Do neighbours matter in technology adoption? The case of conservation tillage in northwest Ethiopia

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Abstract

Conservation tillage (CT) is one of the practices promoted to enhance sustainable agricultural production and the adaptive capacity of smallholder farmers. It is a new farming practice for smallholder farmers in Ethiopia. Lack of information on the existence and use of the technology, as well as its profitability, could deter its adoption. This paper examines the role of social learning in the adoption of CT in rural northwest Ethiopia. We used a spatial econometric model on cross-sectional plot-level survey data to achieve this objective. The results show that neighbour effect is a significant determinant of CT adoption in the study area. This suggests that the adoption of CT is occurring through neighbourhood effects, and that considering progressive farmers when designing technology-promotion programmes can speed up the adoption process.

Key words: conservation tillage; neighbourhood effect; spatial econometrics; Ethiopia

1. Introduction

The issue of why the rate of technology adoption is low in developing countries has generated a large number of studies. A number of explanations for why this is the case have been offered in the adoption literature. There are various factors at play in determining the success of the adoption of improved technologies, with different levels of impact depending on the nature of the technology itself, as well as the socio-economic and biophysical conditions of the farmers. Diversity in terms of socio-economic and biophysical conditions is one of the distinguishing features of smallholder farmers in developing countries. This, compounded with market imperfections, could cause differences in the profitability of a given technology among smallholder farmers, which has further repercussions on the technology-adoption decisions. For example, the profitability of hybrid maize and, concomitantly, its adoption was found to be heterogeneous among Kenyan farmers (Suri 2011).

Risk- and loss-averse behaviour are also featured as determinants of the improved adoption of technology in developing countries, where insurance and credit market imperfections are rampant. Dercon and Christiaensen (2011) used survey data to show that fear of consumption risk due to crop failure discourages farmers from taking up chemical fertiliser in Ethiopia. Their finding is supported by experimental studies. Knight *et al.* (2003) found that risk-averse behaviour adversely affects the adoption of improved technologies, while Liu (2013) found that the adoption of Bt cotton in China was delayed due to loss aversion.

Information about the existence of new technology is a prerequisite for technology adoption. Farmers require the necessary information to assess the profitability and suitability of alternative technologies for their farming system and to understand the potential risks associated with their use (Abdulai *et al*. 2008; Foster & Rosenzweig 2010; Baumüller 2012). Farmers exhibit ambiguous risk-averse behaviour when they lack information pertaining to the likelihood of occurrence of the possible outcomes (e.g. yield, costs, profitability) of new technology, which might have a detrimental impact on adoption. Farmers may be uncertain about the economic returns of new technologies due to insufficient knowledge about the types and costs of inputs needed, the yield distribution, expected market prices and the demand for the produce (AbadiGhadim & Pannell 1999). These factors underlie efforts in many developing countries to train extension agents and run public agricultural extension systems at considerable cost. For instance, the Ethiopian government annually invests about 2% of its total agricultural GDP in agricultural extension (Yu *et al*. 2011). Nevertheless, a recent study revealed that government extension services have contributed little to the diffusion of hybrid maize seed and chemical fertiliser in the country (Krishnan & Patnam 2013). Extension agents typically reach a small fraction of farmers who might benefit from new information and often rely on local farmers who adopt technologies to further disseminate the information and adapt technologies that are being promoted. Well-functioning farmer networks could therefore enhance the adoption of technologies across farming communities.

In developing countries, social learning/networks could complement and/or act as substitutes in delivering information and facilitating the technology diffusion process where the impact of public agricultural extension systems is limited and formal markets are missing. Following the seminal work of Manski (1993), recent empirical results suggest that individuals learn from their peers when deciding whether or not to adopt a new technology and how to manage the technology. Although social learning is a theoretically well-developed topic, there is still a paucity of rigorous empirical research to support policy formulation (Foster & Rosenzweig 1995; Bandiera & Rasul 2006). The empirical findings to date are also inconclusive. Krishnan and Patnam (2013) show that social learning plays a pivotal role in technology diffusion. Baerenklau (2005), on the other hand, found that the peer group effect is less relevant in promoting technology diffusion. Conley and Udry (2010) report that the impact of the social effect depends on whether the technology is known in the communities. Therefore, understanding how social networks work in farming communities in developing countries can yield important policy-relevant insights for technology adoption, and in particular for tailoring extension services to farmer needs.

In attempting to enhance the agricultural extension system, the Ethiopian government has implemented a new agricultural extension model that brings together one role model farmer and four neighbouring farmers as a group in order to promote best practices among rural communities through social learning. Furthermore, the government organises annual farmers’ days to recognise the efforts of successful farmers. These events aim to encourage fellow farmers to follow the footpaths of successful farmers. An unstated principle in these interactions is to draw similarities into focus and allow farmers to learn from fellow farmers operating in a similar context. Understanding how farmers interact directly and indirectly in sharing information and adapting technologies in these settings could better inform the dynamics of the dissemination and diffusion process, which is central to the development of effective development strategies at the household level.

