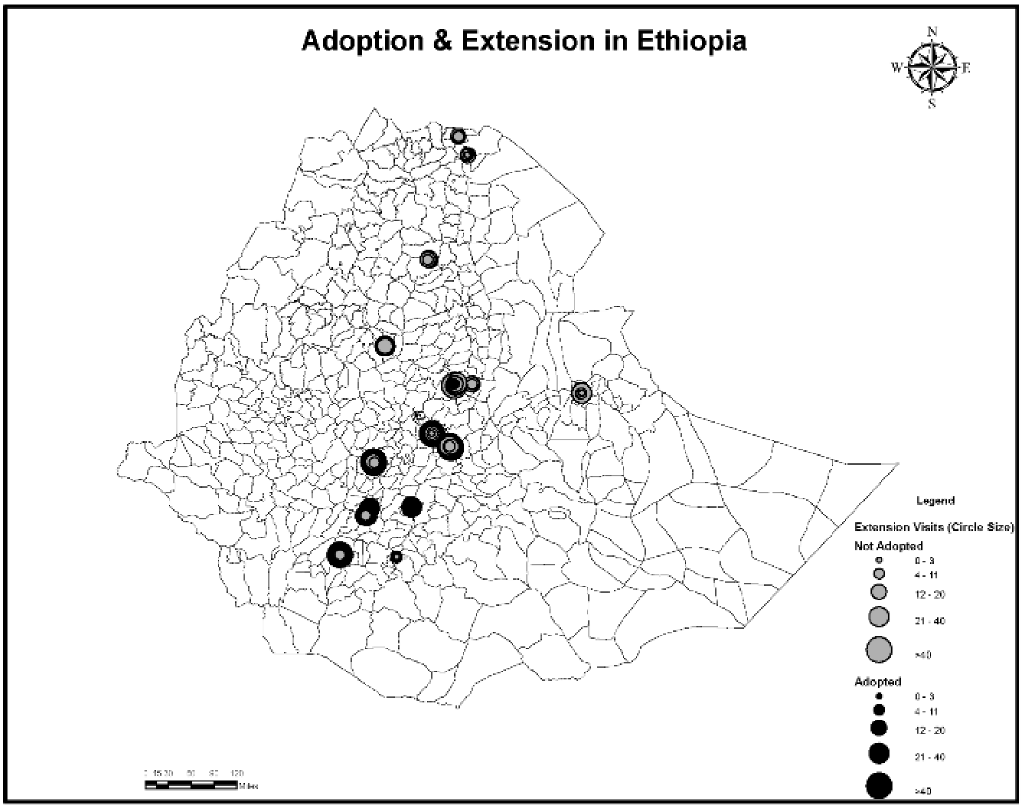
The evidence provided here is based on three rounds of a longitudinal survey of Ethiopian households, in 1999, 2004 and 2009. Details on the survey can be found in Dercon et al. (2009). In brief, the initial survey in 1994 covered 15 peasant associations and 1477 households, across the four main regions and across the various crop farming systems in Ethiopia. Overall, the study area is broadly representative of the agro-ecological diversity in Ethiopia, at least with respect to crops, although (and relevant for the study) more areas were involved in maize and wheat than possibly in the national average; as will be shown below, the use of improved seeds and fertiliser appears somewhat higher than the national average. There were surveys in earlier years : however, detailed information on adoption of new seed and fertiliser is only available in these three years. In this paper, we only focus on farmers that were involved in cereal production, and for whom we have complete information for all three years (954 farmers).

Table 2 below offers summary evidence on the average adoption rates in the three years. The adoption rate stayed much the same across years: for new seed, rising slightly from 18% in 1999 to 23% in 2009; for fertiliser, growing from 62% in 1999 to 64% in 2009, with a sharp dip in 2004 to 25%. It should be noted that in 2002-3 there was a serious drought and hence 2004 represents a sharp response to this: there was a significant drop in the percentage of farmers using fertiliser. In this year, we are unable to pin down the use of improved seed accurately: we are able only to obtain whether seed was purchased (which includes bought local seed) and this share is far higher at 31%. Admittedly, local seed is more likely to be saved than bought, while the contrary is true for improved seed and this pattern can be seen in both 1999 and 2009.

It should be noted that the use of improved seed is difficult to establish with precision. The questions posed in both 1999 and 2009 ask whether the farmer uses local or improved varieties - and within each of these, whether the seed is saved or bought (or also exchanged in the case of local varieties). The measure used here is that of such self-reported use of improved seed, whether saved or bought. However, in 2004, this question was simply phrased as whether any seed was bought and consequently, the measure of seed use here includes all seed bought including local, non-improved varieties. A further complication is that the use of improved seed varies by crop: while improved seed can be saved for use in the case of wheat and teff for instance, improved seed for maize cannot be saved thus. For maize (as for rice, millet and sorghum), the seeds are obtained as hybrids and are effectively incapable of regeneration the following year. It is also thought that returns from improved seed are much enhanced if used with fertiliser and most households do use fertilizer with new seed, with 96% doing so in 1999 and about 82% in 2009. In 2004, given the sharp fall in fertiliser use, only 9% used (bought) seed with fertiliser. Given the measurement error in the use of improved seed in 2004, we present the cross-section results by year and also the change in use between 2009 and 1999 as well as the comparison across all three years for seed alone. The figures for fertiliser are less prone to such error for the questions were asked in a similar fashion across all three years and the recorded use of DAP and Urea is easier to establish.

We also note that these figures are somewhat higher than national averages, suggesting somewhat higher potential areas on average than on average in the country. Figure 1 shows the location of the villages, adoption rates and extension visits. The number of extension visits in the village is shown by the size of the circle; green circles show the number of non-adopters and red circles show the number of adopters.

Figure 1: Location of the villages, adoption rates and extension visits 2009



At the same time, these figures are well below what potentially could be obtained as we are focusing on farmers involved in cereal production. Seed adoption seemed to respond slightly more to neighbour's use of seed, relative to visits by extension agents with the correlation between own and neighbours' adoption higher in both years, at 0.47 in 1999 and 0.29 in 2009. Note also the striking increase in the average number of extension visits, going from about 0.3 to 5.5 visits per farmer, reflecting the vast expansion of the supply of development agents or extension agents in this period. In sum, adoption of seed has increased very little over the decade and the use of new seed remains rather low but the use of fertiliser has remained relatively high and steady. These figures rely on panel data - and it might well be the case that with heterogenous returns, only those farmers who expect to profit take this up in the first instance and hence it is unsurprising to see little change. However, there is a lot of churning which the seeming stability of figures disguises as is evident in Tables 3 and 4.

