Adoption and Diffusion of Agricultural Innovations in Ethiopia: The Role of Education

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Abstract Schooling has been shown to provide substantial externality benefits by increasing farm output and shifting the production frontier outwards. This paper investigates the role of schooling at the household- and site-levels in the adoption and diffusion of agricultural innovations in rural Ethiopia. We find that household-level education is important to the timing of adoption but less crucial to the question of whether a household has ever adopted fertiliser, i.e., early innovators tend to be educated and to be copied by those who adopt later, obscuring the relationship between education and adoption at the household-level. By contrast, site-level education appears not to affect the timing of an innovation's introduction to the site, but does influence the extent of diffusion. Thus, there are two externality effects: educated farmers are early innovators, providing an example which may be copied by less-educated farmers; and educated farmers are better able to copy those who innovate first, enhancing diffusion of the new technology more widely within the site.

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1. Introduction

Schooling may provide substantial externality benefits by increasing farm output and shifting the production frontier outwards. Evidence of production externalities was presented in Weir and Knight (2000), who analysed the internal and external benefits of schooling in rural Ethiopia using both average and stochastic frontier production functions. They showed that education externalities in production may be primarily mediated through the role of education in shifting the production frontier outwards (e.g., through the adoption and diffusion of innovations). The purpose of this paper is to consider this finding further by examining directly the role of education in the adoption and diffusion of agricultural innovations using the same data set. Together, these static and dynamic approaches should provide a fuller picture of the extent and nature of externalities to schooling in Ethiopian agriculture than has previously been possible.

Although farming methods in Ethiopia are still rather traditional,[1] farmers in many areas do have the option of using new, higher-yielding crop varieties and some modern inputs, primarily chemical fertilisers. Rates of adoption of such innovations vary widely from one part of the country to another, allowing us to compare sites at different stages in the adoption and diffusion process. A better understanding of the relative importance of household-level versus site-level characteristics is possible by comparing areas where almost all farmers have adopted a new input against those where very few farmers have taken up the input.

An understanding of the sources of agricultural productivity gains - and the role played by education - is particularly important in a country such as Ethiopia, where very few children go to school and food security is extremely tenuous. The implied link between these two issues is intentional. Weir (1998) showed that a primary reason cited by many people for never attending school or for quitting school early was that they were needed to help with farm or household activities. If the expected private returns from schooling for parents who make enrolment decisions is low, and does not take into account externality effects of education upon site farm productivity, too little investment in education will occur. A vicious cycle of poverty and low school enrolment will be set in motion.

Section 2 outlines the ways in which different types of education may act to encourage the adoption and diffusion of innovations and summarises some relevant literature on social learning externalities and the diffusion of innovations. Section 3 describes the data. Evidence to show that social networks facilitate externality benefits of schooling is presented in Section 4. Section 5 outlines the econometric hypotheses and methodology and presents the results. Section 6 concludes.

2. Some Relevant Literature

Cotlear (1990) categorises different types of education: formal, non-formal and informal. Formal education may provide specific or general knowledge which increases farm productivity. Non-formal education may be useful to impart specific information about

[1] As little as 10 percent of farmers used new high-yield seeds and fertilisers, and those who adopted these innovations used less than in other developing areas, according to official data for the early 1990s (Yao 1996).

innovations or sound practices. Informal education may serve mainly to shape attitudes, beliefs and habits. All three types of education are important in the diffusion of innovations and the creation of schooling externalities. Formally educated farmers may take the initiative in the adoption of innovations or may be most likely to be selected by agricultural extension workers for non-formal education. Other farmers may observe the practices of formally or non-formally educated farmers and copy them, constituting a type of informal education. Formal and non-formal education have received most attention in the literature, perhaps owing partly to greater ease of measurement and partly to greater potential for policy intervention. However, informal learning that occurs as farmers copy their more productive (and perhaps more educated) neighbours is an area of increasing interest to researchers, as the growing literature on social capital indicates.