This paper contributes to a small but influential literature on social learning in developing countries. Specifically, the paper adds value to existing adoption literature in three ways. The first contribution of the paper is that it uses recent advances in spatial econometric techniques to examine the existence of information externality in the adoption of conservation tillage (CT)[1] in Ethiopia. This provides twofold benefits. First, it seeks answers to an important policy question about the role of the social effect in stimulating technology adoption. Second, it enables us to appropriately measure the relative importance of other drivers of CT adoption (Case 1992). A further contribution of the paper is that it considers both the endogenous and exogenous social effect, which has not been well addressed in previous technology adoption studies (see, for example, Holloway *et al*. 2002; Ward & Pede, 2014; Wollni & Andersson, 2014). Disentangling the social effect into its exogenous and endogenous components is of paramount importance in terms of helping to identify appropriate strategies to promote the adoption of CT. In the presence of a social endogenous effect, an effective strategy increases the adoption of CT by targeting farmers not only directly, but also indirectly by way of increasing the adoption of the technology by their neighbour farmers, which in turn brings about a multiplier effect in the adoption of the technology by target farmers. However, in the case of a social exogenous effect, such multipliers do not exist (Manski 1993).

The third contribution of the paper is that, unlike previous studies which focused on crop technology and chemical fertiliser use (e.g. Conley & Udry 2010; Krishnan & Patnam 2013; Ward & Pede 2014), we studied the adoption of CT, which is a relatively new technology in Ethiopia. It was introduced into the country a decade ago by Sasakawa Global 2000, an international non-governmental organisation, to enhance long-term productivity and reduce yield variability by conserving soil moisture and checking soil erosion. Field experiments conducted on farmers' plots showed that higher profits are obtained under CT than by conventional tillage, particularly in the long term (Ito *et al*. 2007). Given that the technology is relatively new and its benefits are reaped mainly in the long term, smallholder farmers might adopt a 'wait and see' strategy to free ride on early adopters. The adoption of CT has not yet reached equilibrium and it is hypothesised that social learning could play a significant role in the adoption pathway. Thus, CT provides an interesting case to explore the existence of the aforementioned social effects in technology adoption.

The remainder of the paper is organised as follows: The next section discusses the adoption literature, with particular reference to social learning. Section 3 develops the theoretical framework underlying the study. This is followed by a presentation of the analytical framework. The results and discussion of the study are presented in section 5. The final section contains the summary and conclusions.

2. Related literature

In this section we present a brief review of the literature on the economics of conservation tillage and the role of social learning in technology adoption.

2.1 Conservation tillage

CT entails zero tillage or single pass together with mulching. It abates soil erosion, conserves soil moisture and replenishes the soil with essential nutrients from crop residues. In so doing, it provides both economic and environmental benefits. However, it is mainly the economic benefits that factor in the adoption decision at the farm level. There has been widespread adoption of CT in North America, South America and Australia. Studies also point to the potential of conservation tillage in the tropics, including in sub-Saharan Africa (Ito *et al*. 2007; Baudron *et al*. 2014). Farm households earn higher income with CT than with conventional tillage, particularly in the long term (Teklewold

[1] CT involves minimum soil disturbance and leaves crop residues on the soil surface.

et al. 2013; Tessema *et al*. 2015). The findings also show that conservation tillage reduces production risk and confers quasi-option value (Magnan *et al*. 2011; Kassie *et al*. 2015).

2.2 The role of social learning in technology adoption

The adoption literature is large and diverse, and it documents many important variables that affect the adoption of improved technologies. However, in this section we confine ourselves to studies that have investigated the impact of social learning on technology adoption. The role of social effects on technology adoption was initially brought to the surface by sociologists (e.g. Rogers 1983). In recent years there have been a growing number of economic studies that analyse the role of social effects in technology diffusion. However, these studies tend to differ in the way they approach social effects on technology adoption.

The most common and least rigorous approach is to introduce the size of the social capital a farm household owns as a proxy for information access and social insurance (see, for example, Isham 2002; Di Falco & Bulte 2011; Teklewold *et al*. 2013). However, these studies pay little attention to the farmer's behaviour in social groups and the characteristics that influence such behaviours. Therefore, these studies offer little empirical evidence about the existence of a peer effect in technology adoption.

Another set of studies is motivated by social learning theory (see, for example, Manski 1993). These studies can be classified into two categories according to how social groups are defined. The first approach is to elicit the network of the household by asking directly from whom they learn about the new technologies (Conley & Udry 2010). The shortcoming of this approach is that it is burdensome to trace back the social networks of a household. Apart from this, the sample taken might not be representative enough to draw inferences (Maertens & Barrett 2013). The second approach is to group households using their geographical proximity to each other as a measure of the social network (Foster & Rosenzweig 1995; Krishnan & Patnam 2013). This approach also has limitations, as the social network might not be confined to their geographical proximity only.