Table 2: Rates of adoption: 1999 - 2009

	1999	2004	2009
Adopt new seed %	18	31^n	23
Use fertiliser %	62	25	64
Neighbours adopting new seed %	17	31^n	21
Neighbours using fertiliser %	59	26	63
Correlation: own and neighbour seed adoption	0.47	0.37	0.29
Correlation: Own and neighbour fertiliser adoption	0.59	0.55	0.57
Correlation: seed adoption and extension visits	0.29	0.04	0.16
Correlation: fertiliser adoption and extension visits	0.19	0.04	0.11
Number of extension visits in past 5 seasons	0.29	1.06	5.5

^{n}Note:Adoption of new seed is 31% but those using both seed & fertiliser is 9%

In particular, the tables report whether the same farmers continue to use new seed or use fertiliser over time. Learning about new seed seems to matter more than that of fertiliser use: only 7.5% of new seed users (as opposed to 45.5% of fertiliser users) continued to use new seed in 2009, once taken up in 1999. Only 4% of farmers continued to use new seeds and (19% of fertiliser users) through the period, once adopted in 1999. Clearly, such churning demands explanation. A first step is to examine the characteristics of adopters and non-adopters in each period: are there clear correlates of adoption?

Table 3: Adoption of new seed across the decade

	Not adopt 2009	Adopt 2009
no adoption 1999 & 2004	51	9
no adoption 1999 but adopted 2004	17	7
adopted 1999 but not 2004	5.5	3.5
adopted 1999 & 2004	3	4

Table 4: Adoption of fertiliser across the decade

	did not adopt in 2009	adopted in 2009
no adoption 1999 & 2004	26	15.5
no adoption 1999 but adopted 2004	0.7	3
adopted 1999 but not 2004	7	26.5
adopted 1999 & 2004	2.3	19

Table 5 below offers a summary of the differences in characteristics between adopters and non-adopters of new seed. The main difference, in 1999, between adopters and non-adopters of in the first year is the visit of extension services over the previous 5 years, where over two thirds of adopters report being visited at least once relative to about 5% of non-adopters. This difference falls in 2009, with 47% of non-adopters being visited. Recall that this is in a context of a vast increase in the numbers of extension agents and corresponding visits as shown in table 2. Adopters in all three years are slightly more educated, have slightly better quality land but do not differ significantly in terms of assets measured as livestock. However, the key difference across all years appears to be that adopters are more likely to have neighbours who are adopters too.

Fertiliser adoption is confined to the wealthy farmers (table 6). They also have more and slightly better land and are better educated, with the differences narrowing by 2009. Again, the visit of extension agents seems to define the adopters particularly in 1999 - but again, the key difference across the decade is that adopters had neighbours who also adopt. This sets the stage for the results in the regressions below, where we control for the endogeneity of the decision of neighbours to adopt new seeds or use fertiliser.

Table 5: Differences between adopters and non-adopters of new seed

Years	1999		2004		2009	
	Adopt seed	Not adopt	Adopt seed	Not adopt	Adopt seed	Not adopt
Sample size	151	803	300	654	225	729
Extension visits	0.64	0.05 *	0.28	0.23	0.62	0.47 *
Seed (N'bours)	0.46	0.11*	0.47	0.24*	0.34	0.17*
Extension (N'bours)	0.37	0.10*	0.81	0.7	0.52	0.47
Land (hectares)	0.80	1.23*	1.72	1.67	1.55	1.48
Irrigated plot	0.19	0.10*	0.24	0.25	0.41	0.35
Share lem land	0.66	0.49*	0.62	0.53	0.69	0.48*
Value of livestock	2090	2284	2697	3121	9621	8961
Oxen	0.96	1.28*	0.92	1	1.2	1.05
Male-headed	0.84	0.77*	0.71	0.68	0.69	0.64
Some schooling	0.36	0.29*	0.42	0.27*	0.60	0.50

* Indicates significant differences across adopters and non-adopters

Table 6: Differences between adopters and non-adopters of fertiliser

	1999		2004		2009	
	Adopt fert	Not adopt	Adopt fert	Not adopt	Adopt fert	Not adopt
Sample size	526	428	240	714	612	342
Extension visits	0.23	0.03 *	0.28	0.23	0.54	0.43 *
Fertiliser (N'bours)	0.73	0.36 *	0.35	0.29	0.78	0.36*
Extension (N'bours)	0.18	0.10	0.78	0.73	0.50	0.45
Land (hectares)	1.31	0.90*	2.34	1.46*	1.73	1.08*
Irrigated plot	0.12	0.10	0.29	0.23	0.45	0.22
Share lem land	0.61	0.38*	0.52	0.57	0.57	0.45*
Livestock value	2763	1394*	4543	2464*	11623	4679*
Oxen	1.39	0.94*	1.1	0.8	1.3	0.69*
Male-headed	0.83	0.70*	0.72	0.68	0.69	0.58*
Some schooling	0.34	0.23*	0.38	0.29	0.58	0.43*

*Indicates significant differences across adopters and non-adopters

Results: Neighbours' adoption and extension agents

The sample is restricted to cereal farmers and households that have identified GPS locations. We use a sample of 954 households across the three years for whom we have consistent panel data. Recall that we construct spatial neighbours based on a distance of 1 km from the household[12]. We instrument for the average neighbour's decision to adopt by using the non-overlapping sets of neighbours - or neighbours of neighbours, who can be thought of as affecting the decisions of spatial neighbours directly - but not the household's own decision. It might be argued that extension visits are also endogenous and ought also be instrumented for. However, in this context, it appears that village level variables (distance to the nearest extension office) are critical in explaining extension visits. One was more likely to be visited by extension agents in both years if one had more land, had some irrigated plots, had better quality and possessed more assets in livestock. In addition, one was more likely to be visited in 2009 if the household head was better educated. We take the view in what follows that the visit of extension agents can be regarded as largely exogenous and control for both own characteristics (in the form of all these variables) and village-level fixed effects[13]. In addition, we also present the results in first differences: these in turn allow us to look at the robustness of these results in the presence of unobserved fixed

[12]Note that two alternative definitions of neighbours based on self-reported neighbourhoods as well asthe overlap between distance and self-reported neighbourhoods was used. The estimators here rely on the fact that such spatial neighbours vary in number (as opposed to the simpler definition using the five closest neighbours). However, estimates remain unaffected by such considerations.