The new growth theory literature (Romer 1986; Lucas 1988; and others) has focused on intergenerational transfers of knowledge under conditions of increasing returns. Each generation benefits from the stock of knowledge left by the previous generation. However, too little knowledge is created by previous generations, since there is no market in which knowledge can be sold to future generations. The theory suggests that economic growth is driven by endogenous technological progress, which arises as a result of knowledge spillovers. This idea has been extended laterally to consider knowledge spillovers between contemporaneous agents in the social learning literature, a subset of which is concerned with the adoption and diffusion of innovations.

One strand of the social learning literature suggests that adoption behaviour depends on the risks involved. If a new technology will definitely be superior, adoption will occur. However, if a potential adopter faces uncertainty about the outcome, there is an incentive not to adopt because of direct loss if the innovation fails as well as the loss of the adopter's network, since everyone else will continue to use the old technology. If there is uncertainty, people will act in herds to avoid isolation (Choi 1997). Banerjee (1992) introduced the concept of 'herd behaviour' whereby individual actors make decisions based on the previously made choices of other actors rather than on their own priors. In a similar vein, the term 'penguin effect' was coined by Farrell and Saloner (1986) to describe the reluctance of early potential adopters to be the first to test the water. To the extent that educated farmers are more likely to be willing to take risks with new technology and more likely to be adopters of successful innovations, there are possibilities for positive external returns to schooling in this context.

The externalities transmitted by social learning are not necessarily positive. Herd behaviour can be inefficient, and represents a negative externality, if all actors have equally good priors, since actors will ignore their own priors and simply follow the leader, even if the leader makes a bad choice. However, if those with schooling act first and less educated actors follow the educated, and the priors of the educated are better than those of the less educated, such behaviour is more efficient than if everyone acts according to their own priors. Burger, Collier and Gunning (1993) build on Banerjee (1992) and Ellison and Fudenberg (1993), suggesting that economic actors may place more weight on the choices of other actors who are similar to themselves. They may be expected to evaluate risk in the light of the experiences of others with whom they share commonalities. Thus, schooling for some villagers may help to ensure that farmers without education have a chance to be exposed to, and influenced by, the practices of educated farmers who are in other ways very similar to themselves.

Nelson and Phelps (1966) model the diffusion of technological innovations in terms of the gap between actual and possible levels of technology and the amount of education of the work force. Returns to education are greater the more the opportunities for adoption of technical innovation. Since there are externalities to innovation, if education stimulates innovation, there are externalities to schooling. Besley and Case (1993) describe two types of externality for farmers. There are network externalities whereby, when a new crop is adopted, farmers benefit from building up a market infrastructure, as well as learning externalities. Both could be unleashed by education.

The applied literature on the effect of education on innovation in developing countries is limited. However, Jamison and Moock (1984) test the effect of schooling and extension contacts on the adoption and diffusion of agricultural innovations in Nepal. They find that schooling does influence adoptive behaviour but that household income mediates the adoption decision. Individual extension contacts are less important than extension activities in the site in influencing the adoption and spread of innovations, providing evidence of an externality effect of innovation. Cotlear (1986) finds for his sample of households in three regions in the Peruvian Sierra that education plays a greater role for early adopters, who use education to decrease the costs of obtaining new information and learning to apply new techniques, than for late adopters, who may simply copy their neighbours' behaviour. Using panel data on rural households affected by the Green Revolution in India to measure learning spillovers, Foster and Rosenzweig (1995) find that farmers with experienced neighbours (i.e., neighbours who have already adopted the new technology) are more profitable than those without such neighbours. Their focus is on returns to experience rather than to education, but their approach is applicable to schooling externalities. For example, if those with education tend to be early adopters and consequently are the first (and perhaps the most effective) in developing experience with new technologies, the externality benefits of their experience are partly due to their schooling.

There is some evidence on the role of schooling in the adoption - if not diffusion - of innovations using Ethiopian data. For example, Croppenstedt, Demeke and Meschi (1998), using data from a 1994 USAID fertiliser marketing survey, find that literate farmers are more likely to adopt use of fertiliser than those who are illiterate. This suggests that the educated are early adopters but it provides no information on whether uneducated farmers are likely to copy their innovative behaviour. That will be a focus of this paper.