These studies also differ in the econometric techniques employed. Both the frequentist and the Bayesian approaches have been employed in the literature. Once the peer effect is introduced into the adoption equation, the least squares technique yields inconsistent and biased estimates due to the endogeneity problem. On the other hand, the application of the alternatives, such as the maximum likelihood technique, is challenging as it involves *n*-integrals. The usual approach is to apply general method of moments (GMM) estimation (Kelejian & Prucha, 1999) or Bayesian econometrics (Holloway *et al*. 2002).

3. Theoretical framework

The theoretical framework for this study draws from Abdulai *et al*. (2008). This study uses expected utility theory as its theoretical framework. For simplicity, it is assumed that both old and new technologies are risk free, except that there exists uncertainty about the new technology, as the farmer is not acquainted with it. In the Ethiopian context, one of the reasons CT is promoted is to conserve soil moisture and thus reduce the chance of crop failure in times of drought. Thus, the risk-free assumption is not strong, unlike other improved technologies that often are risk increasing. There could be two sources of uncertainty that deter uptake of a new technology – uncertainty about how to use the new technology, and uncertainty about the profitability of the new technology (Foster & Rosenzweig 2010). The application of CT may not be technically demanding and it is assumed that the uncertainty emanates mainly from limited information about the profitability of the technology. Furthermore, it is assumed that the uncertainty that surrounds the profitability of the new technology diminishes as farmers get to know more farmers in their vicinity who have adopted the new technology.

The profit function for the new technology is defined as follows:

$$G(n,\bar{x}) = g(n,\bar{x}) + A(n)\varepsilon \quad (1)$$

where $G(n,\bar{x})$ denotes the profit of the technology with complete information; $g(n,\bar{x})$ is the farmer's belief about the average profit of the new technology; $A(n)\varepsilon$ is the error the farmer commits in predicting the profitability of the new technology; n is the number of nearby farmers who have adopted the new technology; and $\bar{x}$ is other inputs, household and market characteristics that influence profitability. $g(n,\bar{x})$ and $A(n)$ are assumed to be an increasing and decreasing functions with respect to n respectively. This reflects the role of information from neighbours in reducing prediction error. ε is assumed to have a mean of zero and a variance of 1. The variance of $G(n,\bar{x})$ is then computed as:

$$Var(G(n,\bar{x}) = [A(n)]^2 \quad (2)$$

The technology adoption decision follows the expected utility framework (see, for example, Koundouri *et al*. 2006). Letting $f(\bar{x})$ represent the profitability of the old technology (conventional tillage), the farmer switches to the new technology if

$$E(U(g(n,\bar{x}) + A(n)\varepsilon) > U\big(f(\bar{x})\big) \quad (3)$$

$$E(U(g(n,\bar{x}) + A(n)\varepsilon)) = U(CE(g(n,\bar{x}) + A(n)\varepsilon)) \quad (4)$$

where CE is the certainty equivalent of CT. This is the sure amount of profit that makes a decision maker indifferent to a higher but uncertain amount of profit. Mathematically, it can be expressed as follows:

$$CE = g(n,\bar{x}) - RP \quad (5)$$

where RP is the maximum amount that a decision maker is willing to pay to eliminate uncertainty. It can be approximated by a second-order Taylor series expansion, as follows:

$$RP \approx 1/2r_a Var(G(n,\bar{x}) = 1/2r_a[A(n)]^2 \quad (6)$$

where r_a is the Arrow–Pratt coefficient of absolute risk aversion.

It is evident from the above equations that a mere increase in the profit of a new technology does not necessarily lead to its adoption. A farmer abandons conventional tillage only if $CE > f(\bar{x})$. The certainty equivalent of the new technology depends not only on the actual profit of a new technology, but also on the error a farmer commits in predicting the profitability associated with it, which in turn could depend on the number of nearby adopters. In the above model, it is conjectured that a farmer's current decision is affected by the contemporaneous decisions and characteristics of nearby farmers. Ideally, a spatial model could be designed in a dynamic setting in which farmers' learning behaviour from the past practice of their fellow farmers can be studied. This study, however, is based on cross-sectional data and is therefore not amenable to such analysis.

4. Empirical framework

According to Manski (1993), similar adoption patterns among fellow farmers in the same location are not necessarily ascribed to the adoption behaviour of fellow farmers. He distinguishes three potential pathways for similarity. First, the endogenous effect is the adoption behaviour of individual farmers, which might be influenced by their neighbours' adoption outcomes. This could be a result of peer learning about the profitability or the appropriate use of the new technology, or of merely wanting to conform with observed peer behaviour. Second, the exogenous effect is the influence of peer group characteristics of the adoption behaviour of individual farmers – the context. Third, the correlated effect could be due to commonly observed and unobserved characteristics of the group, for example sharing a common institutional or physical environment.