[13]These results are presented in the appendix.

factors at the household level that might bias the estimates for each year, including those linked to the placement of extension services.

The estimates below are based on the following specification:

$$y_{itk} = \alpha + \beta_1(Extension\ visits) + \beta_2(share\ of\ neighbours'\ adopting) + X'\gamma + v_i + \epsilon_{itk}$$

where: y_{itk} is a discrete variable denoting whether household i,adopted technology k at time t, X denotes a vector of individual and household characteristics, including the characteristics of the plots on which cereals are grown and v_i denotes village level fixed effects. The first-differenced specification retains the village fixed effects to account for different trends in placement of extension services at the village level. The share of (direct) neighbours who also adopt the technology is instrumented for using a first-stage regression where their average decision to adopt is predicted using their own characteristics and the share of their direct but non-overlapping neighbours who adopt new technology. The full specification of these regressions is presented in the tables in the appendix but we offer summary tables that focus on the impacts of the key variables below.

Table 7 presents both probit estimates and the probit using instrumental variable estimation of the effects of extension services and neighbours' adoption decisions on one's own probability of adopting new seeds in both 1999 and 2009. All estimates control for a wide variety of household and farm level variables (including land, land quality, livestock, household composition, education) and community fixed effects. The appendix reports the full results. The reported results below are marginal effects, i.e. the impact of each variable on the probability to adopt evaluated at the average of all variables. Cragg-Donald F-test statistics are offered, and throughout we can reject that the decisions of the neighbours' neighbours are weak instruments.

Table 7: Adoption of new seed (Marginal Effects)^{note}

	Adoption 1999		Adoption 2004		Adoption 2009	
	Probit	IV Probit	Probit	IV Probit	Probit	IV Probit
Extension	0.03***	0.03***	-0.0	-0.002	0.003**	0.003**
(s.e.)	(0.01)	(0.01)	(0.0)	(0.003)	(0.001)	(0.001)
Neighbours adopt	-0.15**	0.46**	-0.17**	0.68***	-0.11	0.47**
(s.e.)	(0.07)	(0.20)	(0.09)	(0.32)	(0.07)	(0.25)
Cragg-Donald F		136.47		89.47		57.94
Sample Size				954		

*Significant at 10%; ** Significant at 5%; ***Significant at 1%

^{note}Controls for individual and plot characteristics as well as village fixed effects - see Appendix

The results suggest that there is a strong relationship between the adoption decisions of neighbours and one's own decision to adopt new seed, with a strong and significant coefficient of approximately 0.46 in both 1999 and 2009 (with a slightly higher estimate of 0.68 in 2004) in the IV regressions. We can transform the coefficients here to standardised values which allows us to interpret the effects clearly. In brief, an increase of one standard deviation in the average neighbours' adoption raises the probability of own adoption by about 11% in 1999, by 19% in 2004 and 12% in 2009. Average adoption rates range from 0.18-0.23, so this is large - more than double current levels. In 2009, the effect is similar. An increase of one standard deviation in extension visits (by 1.3 visits in 1999) raises the probability of own adoption by 3.7%, falling to 1.3% in 2004; while in 2009 this effect is at 2.9% (but then linked to an increase of one standard deviation which is then 9.9 visits). These results also show that there is a clear collapse in the return to one extra visit, for those not yet visited: the increased probability of adopting in 2009 is only one-tenth what it was in 1999. Clearly the impact of neighbours' decisions drowns out any impact through extension. These effects correct for endogeneity - but might still be contaminated by the changing environment over time that is unaccounted for in each regression. To examine the robustness of these estimates, we estimate a regression differenced between the three periods (this time using a linear probability model) and examining the robustness of the basic specification to including controls for previous years and lagged adoption The estimates are presented below in Table 8.

Table 8: Panel Estimates of Adoption of Seed: 1999-2009^{note}

	OLS (fe)	IV (fe)	IV (round/fe)	IV (lags/fe)
neighbours adopt	0.394***	0.938***	0.901***	0.891***
	(0.043)	(0.061)	(0.083)	(0.157)
extension visits	0.004***	0.003**	0.051***	0.004**
	(0.001)	(0.001)	(0.012)	(0.002)
neighbours adopt 04			0.014	
			(0.092)	
neighbours adopt 09			0.001	
			(0.096)	
extension 04			-0.052***	
			(0.013)	
extension 09			-0.048***	
			(0.012)	
(Lag) neighbour adopt				0.018
				(0.114)
Observations	2859	2859	2859	1902
F	15.084	24.953	20.489	8.264
Cragg-Donald		2125.609	603.177	229.010

Robust standard errors in parentheses

^{note}Controls for individual and plot characteristics as well as village fixed effects - see Appendix

These results confirm the importance of neighbours' adoption on own adoption, with results suggesting much higher impacts of neighbour adoption, controlling for household fixed effects. The effects of neighbour adoption are stable at 0.9 and as column three indicates, the impact of previous rounds is negligible. This is distinct from the effect of extension visits: here, the effect is large in 1999, but collapses in 2004 and 2009. In fact, the low and significant average effect of 0.003 is the direct consequence of this pattern. As the results above are marginal effects at the mean from a probit model, while in table 8, they are from a linear regression model, a comparison between table 8 and table 7 is only suggestive (and valid around the mean of all variables). Nevertheless, it is striking that they mimic the findings in table 8 for 2009, including regarding the impact of extension which is very small but significant. This would suggest that by 2009, extension services are widespread, and perhaps not targeting particular farmers. The fact that the coefficient is only one-tenth of the effect in 1999 in table 7 suggests that initially farmers more likely to adopt were targeted, but this has disappeared. In any case, they confirm the result for 2009: the impact of extension is small and the role of neighbours' decisions is relatively strong.