3. Data

The economic and demographic data for this research are drawn from the Ethiopia Rural Household Survey (ERHS)[2] (Dercon and Krishnan 1994). The survey covered 1477 households in 18 Peasant Associations (villages) spanning 15 Woredas (districts) in six regions. Six of the sites, primarily located in drought-prone areas, had previously been surveyed by IFPRI in 1989. The remaining nine were chosen to reflect most of the important agro-economic variations found in rural Ethiopia. Together, the 15 sites provide a realistic mix of cultivation categories and standard of living strata.

[2] The initial round of this large panel survey was conducted by the Department of Economics, Addis Ababa University, in collaboration with the Centre for the Study of African Economies, Oxford, and the International Food Policy Research Institute (IFPRI), Washington, in 1994.

The number of households surveyed in each site reflects the size of the Peasant Association (PA) in relation to the total size of all PA's surveyed. Households were selected randomly using the PA registers, with female-headed households proportionally represented. Each household was surveyed three times within approximately twelve months (early in 1994, later in 1994 and early in 1995), providing a picture of both past and present. Questions were asked on a wide range of issues affecting rural households, including production inputs and outputs and demographics. The first round also included a few key questions on educational status and attainment. Further information on education, as well as historical recall on agricultural innovations, was provided in the second round of the survey. Since the three rounds were conducted at short intervals, and the educational investment and innovation questions involved historical recall, data on education and innovation from the second round may be matched with information on production inputs and household demographics from the first round.

The Ethiopia Rural Household Survey provides a useful dataset with which to examine the role of education in facilitating the adoption and spread of innovations: cross-sectional data supplemented by historical recall information. Historical recall data on adoption and use of new inputs as well as new crop outputs will allow us to identify 'progressive' farmers from each site and study the constraints on innovation and adoption of new technologies. The spread of new technologies from educated farmers to their less educated neighbours can also be documented, if such a schooling externality exists.

Table 1 describes the data. Means are presented for the sub-sample of observations used in the econometric analysis. The full sample for the ERHS contains 1477 households. However, the final sample employed for the present analysis includes only 1191 households, since observations with missing information were omitted.[3] While farming methods in Ethiopia are still rather traditional, farmers in many areas do have the option of using new, higher-yield crop varieties and some modern inputs, such as fertiliser. Thus, it is possible to identify progressive farmers from each site and to study the process of innovation and adoption of new technologies.[4] Of the 1477 households surveyed, we have complete information on adoption for 1464 households, of whom 773 are current or past users of 'new technologies' (e.g., fertiliser, hybrid seeds, pesticides, etc.) and 691 have never adopted such innovations. Of those who have innovated, 331 households have adopted more than one new input and an even higher number (624) have adopted one or more innovative crops along with one or more modern inputs.

In the econometric estimation, the dependent variable will be either a dichotomous variable set to one if the household has adopted use of the new input or a categorical variable where each household is assigned a category based on whether they were early adopters, medium-term adopters, late adopters or non-adopters. This specification is preferred over the use of a continuous dependent variable indicating years since the innovation was adopted because of the large number of households who have not adopted use of new inputs. A standard solution to this problem, the Tobit model, is not reliable in the face of heteroscedasticity, which is likely to arise given the clustered nature of the data collection process (Deaton 1997, 87-88).

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[3] No bias is expected to result from the omission of these observations, as the missing information is plausibly random.

[4] Education may affect the propensity to innovate both directly and indirectly, through its effect on attitudes towards risk-taking. This indirect mechanism is investigated in Woldehanna, Weir and Knight (2000).

Several different variables are available to proxy education at the household level. Households with an uneducated household head need not necessarily be less productive than those in which the household head has been to school, if some other member of the household, or even a neighbour, has some schooling (Foster and Rosenzweig 1996). Basu and Foster (1998) argue that only one person needs be educated in the household for the entire household to benefit from the cognitive skills acquired in school. This is particularly likely to apply to the allocative benefits of schooling, such as may be derived from adopting the use of modern farm inputs (Green, Rich and Nesman 1985). By extension, only one, or a few, households in a neighbourhood need be educated for the other households to benefit. We focus on average years of schooling obtained by adults within the household. Education at the site- or neighbourhood-level will be measured by aggregating years of schooling of adult household members within the cluster.