As indicated in the introduction, this study aimed to uncover the role of the social effect in stimulating the diffusion of technology by taking into account the effect of other confounding variables. In this regard, the following structural adoption equation is formulated (Krishnan & Patnam 2013):

$$y = \rho wy + \delta wx + x\beta + \varepsilon \tag{7}$$

where y is $n\ x\ 1$ vector of adoption decisions for n farmers; ρ is a scalar that denotes the spatial autoregressive effect (endogenous effects); δ is a scalar and represents exogenous effects; x is $n\ x\ k$ matrix of observations on k individual specific exogenous characteristics; β is $k\ x\ 1$ vector of coefficients for the individual specific characteristics, and ε is $n\ x\ 1$ vector of the error terms. wx is $n\ x\ 1$ vector of the average characteristics of a group to which a farmer belongs; and wy is the spatial lag vector with $n\ x\ 1$ dimension. It is the average adoption decision of the group to which a farmer belongs. w is the row-standardised spatial weight matrix with an $n\ x\ n$ dimension; a value of 0.25[2] is assigned if a farmer is a member of a group, assuming that each neighbour has equal influence; 0 is assigned for non-members and for the individual under consideration in order to avoid 'self-neighbour'.

Unlike conventional econometric models, the above equation introduces a spatial lag and weighted neighbours' characteristics. Ignoring the social effect leads to biased and inconsistent estimates, unless there is no social effect on the adoption behaviour of farmers. It is worth mentioning that we ruled out the possibility of common unobserved characteristics amongst neighbouring farmers that could affect their adoption decisions. This is because we included most of the variables that are considered important in the adoption literature, including plot characteristics and rainfall conditions.

In order to estimate the above equation, we had to define the social group. In the Ethiopian context, farmers with similar lineage or blood connections, and strong social bondage, tend to cluster in the same area. Thus, the social distance can reasonably be approximated by geographical distance. There is a possibility that a farmer's choice of his/her social group could be endogenous, in which case estimation could be more complicated. In this study, social group was defined in terms of geographical proximity, in other words where close relatives live together. Therefore, it appears that the social group choice is exogenous, as individuals cannot choose their relatives. GPS data were used to compute Euclidean distances, and five nearby farmers were taken to be 'neighbours'. A recent study on seeds and fertiliser in Ethiopia by Krishnan and Patnam (2013) also used five nearby farmers to define the social group to which a farmer belongs. Recently, a new extension model was implemented in the country – one that forms groups composed of a role model farmer and his four nearby farmers.

[2] Each farmer is assumed to have four neighbouring farmers. We further assumed that each neighbour has equal influence. Thus, each neighbour has a weight of 0.25 in a row-standardised spatial weight matrix.

The reduced form of equation (7) is given as:

$$y = (I - \rho)^{-1}(\delta w + \beta I)x + (I - \rho)^{-1}\varepsilon \quad (8)$$

$$wy = w(I - \rho)^{-1}(\delta w + \beta I)x + w(I - \rho)^{-1}\varepsilon \quad (9)$$

As shown in equation (9), the introduction of spatial lag poses a challenge in the estimation process, as the spatial lag is correlated with the error term. In the presence of an endogenous right-hand side variable, the ordinary least squares estimate is inconsistent. To overcome this problem, we employed the instrumental variable technique (Krishnan & Patnam 2013).

It is possible that the above formulation could create a simultaneity problem between group outcomes and group characteristics, making identification difficult. However, Bramoullé *et al*. (2009) have shown that, if the social network consists of intransitive triads (i.e. the case where farmer A and B belong to the same social group, and farmer B and C belong to the same social group, but farmer A and C belong to different social groups), the problem of identification would then be resolved. Our social network has intransitive triads, and so we used the average characteristics of the neighbours of neighbours (w^2x_j) as an instrument for the spatial lag (wy). This instrument does not affect y directly, but indirectly through its effect on wy.

Finally, we needed to specify the econometric model used in the study. Our dependent variable is plot-level adoption of CT, which is specified as a dummy variable. The adoption choice is made based upon the utility a farmer derives from adopting CT as opposed to the non-adoption decision, as motivated in the conceptual framework. Adoption by a farmer is worthwhile if the utility he/she derives from adopting CT outweighs the utility from adopting conventional tillage. The difference in utility obtained from the two technologies can be expressed as a linear regression function, as follows:

$$y^* = \rho wy + \delta wx + x\beta + \varepsilon \quad (10)$$

where y^* is the latent variable that measures the difference in utility a farmer derives between adopting conservation or conventional tillage. However, we cannot estimate the above equation directly due to a lack of information on the dependent variable. We only observe the adoption decision (y), which is a dummy variable defined as:

$$y = \begin{cases} 1 \ if \ y^* > 0 \\ 0 \ if \ y^* \leq 0 \end{cases} \quad (11)$$

The study used the IV probit model, which assumes that the data-generating process is a standard normal distribution. This is given as:

$$Pr(y = 1/(wy, wx, x)) = \Phi(\rho wy + \delta wx + x\beta) \quad (12)$$

where $Pr(.)$ is the likelihood that a farmer adopts CT; and $\Phi(.)$ is the cumulative distribution function for the standard normal, which maps continuous unobserved utility onto the probability measure [0,1]. It is important to notice here that the spatial lag (wy) is not a dummy variable, since it is a weighted adoption decision of neighbour farmers. Thus, it is amenable to the application of the IV probit model.