The next two tables, Tables 9 and 10 display the results of a similar analysis for the use of fertiliser over time.

Table 9: Neighbours' influence and extension agents in fertiliser adoption^{note}

	1999		2004		2009	
	Probit	Probit IV	Probit	Probit IV	Probit	Probit IV
Extension	0.22***	0.22***	0.003	0.003	0.002	0.002
(s.e.)	(0.05)	(0.048)	(0.003)	(0.004)	(0.002)	(0.002)
Neighbours adopt	0.18*	0.53**	0.06	0.13	0.10	0.53
(s.e.)	(0.09)	(0.21)	(0.09)	(0.33)	(0.11)	(0.36)
Cragg-Donald F		22.98		79.48		57.94
Sample Size				954		

*Significant at 10% ** Significant at 5% ***Significant at 1%

^{note}Controls for individual and plot characteristics as well as village fixed effects - see Appendix

The results tell us that a one standard deviation increase in the average fertiliser adoption of neighbours (0.35) raise own probabilities of adoption of fertiliser by 19%. The effects are similar in both 1999 and 2009 , even if estimated with higher standard errors in 2009. (The effect in 2004 is negligible, which is unsurprising given the fall in credit facilities in this period). This is still a substantial effect given that adoption is already about 62% in the survey areas. The effect of extension visits in 1999 seems to be large and significant. The impact of an extra extension visit in 1999 is to add 22% to the probability of adopting fertiliser; a one standard deviation increase (1.3 visits) would add 28%. But by 2009, and similar to seed adoption, the effect becomes negligible and insignificant by 2009. Table 10 offers the results using first differences, thereby controlling for household fixed effects. Again, the results look more like the 2009 effects than the 1999 effects, with a collapse of the extension coefficient. It is likely that in 1999 extension agents targeted farmers who were likely to adopt fertiliser. The 'true' impact of extension services on the typical farmer was small and possibly negligible after all. The impact of neighbours adopting is again high as compared to the cross-section results in table 9, but significant and as large as the effects for the adoption of seed. The impact of a one standard deviation increase (0.25) is about 10%.

Table 10: Panel Estimates of Fertiliser Use: 1999-2009[note]

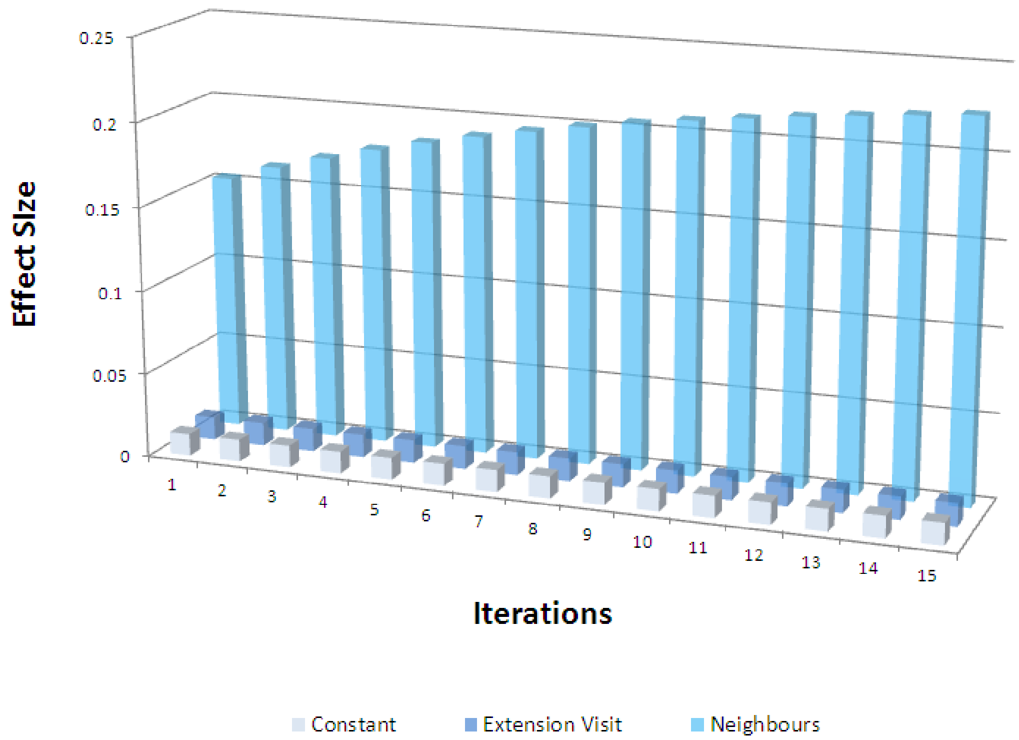
	OLS (fe)	IV (fe)	IV (round/fe)	IV (lags/fe)
neighbours adopt	0.501***	0.937***	0.929***	0.907***
	(0.039)	(0.054)	(0.061)	(0.096)
extension visits	0.001	0.001	0.029**	0.001
	(0.001)	(0.001)	(0.012)	(0.002)
neighbours adopt 04			0.019	
			(0.062)	
neighbours adopt 09			-0.006	
			(0.056)	
extension 04			-0.028**	
			(0.012)	
extension 09			-0.028**	
			(0.012)	
(Lag) neighbour adopt				-0.082
				(0.103)
Observations	2859	2859	2859	1902
F	60.961	66.980	52.747	49.323
Cragg-Donald		2188.698	708.353	391.339

Robust Standard errors in parentheses

[note]Controls for individual and plot characteristics as well as village fixed effects - see Appendix