4. Evidence on the Operation of Social Networks

Implicit in the hypotheses and econometric analyses which follow in Section 5 is the assumption that social networks exist and aid the diffusion of new technologies. However, before turning to the econometric estimation of the probability of adoption, we will consider briefly the importance of social networks to the spread of innovations. If the data show that farmers tend to look to those who are similar to themselves (in terms of age, sex, socioeconomic status, religion, ethnicity, etc.) when making adoption decisions, this will provide some evidence on the operation of social networks in the spread of these innovations. We have specific information for each farmer who has adopted use of a new input on who influenced him (or her) to adopt the new input and who taught him how to apply the innovation. We examine the extent to which farmers indicate that their adoption decisions were influenced directly by social learning, as opposed to interventions by agricultural extension workers or others. In each case, we will consider whether there are differences by level of education to examine the relationship between schooling and the process of social learning.

Farmers were questioned on the innovation adoption process as they experienced it. When asked who or what had taught them to use a modern input (where each respondent may respond more than once if using more than one input), most (49 percent) current users were taught by an agricultural extension worker, 34 percent learned from their friends or neighbours, and 10 percent learned by observing others who had already adopted the input. These percentages vary by site and level of education of the household head (Tables 2-3). For example, more educated household heads are more likely to learn to use a new input from their relatives or neighbours or from observing others than from extension agents. This contrasts with the case for less-educated household heads, supporting the hypothesis that educated people learn more easily from observation than do those with no schooling. There are also differences by site, with extension agents being more active in some sites than in others, where neighbours and relatives or observation take the place of extension activities. Extension appears to act as a substitute for schooling in areas where innovations have not been introduced spontaneously (e.g., by those with schooling).

Current users of modern inputs were asked about the various characteristics of the people who had influenced them to adopt each input (Table 4). In 88 percent of the cases for which we have data respondents said that the person who had influenced them to try the new input was of the same gender. The percentages differ for female-headed and male-headed households.

However, in both cases, heads appear to seek out heads of the same sex to copy. In female-headed households, 53 percent of heads were influenced by other female-headed households. This is disproportionately high in relation to the percentage of households with female heads (22 percent). For male-headed households, 94 percent were influenced by other male-headed households. Once again, this is higher than would be expected based on the proportion of male-headed households in the sample (78 percent). When asked about the socio-economic status of those who had influenced their adoption decision, 33 percent of the time, the respondent said that they were influenced by someone of the same income group, whereas in 62 percent of the cases they were influenced by someone richer and in only 3 percent of the cases by someone poorer. Also, a farmer is more likely to be influenced by someone in the same age cohort or younger (34 and 38 percent of the cases, respectively) than by someone older (27 percent). These informal networks may be important. On average, for each input used (omitting extreme outliers in the data), respondents had discussed adoption of the input with nine people in the past year.

The most educated household heads were less likely than the others to be influenced by people of the same age (Table 4). Indeed, educated household heads generally tended to be more influenced by older people than uneducated heads. This may simply reflect the fact that younger farmers tend to be more educated than older farmers, who have fewer older role models. Indeed, computing average age by category of education of the household head shows that the most educated heads (with more than seven years of schooling) are the youngest, aged 31 years on average, whereas household heads with no education are 51 years of age on average. Few households in either education category were influenced by people with lower incomes than themselves. Educated households more likely to look to richer households than were households with an uneducated or less-educated head. This is consistent with our hypothesis that mean education of adopters falls as the innovation spreads. The educated look to early innovators (who, incidentally, are also hypothesised to tend to be well-educated but who may innovate even if they have little education, if they are highly motivated or highly able) and are quick to copy, whereas those with less education are more influenced by the behaviour of their peers than by observing successful farmers in their site. Thus, the less-educated are expected to be slower to copy an innovation.

Reasons given for never adopting or for desisting from use of an innovative technology include expense (43 percent), lack of availability of the input (15 percent) and a lack of knowledge or skills needed to use the input (10 percent). A significant minority (18 percent) decided that the input was either unsuitable or not needed.[5] Only 36 percent of non-adopters were acquainted with someone who currently used modern inputs. The percentage is even lower for non-adopters with high levels of education (more than four years of schooling of the household head), at only 20 percent. This may suggest the importance of social networks in the diffusion of innovations, particularly for those with more schooling.