5. Results and discussion

5.1 Data and descriptive statistics

The data for this study were obtained from a survey conducted by the International Maize and Wheat Improvement Center (CIMMYT), in collaboration with the Amhara Regional Agricultural Research Institute (ARARI) in South Achefer district, northwest Ethiopia, in 2013. This district was chosen for its potential for CT adoption and its production of maize, an important food security crop in the country. The district is characterised predominantly by a mixed crop production system. Conventional tillage, where oxen are used for draft power, is commonly practised in the area. It involves repeated tilling (more than three times) using oxen-drawn plough. Fourteen *Kebeles*[3] with good maize-production potential were sampled randomly. A total sample of 298 was proportionally allocated to the *Kebeles* based on their population size, and farm households were then randomly chosen in the selected *Kebeles*. Face-to-face interviews were undertaken by experienced enumerators supervised by scientists from the CIMMYT and ARARI. The survey generated plot-level data about plot land quality, plot size, plot ownership, plot distance from homestead and type of tillage practised. Detailed information pertaining to the socio-economic characteristics of the farm households also was gathered, as well as GIS data.

On average, maize covers about 0.67 ha of a farmer's land, representing about 54% of the total amount of land cultivated. Other crops grown in the study area include *teff*, finger millet, wheat, faba bean and field peas. However, the use of CT is limited to maize plots only. The survey results show that, on average, a farmer operates on about 2.6 maize plots. It was found that about 38% of the samples' farm households implement CT on about 23% of the total number of maize plots. About 76% of the adopters practise both conservation and conventional tillage on the maize plots, indicating that plot characteristics matter in the type of tillage choice.

The adoption of CT could lead to weed infestation, unless herbicides are applied or intensive manual weeding is undertaken. The two commonly used herbicides in the area, along with CT, are Primagram and Roundup. The former is applied before sowing and the latter after seed germination. More than 40% of the sampled farmers obtained information related to these technologies from their neighbours (see Figure 1).

[3] *Kebeles* are the lowest administrative units in Ethiopia.