A final question centres around the impact of extension through diffusion: given that extension visits start a cycle of learning, should not a proper assessment of the impact ought to include the indirect effects that such initial impacts generate? To examine this, we use the initial results from Table 7 and simulate the impact on learning, accounting for fixed effects, using a simple adaptive model of learning (hog-cycle model). Figure 2 plots the results of the simulation. First, note that in the absence of either extension or learning from neighbours, adoption is determined entirely by own, fixed characteristics, which implies an adoption rate of 1.3%. Sans any learning from extension but allowing learning from neighbours implies a long run equilibrium level of adoption of 17%. Further adoption requires an injection from other sources: the initial level of average visits (0.27), extension visits, while potent, adds an extra percentage point to the initial level of 1.3%. Of course, it gets a learning cycle going via social learning, but it would take many iterations before we would get higher adoption – after 10 iterations, only 6% extra is added to the initial 17%, with a long set of iterations taking us to the equilibrium of an additional 14% impact. The biggest part of the variation is explained by learning – the independent effect of extension is really small in terms of economic significance. But this is because the number of visits is small. With the same learning technology and same marginal effect of extension, boosting extension visits to 1.06 on average (as in 2004) would have a substantial impact. Here, after one iteration, 4 percent would have been added, and after 10 iterations half the sample would be adopting, or 32% more adoption added on. At levels of 5.5 visits, (the average in 2009), one would get full adoption after only 4 iterations!

Figure 2: Hog-Cycle Model Estimates

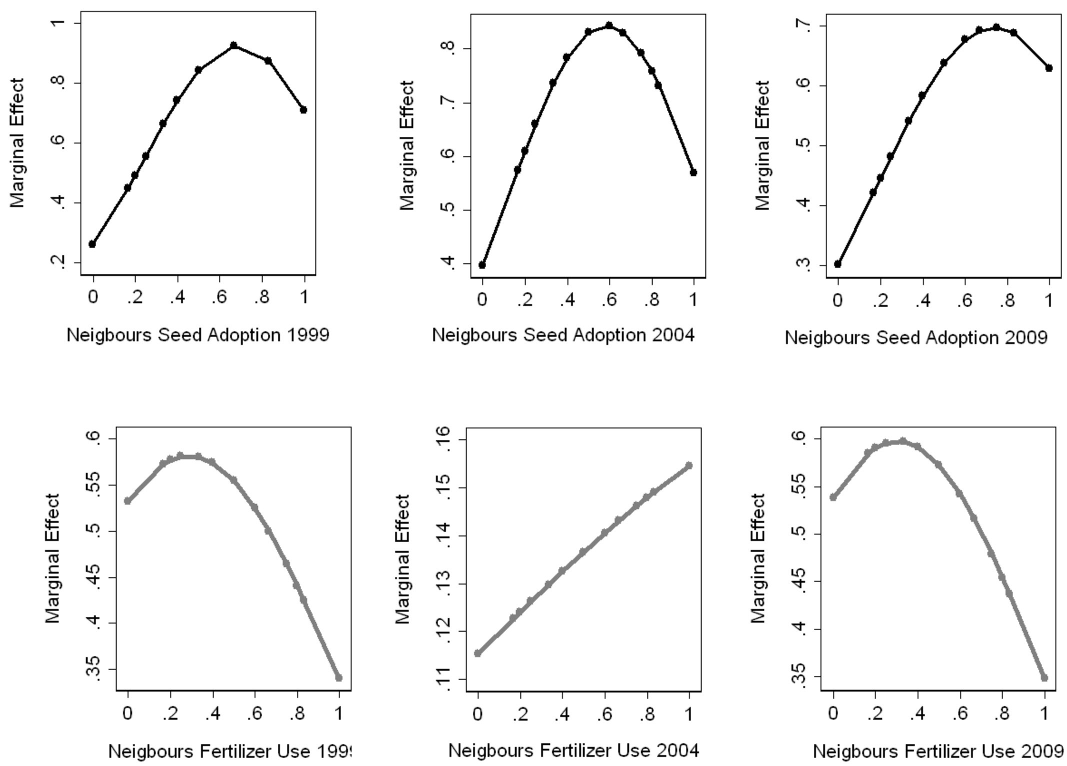


But the regressions also show that this did not happen. By 2004, the marginal return to extension had dropped off and so there was no independent source of boosting adoption. The learning cycle was very slow with only 1% take-up added after a year. We know that this round is less reliable. But by 2009, with massive boosting of visits, we get the same low outcome; the boost to 5.5 visits means that something is added in each iteration, but now after 10 iterations, it would only have boosted overall adoption by about 6%, barely different from the adoption rate from 1999, with the crucial difference that the results obtained in 1999 were achieved with far fewer but seemingly more efficient extension visits. In short, the return from the expansion of extension has had no impact on the speed of adoption, and adoption is still dramatically low. Furthermore, though social learning is crucial, it is also not high enough to sustain itself either.