Years spent in formal education may affect the likely route to adopting an innovation and the likely source of inspiration for innovating. Table 5 gives average years of schooling of the household head by reason for adopting fertiliser and by teacher in the use of fertiliser. In the case of reasons for adopting, all categories of respondent had higher average schooling than the category of non-adopters. The most educated categories were those who were either directly or indirectly influenced by their neighbours and relatives and those who noticed that

[5] The remaining 13 percent listed other reasons or provided no reason for their decision not to adopt.

the crop for which the input would be used fetched a high price or high profit. People influenced by extension agents had slightly lower education on average. The story is similar for average education by category of teacher. Those household heads who learned to use fertiliser from an extension agent had the same average education as the category of non-adopters, suggesting that extension agents may particularly target those with low education who are expected not to adopt otherwise. The categories of adopters with the highest education reported having learned to use the innovation in school or on a training course. Those who were self taught had slightly less education than those who learned directly or indirectly from their neighbours, but were very few in number.

We illustrate the expected pattern of diffusion of innovations within a site, and the relationship of adoption to site-level education, by assuming a community with given households and unvarying household composition over time. Figure 1 shows the expected relationship between the cumulative percentage of households who adopt an innovation and average education of those who have adopted by a given year. The top graph shows an S-shaped diffusion curve (described, for example, by Rogers 1995) reflecting the expected pattern of diffusion: a few households will initially adopt the innovation; 'take-off' occurs after the innovation is adopted by one or more influential households in the community; and the curve gradually flattens as 100 percent diffusion is approached. In the lower graph, we plot the hypothesised pattern of average education of adopters in each year. Here, average education is expected to be high among the early adopters and to decline as the innovation is copied by households with less education.

We illustrate the potential importance of site-level education to the diffusion of innovations in practice for the sites in our sample using graphs showing the cumulative percentage of households to adopt fertiliser use in each site in each year.[6] We take timing of the adoption of fertiliser as a case study, since fertiliser is the most widely used modern input in the widest range of sites. Graph 1 includes a line for each site where fertiliser has been adopted and shows the time path of diffusion of the innovation by site. Sites are ordered from lowest average education to highest. The pattern of diffusion in each site generally tends to be S-shaped, with diffusion occurring slowly at first, increasing sharply during the take-off, and flattening out gradually as the adoption rate rises. Although the number of lines shown in Graph 1 makes it difficult to compare sites, it is possible to discern the general pattern. There are two periods in which diffusion appears to have been particularly active in at least a few of the sites: the first after 1974, when the DERG government took power; and the second after 1991, when the DERG were overthrown. Both periods have seen concentrated policy efforts to improve access to fertiliser. Adoption of fertiliser was encouraged by policies which increased access to fertiliser, expanded agricultural extension activities and, in the early 1990s, liberalised crop prices, increasing the profitability of fertiliser-intensive crops. Graph 2 shows the pattern of adoption and diffusion for all sites taken together. The two periods of policy importance show up as take-offs, with slower diffusion of fertiliser during the years in between.

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[6] The cumulative percentage of households who adopted fertiliser in each year is calculated by dividing the number of households who have adopted fertiliser on or before a given year by the number of households where the oldest member was at least 15 years of age in that year (i.e., percentages are based upon the pool of households which existed in the year). Dips are possible because, for some of the sites, there were years when new households were formed but few or no households adopted use of fertiliser.