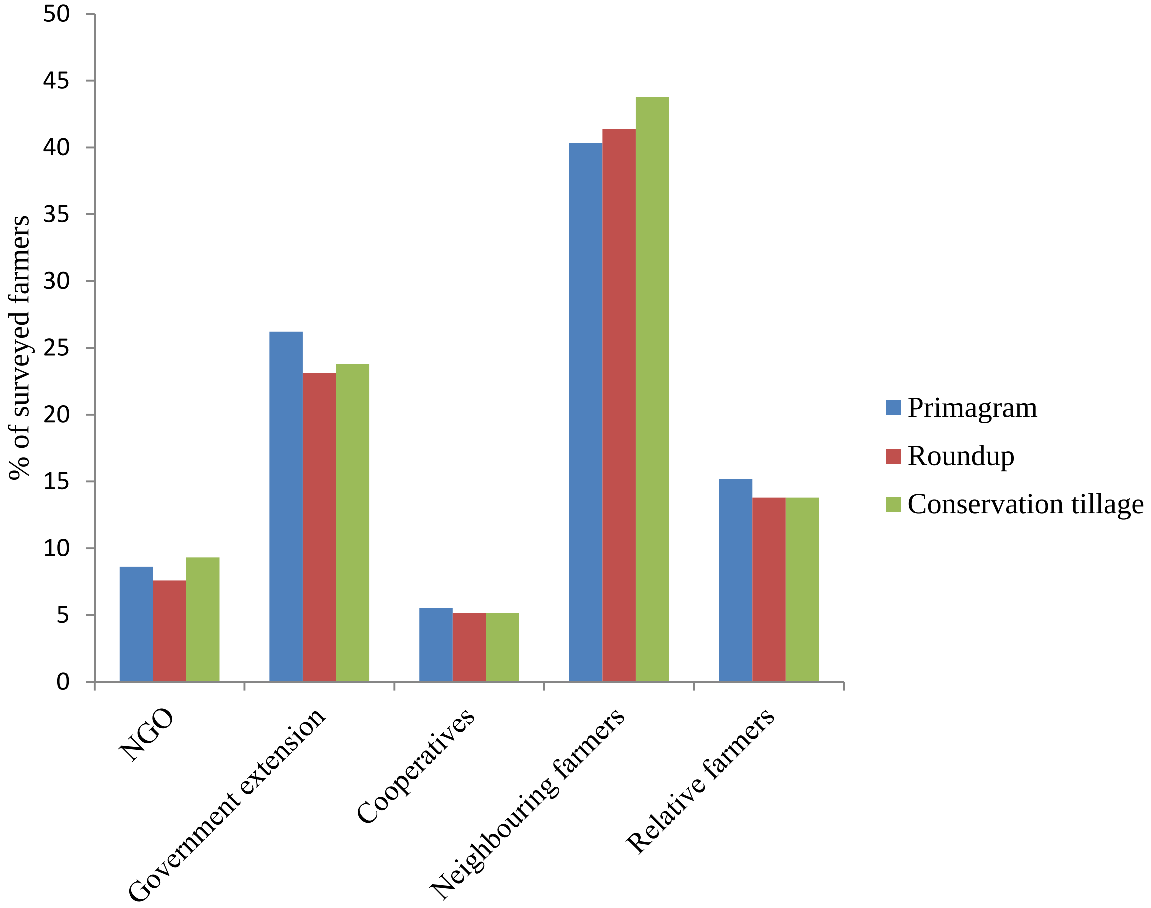

Figure 1: Information sources for conservation tillage, Primagram and Roundup

The respondents were asked about the first time they had heard of these technologies. Most of the surveyed farmers explained that they had heard about these technologies for the first time in 2008, although the technology had been introduced to the country about a decade earlier (see Figure 2). About 60% of the adopters practised the technology for the first time in the 2012/2013 cropping season. However, approximately 84% of the sample of farmers, including non-adopters, showed an interest in using the technology in the future. This might suggest that the performance of the technology has been good and that its low adoption rate could be associated with a lack of information.

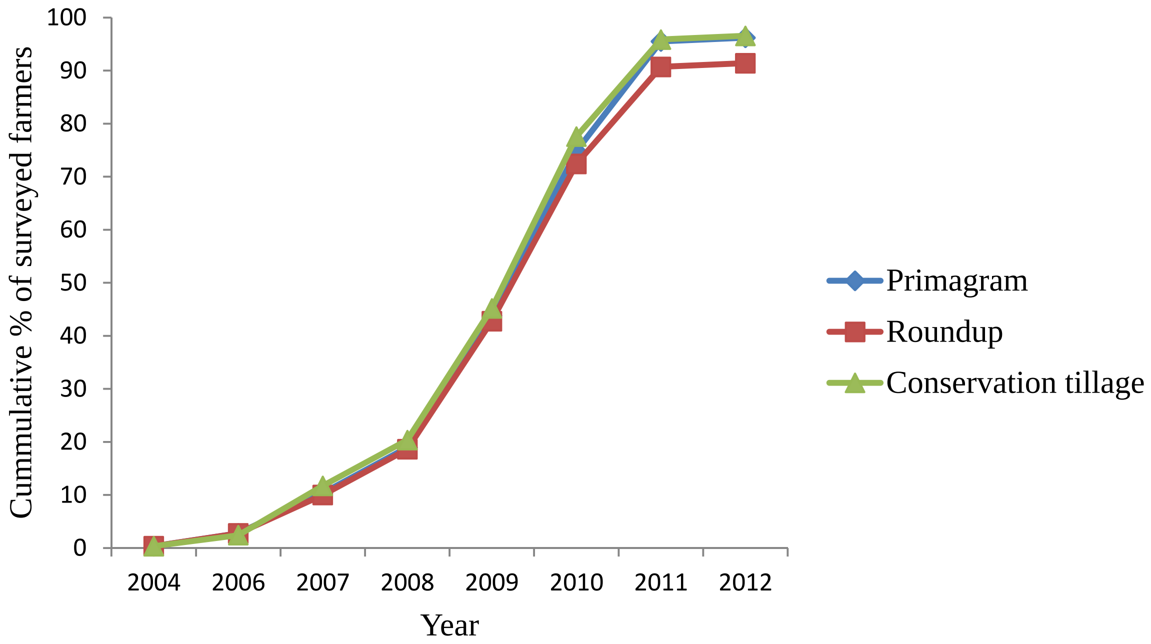

Figure 2: Year farmers first heard about conservation technologies

Table 1 summarises the right-hand side variables deployed in the adoption equation. A simple statistical test was undertaken on key variables to gain some insight into the characteristics of adopters and non-adopters. Adopters tend to own higher social capital than non-adopters in terms of having larger numbers of relatives. It was also found that adopters have better-educated household heads than non-adopters. Adopters also appear to have better access to herbicides than non-adopters. The survey results further indicate that plots with CT tend to differ from conventional plots with respect to plot size, plot distance from homestead and plot ownership type. The Chi-square test was used to assess the existence of a systematic variation in CT adoption among farmers in different villages in the district. The results indicate that there was a significant difference in CT adoption across the villages. However, this association is not necessarily due to neighbourhood effects. It could be due to the possibility that farmers residing in the same village tend to have similar attributes or share common characteristics.