Neighbours and extension visits: Graphical analysis

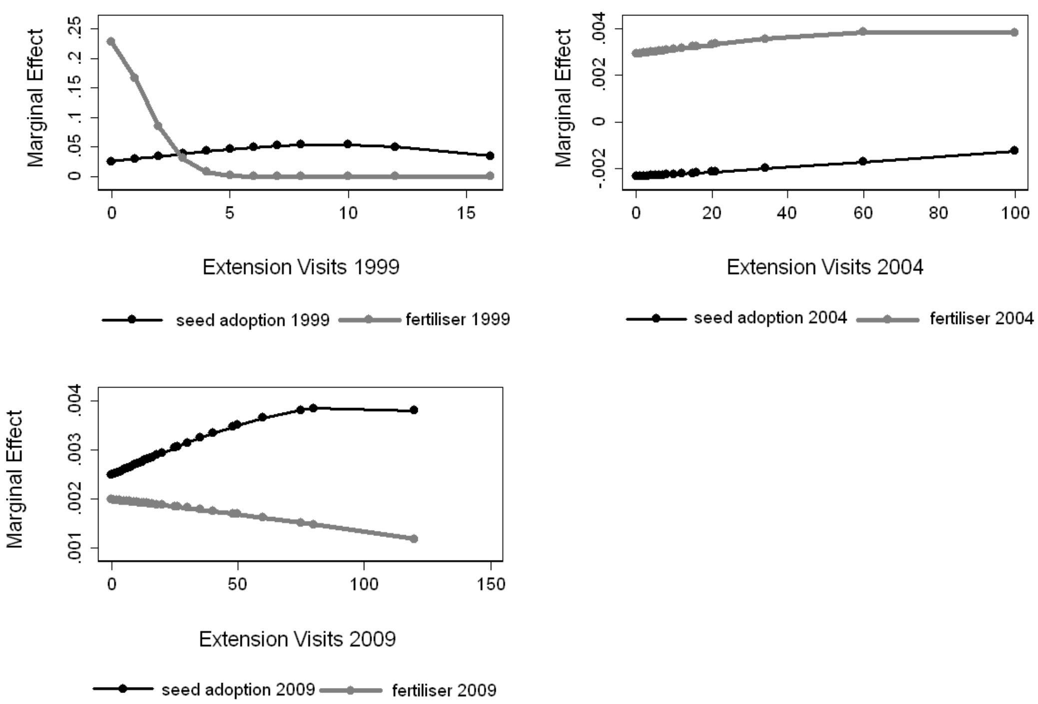
The impact of both neighbours' adoption and extension services is not constant nor linear in its impact. The effects described above simply offer the average impact at the mean of all variables when increasing extension visits or neighbours' adoption rates. Perhaps more illuminating is an examination of the impact (the marginal effects) across the distribution of initial diffusion rates in the neighbourhood or by the number of extension visits. We can use the regression results in table 7 and 9 to calculate the increased probability of seed adoption and fertiliser use at various levels based on initial diffusion levels and extension visits. Figure 3 shows the increased probability of adoption by a farmer for given levels of diffusion if this diffusion increases by 10 percent (based on the marginal effects from the statistical analysis). The figure shows that the speed of diffusion of improved seed through learning from others is likely to continue to increase until local diffusion levels of about 70 percent have been reached, i.e. the returns accelerate until that level. For fertiliser, these benefits from learning appear to tail off once about 30 percent diffusion has been reached. In both cases, they are relevant in size: an increase by 10 percent in diffusion in the neighbourhood increases the probability of adopting by about 5 percent at current levels of diffusion in these villages for seeds and fertilizer. (The figures for 2004 are clearly an anomaly here given the sharp fall in fertiliser use in this year).

Figure 3: Probability of adoption given neighbours' adoption



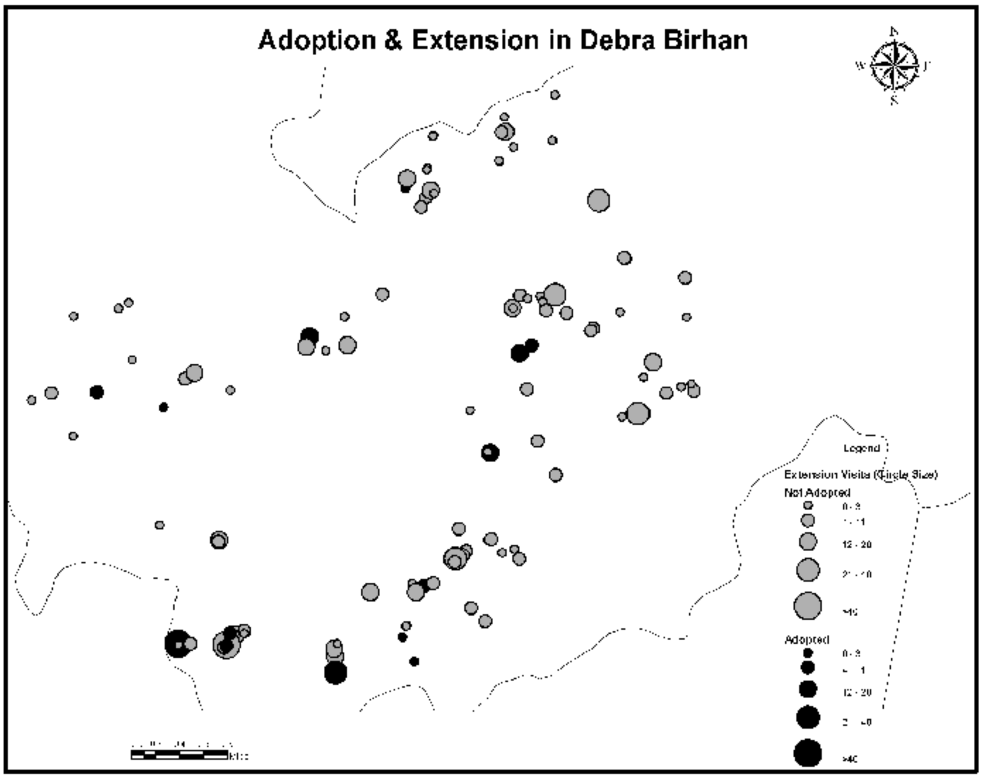
Parallel results for extension are presented in Figure 4. The benefits of further extension visits, in terms of increased probability of using fertilizer were initially high in 1999, although they tailed off sharply at higher levels initial visits. Recall that in the previous section, the fixed effects estimator suggested that in 1999, targeting of those likely to adopt may have taken place, so this effect may be overstated. Still, the effect could partly be explained by the fact that extension agents were involved earlier in supplying fertilizer and seeds themselves. By 2009, the average number of extension visits per farmer in the sample has increased massively, from 0.3 on average in 1999 to 5.5 visits in 2009. But the contribution of an additional visit, even at low initial visits, is considerably lower than in 1999: the return per visit is close to zero, in terms of increased adoption probabilities. Even though extension visits have clearly increased over time, in line with the expansion of these services throughout the country, they are unlikely to contribute to a rapid diffusion of these technologies. For policy, it is important to recognize that the current extension model may only deliver slow if any benefits to adoption of these technologies, even if supply conditions were to change. Learning from others is a more powerful tool, but is not amenable to rapid change through policy, as it reflects steady but careful learning from the experiences of others.

Figure 4: Probability of adoption given extension visits



The limited impact on adoption of the current extension model is well illustrated by Figure 5, showing the lack of correlation between extension visits and adoption of modern number of extension visits and the adoption rates for improved seeds in a number of villages near Debre Berhan in our sample. The size of the circle shows the number of visits by development agents. A red circle is a household that adopted improved seeds, while a green circle shows a household that did not adopt. As can be seen, there was little adoption despite high numbers of visits. Of course, without further analysis, we cannot ascertain whether other useful advice is transmitted in these visits that might be helpful for yield gains. But as a model to encourage adoption it does not seem to be working effectively in the village.