To illustrate more clearly the differences between sites with different average investments in schooling, we first show a smaller selection of sites: the least educated, most educated and a medium educated site (sites 8, 13 and 4 respectively) (Graph 3). In all three sites, policy shocks in favour of greater use of fertiliser are apparent in the mid-70s and early 90s. However, the reaction of households within each site to the shock appears to be affected by average investments in education within the site, with much more rapid and complete uptake of fertiliser in sites 4 and 13 than in site 8. Next, we plot the fertiliser diffusion path with the year the adoption of fertiliser was initiated in each site set to one, so that all sites begin at the same point on the graph (i.e., it is drawn as if fertiliser was adopted in the same year in all sites to facilitate comparison of the individual diffusion paths for each site) (Graph 4). We can see that although there is a promising early take-off in site 8, the diffusion momentum is stalled for a long period of time. By comparison, the more educated sites experience a much more rapid diffusion once take-off has occurred. Ultimately, after 26 years (the length of time that fertiliser had been used in site 8 when the survey was conducted), site 13 has reached a much higher rate of adoption than either sites 4 or 8. Sites 4 and 13, each having had 32 years for the innovation to diffuse, differ in terms of the extent of diffusion at the end of the period: the most educated site, 13, has nearly complete uptake of fertiliser (over 97 percent of households have adopted), whereas in site 4, 87 percent of households have adopted.

Table 6 provides information on various characteristics of the diffusion of fertiliser. Correlating average years of schooling in the site with the percentage of households who had adopted fertiliser use by 1995 (the survey year) confirms this observation. The correlation coefficient is 0.74, significant at the five percent level on a two-tailed test, suggesting that site-level education and the extent of diffusion of the innovation are related (though this provides no evidence on the direction of causation).

It is also interesting to correlate site education with the percentage of households who have adopted fertiliser at different intervals from the initial introduction of the input in the site. Here, we find that the relationship is negative over the first 15 years of the diffusion process. However, the coefficient becomes monotonically smaller as we increase the time interval from 5 to 15 years. The percentages of households who have adopted after 20 and 25 years are positively correlated with site-level schooling and continue the pattern of monotonic increase. Although no correlation is significant, the pattern observed suggests that there is a non-linear relationship between site-level education and the percentage of households who have adopted at a given point in time. Initially, average education in the site has a negative (if insignificant) effect, but for late adopters, living in a site where average levels of schooling are high has a positive effect upon the propensity to adopt. The increasingly positive pattern makes sense in that the innovation may be introduced either exogenously (e.g., by agricultural extension agents) or by a few educated farmers. Thus, average levels of schooling in the site need not be high at the time of initial adoption of the innovation. The importance of site-level education increases over time to encourage the spread of an innovation. Support for this proposition is provided by the fact that there is no significant correlation between the years that the innovation has been used in the site and site-level schooling. However, there is a correlation between the eventual extent of adoption within the site and site-level schooling.

Years of schooling at the household-level and site-level are both significantly correlated with use of innovative inputs as well as a range of other innovative behaviour (including current use of an innovation, adoption of an innovative crop, adoption of both an input and a crop, and adoption of multiple inputs; not shown). To determine whether this correlation between education and innovative behaviour is causal, we need to estimate the determinants of adoption. It is also necessary to distinguish early adopters (the leaders or innovators) from late adopters (the followers).

5. Econometric Hypotheses, Methods and Results

Our main hypotheses are: (1) that educated farmers innovate with better or new farming practices; and (2) that farmers without education copy the practices of the educated. We will employ a two-pronged analysis of innovative behaviour. Firstly, we determine whether educated farmers are early innovators. Secondly, we investigate whether living in a site or neighbourhood where others are educated increases the likelihood, or accelerates the timing, of adopting an innovation. Our analysis involves estimating the probability of having adopted an innovation, using probit estimation techniques, and the probability of having adopted an innovation during a particular time frame, using ordered probits.

In Table 7, the probability of a household having adopted use of fertiliser is estimated using education at the site- and household-levels as explanatory variables. It is necessary to control for age of the household head, since the relationship between adoption behaviour and education may be expected to differ for an older generation of farmers. We also control for sex of the household head, since the behaviour of female-headed households may differ from that of male-headed households. Similarly, households where the head is not primarily engaged in farming may have different probabilities of investing in farm innovations than those for whom farming is the primary activity. Finally, we control for the amount of land used in the production of cereals. This measure of land is used, firstly, because our data on hectares cultivated with cereals are more accurate than the data available on total cultivated land, and secondly, because most modern inputs are used in the cultivation of cereals (Woldehanna, Weir and Knight 2000), making this the most relevant activity. We do not control for other potentially relevant variables, such as household income and land quality, because of possible endogeneity and because current values of such variables may not reflect conditions at the time when the adoption decision was made. Land quality may have been improved but, since it cannot be bought or sold, land quantity is likely to be exogenous.