Table 1: Characteristics of adopters and non-adopters of CT at plot level

	Mean	
	Conventional tillage	**Conservation tillage**
Farm household characteristics		
Sex of household head (1 = male; 0 = female)	0.927 (0.260)	0.94 (0.239)
Age of the household head	44.6 (13.803)	41.7 (12.099)
Education of household head	1.188* (1.776)	2.27 (2.666)
Proportion of females in household	0.470 (0.169)	0.448 (0.171)
Family size in man equivalent	2.896 (1.196)	2.842 (1.197)
Number of relatives	14.848* (17.158)	20.89 (21.528)
Walking distance to agricultural extension office (mins)	37.048 (25.827)	40.45 (28.716)
Walking distance to herbicide market (mins)	86.606* (58.007)	69.7 (41.316)
Walking distance to main market (mins)	115.2 (68.155)	108.25 (58.588)
Oxen in tropical livestock unit[4] (tlu)	3.316* (2.156)	3.855 (2.624)
Non-oxen livestock in tlu	1.879 (1.081)	2.03 (1.068)
Own farm size in ha	4.990 (2.973)	4.770 (3.255)
Rainfall index (1 = best; 0 = worst)	0.680 (0.189)	0.654 (0.241)
Plot characteristics		
Plot size in ha	0.255* (0.140)	0.341 (0.194)
Walking plot distance from home (mins)	7.154* (10.368)	16.931 (16.525)
Plot ownership (1 = own; 0 = otherwise)	0.84* (0.367)	0.614 (0.489)
Deep soil depth (1 = deep; 0 = otherwise)	0.45 (0.498)	0.431 (0.497)
Shallow soil depth (1 = shallow; 0 = otherwise)	0.211 (0.409)	0.169 (0.376)
Gentle plot slope (1 = gentle; 0 = otherwise)	0.712 (0.453)	0.720 (0.451)
Steep plot slope (1 = steep, 0 = otherwise)	0.065 (0.247)	0.061 (0.240)
Good soil fertility (1 = good; 0 = otherwise)	0.101 (0.302)	0.061 (0.240)
Poor soil fertility (1 = poor; 0 = otherwise)	0.631 (0.483)	0.606 (0.490)

Note that standard deviations are in brackets and * indicates statistically significant difference between adopters and non-adopters at 5% or less significance level.

5.2. Econometric results

Table 2 presents the IV probit model results. The descriptive statistics presented above suggest that there is a possibility of a social effect; however, the relationship could be spurious, as confounding variables were not accounted for. It also does not uncover whether the correlation is due to social endogenous or exogenous effects.

Further econometric analysis could provide a more rigorous empirical approach to ascertaining the existence of real social endogenous and exogenous effects in the adoption of CT. Three types of explanatory variables were introduced in the adoption equation (7). These are own farm and plot characteristics, weighted neighbours' adoption decisions, and weighted characteristics of neighbours. It is worth mentioning that not all the weighted neighbours' characteristics were incorporated. Neighbours' market, herbicide, extension and rainfall conditions were not included. Farmers located in the same area share some homogenous characteristics with respect to these variables and they therefore were excluded from the adoption equation, as they strongly correlated with own characteristics and posed a multicollinearity problem.

As mentioned in the methodology section, weighted neighbours' adoption decisions (spatial lag) could correlate with the residual term of the adoption equation, causing estimates to be inconsistent. To circumvent this problem, we instrumented the spatial lag by the weighted characteristics of neighbours' neighbours, as farmers in the same group have non-overlapping neighbours. The Wald test rejected the null hypothesis that the spatial lag is not endogenous. There is the possibility that the errors at village level are correlated, as farmers in the same area could face similar weather and

[4] One tropical livestock unit is equivalent to 250 kg live animal weight.

other shocks. To address this potential problem, we computed robust standard errors clustered at the village level.

Table 2: Pooled IV probit model results

	Coefficients	Robust standard error	Marginal effects
Constant	-2.366**	0.93	
Own characteristics			
Sex of household head	-0.338	0.345	-0.104
Proportion of females in household	-0.019	0.369	-0.005
Age of household head	-0.004	0.008	-0.001
Education of household head	0.067**	0.031	0.018
Distance to agricultural extension office	0.002	0.002	0.001
Distance to herbicide market	-0.003*	0.002	-0.001
Distance to main market (x 10^3)	0.014	1.349	0.004
Family size (man equivalent)	0.017	0.052	0.005
Number of relatives	0.008**	0.004	0.002
Non-oxen livestock size (tlu)	0.04	0.035	0.011
Oxen livestock size (tlu)	-0.164***	0.055	-0.045
Own farm size (ha)	-0.003	0.048	-0.001
Rainfall index	-0.114	0.287	-0.031
Plot size (ha)	1.688***	0.452	0.461
Plot distance from homestead	0.026***	0.006	0.007
Plot ownership	-0.431*	0.243	-0.130
Deep soil	-0.072	0.1	-0.020
Shallow soil	-0.187	0.213	-0.049
Gentle slope	0.241***	0.093	0.063
Steep slope	0.007	0.225	0.002
Poor soil fertility	-0.422*	0.249	-0.098
Good soil fertility	-0.285*	0.16	-0.080
Exogenous social effects (weighted neighbours' characteristics)			
Sex of household head	0.694	0.454	0.189
Proportion of females in household	1.464	0.94	0.399
Age of household head	0.005	0.013	0.001
Education of household head	0.039	0.099	0.011
Family size (man equivalent)	0.008	0.098	0.002
Number of relatives	-0.009	0.007	-0.002
Non-oxen livestock size (tlu)	-0.038	0.051	-0.010
Oxen livestock size (tlu)	-0.257*	0.131	-0.070
Own farm size (ha)	0.083	0.059	0.023
Endogenous social effect			
Weighted neighbours' adoption	1.56***	0.453	0.426
Number of plots	560		
Wald chi^2	1029.96		
Prob > chi^2	0.0000		

***, ** and * are the 1%, 5% and 10% significance level respectively. Note also that robust standard errors are clustered at *Kebele* level.