Figure 5: Adoption and Extension visits in villages near Debre Berhan



The results obtained here are consistent with evaluations of extension services both in Ethiopia and elsewhere in sub-Saharan Africa. Davis (2008) offers an overview of the evidence and suggests that the impact of extension services has been mixed. Other evaluations cited there suggest that while the Ethiopia's Participatory Demonstration and Training Extension System (PADETES), based on Sasakawa Global 2000's (SG-2000) approach to extension did raise adoption initially, farmers also stopped using new seed and fertiliser packages (see Bonger et al, 2004(8)). Spielman et al (2011) (39) summarise four recent studies on the impact of extension services and conclude that: "*Nonetheless, the entire body of evidence on agricultural extension suggests that the impact on productivity and poverty has been a mixed experience to date. Although many farmers seem to have adopted the packages promoted by the extension system, up to a third of the farmers who have tried a package had discontinued its use (Bonger, et al 2004; EEA/EEPRI 2006). In-*

deed, Bonger et al. (2004) also find that poor extension services were ranked as the top reason for non-adoption."

Conclusions

The traditional explanation for the observed differences in the adoption of new technology is heterogeneity in characteristics - some farmers are simply more receptive or entrepreneurial than others. More recent explanations centre around the notion that returns are both heterogenous and uncertain. In these circumstances, neighbours' decisions to use a new technology suggests that they think it is profitable and subsequent experience with it serves as an additional source of information. Social learning provides a natural explanation for the gradual adoption of new technology even in a homogeneous population.

In this study we find evidence that social learning is a powerful force for adoption of new technologies. The returns to extension may have been high in 1999, but by 2009 they appear to have collapsed to very low levels. The current extension model, and intensity of visits may transmit useful information to the farmers, but as a model to encourage modern input adoption, it does not appear to be very effective. This is not inconsistent with the general evidence on extension which suggests that extension services have an important role in raising awareness in the early stages of adoption but the impact on diffusion falls over time.

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APPENDIX: SEED AND FERTILIZER ADOPTION

Table 1: Peer Effects: Adoption & Fertilizer 2009

	(1) OLS	(2) IV: I	(3) IV: II	(4) OLS	(5) IV: I	(6) IV: II
Neighbours Adopt.	-0.110		0.444*			
	(0.073)		(0.231)			
Neighbours Fert.				0.113		0.507
				(0.109)		(0.354)
Neighbours' Predicted Adoption		1.117**				
		(0.125)				
Neighbours' Predicted Fertilizer					1.015**	
					(0.103)	
# Extension Visits	0.003**	-0.001	0.003**	0.002	-0.000	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.002)
Fertility Decrease†	-0.045	-0.003	-0.043	-0.071*	-0.013	-0.064
	(0.030)	(0.011)	(0.030)	(0.042)	(0.011)	(0.042)
Lem Share	0.094**	0.007	0.097**	0.067	0.009	0.050
	(0.037)	(0.015)	(0.037)	(0.055)	(0.015)	(0.057)
Medda Share	-0.067	0.003	-0.076	-0.057	0.007	-0.053
	(0.050)	(0.017)	(0.049)	(0.064)	(0.020)	(0.064)
Plot Area	0.043**	0.004	0.041**	0.005	0.004	0.002
	(0.017)	(0.006)	(0.016)	(0.031)	(0.006)	(0.031)
Plot Irrigated†	0.013	-0.005	0.007	0.214**	-0.023*	0.219**
	(0.034)	(0.013)	(0.034)	(0.041)	(0.012)	(0.041)
HH Head School†	0.048	0.014	0.054*	0.042	-0.006	0.047
	(0.030)	(0.012)	(0.030)	(0.046)	(0.012)	(0.046)
HH Size	0.010	-0.002	0.010*	0.003	-0.001	0.003
	(0.006)	(0.002)	(0.006)	(0.009)	(0.003)	(0.009)
HH Head Age	-0.001	0.000	-0.001	-0.000	-0.000	-0.000
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
HH Head Male† (d)	-0.040	-0.003	-0.036	0.012	-0.002	0.015
	(0.031)	(0.012)	(0.032)	(0.046)	(0.012)	(0.046)
Livestock Value (Log)	0.023**	0.002	0.020*	0.033**	0.004	0.031**
	(0.010)	(0.004)	(0.010)	(0.013)	(0.003)	(0.013)
# Oxen	-0.014	-0.002	-0.007	0.032	-0.002	0.033
	(0.015)	(0.006)	(0.016)	(0.027)	(0.006)	(0.027)
Risk Loving†	-0.064**	-0.001	-0.063**	-0.018	0.002	-0.017
	(0.027)	(0.011)	(0.028)	(0.045)	(0.011)	(0.045)
Patient (Long Term)†	0.011	0.005	0.009	0.006	0.008	-0.004
	(0.029)	(0.011)	(0.030)	(0.042)	(0.011)	(0.043)
Model Farmer† (d)	0.037	0.001	0.032	0.054	-0.011	0.058
	(0.057)	(0.021)	(0.057)	(0.079)	(0.020)	(0.077)
PA F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	954	954	954	954	954	954
Cragg-Donald F		110.758			103.942	
Shea partial r2		0.10			0.101	

Notes:
1. Robust Standard errors in parentheses
2. *indicates significance at 10%; ** at 5%; *** at 1%
3. Marginal Effects of coefficient estimates reported in columns
4. † Indicates dummy variable.