The primary interest of this study was to analyse the role of social effects in the adoption of CT. The results indicate that the social endogenous effect, which is represented by the weighted share of neighbours' adoption decisions, is statistically significant and has a positive effect on the adoption of CT. This implies that a farmer's decision to adopt CT is significantly affected by the adoption decision of his or her neighbours. Previous empirical studies also support the positive influence of social endogenous effect on the adoption of improved technologies among smallholder farmers (see, for example, Krishnan & Patnam 2013; Ward & Pede 2014; Wollni & Andersson 2014). From a policy perspective, this suggests that it is imperative to support early adopters, as this could lead to a multiplier effect. However, our results indicate that social exogenous effects do not significantly affect the farmer's decision to adopt CT. We also found that access to agricultural extension is not a significant determinant of the CT adoption decision. Anecdotal evidence suggests that, in Ethiopia, CT has not received adequate attention from the government extension system. Ward and Pede (2014) found similar results in Bangladesh.

Consistent with our *a priori* expectation, the educational status of the household head positively contributes to the adoption of CT. This result could be attributed to the tendency to have better access to information with an increased level of education. This might further support the idea that the low level of CT adoption observed might be due to lack of information. The probability of adoption of CT increases with the number of relatives in a household. Relatives could serve as a source of information or support in times of adversity. On the other hand, the coefficient for oxen turns out to be negative and significant. This implies that oxen-poor farmers are more likely to adopt CT than their counterpart oxen-rich farmers. In this regard, CT appears to be pro-poor. On a different note, this finding suggests that farm resources need to be reconfigured in order to promote wide-scale adoption of CT. Unless CT brings substantial yield advantages, oxen-rich farmers might find it less attractive to take-up CT because of their comparative advantage in conventional tillage.

Plot characteristics were also included as right-hand side variables, as they might influence the benefits of CT and thereby its adoption. The results show that plot size positively and significantly affects the adoption of CT. This could perhaps be due to possible economies of size associated with the adoption of CT. The location of a plot was also found to be an important determinant of CT adoption. The propensity to switch to CT is higher on plots located farther from homesteads than on nearby plots. The adoption of CT is likely to reduce human labour and draft power. In order to minimise their effort, therefore, farmers might find it more appealing to opt for CT on distant plots than on nearby ones. The results further indicate that farmers are more likely to adopt CT on plots with a gentle slope than on those with steep slopes. Our expectation was that conventional tillage, which involves repeated tilling, exposes steep plots to soil erosion, thereby raising the incentive for opting for CT on such kinds of plots. During the survey, plot slopes were not measured, but rather elicited from the farmers based on their subjective judgment. Thus there might be errors of measurement and this result should be taken with a grain of salt.

6. Summary and conclusions

Past adoption studies paid little attention to the endogenous effects or were unable to disentangle the endogenous and exogenous effects. This causes bias and inconsistency in the estimates of the drivers of technology adoption, unless such effects can be regarded as insignificant. They also failed to address an important policy question about the role of peer groups such as neighbouring farmers in technology diffusion. This study investigated the role of neighbours' characteristics and adoption decisions in relation to CT in the diffusion of this technology among smallholder farmers. We estimated an IV probit model using cross-sectional plot-level data collected in northwest Ethiopia, and found that the likelihood of a farmer adopting CT increases if his/her neighbours adopt. From a policy perspective, this suggests that, in developing countries where resources are more limited, extension efforts could target selected farmers with target attributes such as early adopters to create a bandwagon effect. However, the findings do not support the existence of social exogenous effects in the diffusion of CT.

Our results also show that the adoption of new technology is not necessarily limited to neighbour effects. We considered the number of relatives a farm household has as an explanatory variable. The coefficient for this variable was positive and significant, which further supports the positive role of social effect in technology diffusion. Further, the results suggest that the level of education of a household head positively influences the uptake of CT. Current endeavours to organise farmers into groups and recognise successful farmers seem to be a move in the right direction. It is also important to increase awareness of CT among both farmers and development agents.

Although it has presented some useful results on the effect of social networks on technology adoption, this study could be improved in future work in a number of ways. Firstly, learning about new technology from neighbours does not happen overnight and might not necessarily be translated into technology adoption in the same season. The use of panel data therefore would help to capture the time lag element in CT adoption. Furthermore, spurious correlations of adoption amongst smallholder farmers could be generated by common or similar unobserved characteristics. In this regard, panel data would help to filter out time-invariant, similar unobserved characteristics that otherwise might cause spurious associations.

In this study, we defined a social group based on geographical proximity. This can be justified from the fact that farmers with social proximity tend to cluster in the same area and have relatively homogenous individual and environmental characteristics, which simplifies learning from each other. However, we acknowledge that information exchange could take place in other social groups formed along the lines of religion, ethnicity, social class and more. Thus, future work could evaluate the effectiveness of some of these social groups in transmitting information, so that the best social group could be utilised for technology diffusion.

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