Table 2: Peer Effects: Adoption & Fertilizer 2004

	(1) OLS	(2) IV: I	(3) IV: II	(4) OLS	(5) IV: I	(6) IV: II
Neighbours Adopt.	-0.174*		0.719**			
	(0.093)		(0.317)			
Neighbours Fert.				0.059		0.129
				(0.091)		(0.332)
Neighbours' Predicted Adoption		0.842**				
		(0.098)				
Neighbours' Predicted Fertilizer					0.910**	
					(0.107)	
# Extension Visits	-0.000	0.001	-0.002	0.003	0.000	0.003
	(0.003)	(0.001)	(0.003)	(0.004)	(0.001)	(0.004)
Fertility Decrease†	0.026	-0.004	0.024	0.018	0.009	0.017
	(0.037)	(0.012)	(0.036)	(0.041)	(0.011)	(0.041)
Lem Share	-0.015	-0.005	-0.001	-0.017	-0.008	-0.016
	(0.041)	(0.014)	(0.041)	(0.044)	(0.013)	(0.044)
Medda Share	-0.009	0.004	-0.010	-0.046	0.003	-0.047
	(0.052)	(0.016)	(0.052)	(0.059)	(0.016)	(0.059)
Plot Area	-0.000	0.000*	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Plot Irrigated†	0.100**	-0.011	0.118**	0.131**	0.014	0.129**
	(0.051)	(0.014)	(0.050)	(0.059)	(0.014)	(0.060)
HH Head School†	0.087**	0.002	0.060	0.041	-0.005	0.040
	(0.038)	(0.013)	(0.038)	(0.043)	(0.011)	(0.043)
HH Size	0.014*	0.003	0.008	0.019**	-0.000	0.019**
	(0.008)	(0.003)	(0.008)	(0.008)	(0.002)	(0.008)
HH Head Age	0.001	0.000	0.001	-0.002*	-0.000	-0.002*
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
HH Head Male†	-0.028	-0.001	-0.025	0.053	-0.005	0.055
	(0.039)	(0.012)	(0.038)	(0.040)	(0.012)	(0.039)
Livestock Value (Log)	0.016	-0.007*	0.021*	0.036**	0.003	0.035*
	(0.013)	(0.004)	(0.012)	(0.018)	(0.003)	(0.018)
# Oxen	0.009	0.006	0.008	0.009	0.001	0.009
	(0.019)	(0.007)	(0.018)	(0.023)	(0.006)	(0.023)
Risk Loving†	-0.023	0.001	-0.035	-0.004	-0.005	-0.003
	(0.036)	(0.011)	(0.035)	(0.041)	(0.011)	(0.041)
Patient (Long Term)†	-0.013	0.008	-0.015	-0.014	0.002	-0.014
	(0.034)	(0.012)	(0.034)	(0.037)	(0.011)	(0.037)
Model Farmer† (d)	0.017	-0.011	0.019	0.172*	0.014	0.172*
	(0.064)	(0.021)	(0.063)	(0.093)	(0.021)	(0.092)
PA F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	954	954	954	954	954	954
Cragg-Donald F		85.077			79.486	
Shea partial r2		0.084			0.079	

Notes:
1. Robust Standard errors in parentheses
2. *indicates significance at 10%; ** at 5%; *** at 1%
3. Marginal Effects of coefficient estimates reported in columns
4. † Indicates dummy variable.

Table 3: Peer Effects: Adoption & Fertilizer 1999

	(1) OLS	(2) IV: I	(3) IV: II	(4) OLS	(5) IV: I	(6) IV: II
Neighbours Adopt.	-0.163**		0.452**			
	(0.076)		(0.212)			
Neighbours Fert.				0.193*		0.481**
				(0.100)		(0.217)
Neighbours' Predicted Adoption		0.840**				
		(0.077)				
Neighbours' Predicted Fertilizer					1.082**	
					(0.066)	
# Extension Visits	0.032**	0.002	0.028**	0.219**	0.002	0.218**
	(0.010)	(0.003)	(0.011)	(0.049)	(0.004)	(0.048)
Fertility Decrease†	0.039	0.001	0.038	-0.013	-0.009	-0.013
	(0.025)	(0.008)	(0.027)	(0.045)	(0.013)	(0.044)
Lem Share	-0.001	-0.004	-0.001	0.053	-0.002	0.056
	(0.031)	(0.009)	(0.033)	(0.055)	(0.015)	(0.054)
Medda Share	0.009	-0.001	0.017	0.037	-0.008	0.044
	(0.041)	(0.011)	(0.043)	(0.070)	(0.017)	(0.070)
Plot Area	0.003	0.002	-0.003	0.090**	0.012	0.085*
	(0.016)	(0.005)	(0.017)	(0.044)	(0.008)	(0.044)
Plot Irrigated†	0.138*	0.013	0.104	0.200**	0.002	0.187**
	(0.074)	(0.014)	(0.068)	(0.065)	(0.022)	(0.068)
HH Head School†	0.011	0.005	0.009	0.018	-0.001	0.020
	(0.027)	(0.008)	(0.029)	(0.050)	(0.013)	(0.049)
HH Size	0.012**	0.000	0.012**	0.017*	-0.000	0.016*
	(0.004)	(0.002)	(0.005)	(0.009)	(0.002)	(0.009)
HH Head Age	-0.002*	0.000	-0.002*	-0.003*	-0.000	-0.003*
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
HH Head Male†	0.041	-0.008	0.055*	0.180**	-0.003	0.184**
	(0.028)	(0.009)	(0.030)	(0.054)	(0.014)	(0.054)
Livestock Value (Log)	0.001	-0.000	-0.001	0.046**	0.001	0.044**
	(0.010)	(0.003)	(0.010)	(0.017)	(0.004)	(0.017)
# Oxen	0.007	-0.005	0.012	0.071**	-0.002	0.074**
	(0.018)	(0.005)	(0.019)	(0.032)	(0.008)	(0.032)
Risk Loving†	0.034	-0.001	0.038	-0.031	-0.013	-0.028
	(0.027)	(0.008)	(0.028)	(0.049)	(0.012)	(0.048)
Patient (Long Term)†	-0.005	0.004	-0.014	0.096**	0.002	0.087**
	(0.025)	(0.007)	(0.026)	(0.043)	(0.012)	(0.043)
Model Farmer† (d)	0.122**	-0.003	0.121*	0.071	-0.013	0.069
	(0.061)	(0.020)	(0.065)	(0.096)	(0.018)	(0.094)
PA F.E.	Yes	Yes	Yes	Yes	Yes	Yes
N	861	954	861	912	954	912
Cragg-Donald F		197.427			296.768	
Shea partial r2		0.176			0.243	

Notes:
1. Robust Standard errors in parentheses
2. *indicates significance at 10%; ** at 5%; *** at 1%
3. Marginal Effects of coefficient estimates reported in columns
4. † Indicates dummy variable.

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