The first equation shows that average education at both the household- and site-levels significantly influence fertiliser adoption.[7] However, education at the site-level appears to have a much stronger effect than education at the household-level. An additional year of education on average in the site raises the probability of adopting an innovation by 22 percentage points, a rise from the mean (46 percent) to 68 percent. By contrast, an extra year of schooling at the household-level raises the probability of adopting fertiliser by only one percentage point, to 47 percent. Unfortunately, it is not possible to separate completely the effects of education at the site-level from other site fixed effects. Thus, the site education coefficient may overstate the true externality effect of education in the adoption of new inputs.

[7] To control for other important site variables, distance to the nearest town and distance to the nearest all-weather road are included in equation 1. These were chosen because they are likely to be constant over time (e.g., as opposed to other potentially relevant, but non-constant, variables, such as average rainfall in the three-month period immediately preceding the survey), since for many, the adoption decision may have been taken many years in the past.

To control for site fixed effects, it is necessary to consider education at the neighbourhood-level, rather than at the site-level. There are 48 different neighbourhoods in total. The number of neighbourhoods in each site was determined by the particular geographical features of the site and the distribution of households within the site (which was determined from the enumerators' site maps with each surveyed household marked) and ranged from two to nine.[8] Examining education at the neighbourhood-level, rather than at the site-level, allows all other site fixed effects to be controlled by the inclusion of site dummy variables.

The results are presented in equation 2. Here, the variable used to proxy educational attainment in the neighbourhood is average years of schooling of adults in the neighbourhood.[9] This specification was chosen after experimentation with several alternatives (results not shown). The effect is lower and less significant than that obtained for site-level education in the previous specification. The marginal effect is to increase the likelihood of adopting by 15 percentage points for each year of schooling, on average, in the neighbourhood. However, this is not surprising since the full externality effects of schooling are not expected to be apparent at a sub-site level. Households may have network contacts with other households living outside their neighbourhood (e.g., through their religious, ethnic or other social links). The true external effects of education on the probability of adopting an innovation are expected to fall between the coefficients on the two alternative aggregate education variables presented in equations 1 and 2. Thus, it appears that the externality effect of aggregate education is substantial. This supports our hypothesis that sites with more education will enjoy a wider diffusion of innovations than sites with less education on average.

When all site-specific fixed effects are controlled for (in equation 2), the effect of education at the household-level rises to three percentage points for each additional year of schooling. This effect is small in comparison with the neighbourhood-level effect, but it is positive and statistically significant. Since households which have successfully adopted fertiliser may be more prosperous than other households and may invest in schooling for younger household members, the household education variable may be endogenously related to whether or not the household adopted fertiliser. To avoid this possibility, the equations are re-estimated using average age of all adult household members as an instrument. This is a relevant instrument because education has expanded over the past few decades in rural Ethiopia, and older respondents will tend to have fewer years of schooling than younger respondents. The Hausman test was performed and the null hypothesis of weak exogeneity was rejected for at least one of the relevant specifications, suggesting the need for instrumentation (as shown in equations 3 and 4).

When household education is instrumented, the coefficient falls and becomes much less significant, indicating a weaker relationship between household schooling and the propensity to adopt fertiliser than previously estimated. Although household education is expected to play an important role in innovation, if innovations have spread throughout the site from the more educated early adopters to less educated or uneducated late adopters, the effect of schooling upon adoption may be obscured.

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[8] There were two sites for which no maps were available; these have been treated as single neighbourhoods for the purpose of calculating neighbourhood-aggregated data.

[9] The neighbourhood education variable is purged of the data pertaining to each household in turn. This avoids unintended interactions between the neighbourhood and household education variables. The resulting variable represents 'education in the neighbourhood outside the household'.

It remains for us to demonstrate that early adopters tend to be more educated than late adopters or non-adopters. To do so, we need to utilise historical recall data on the timing of adoption. We have data on the year in which each household adopted fertiliser. Table 8 presents ordered probit results on the likelihood of adopting use of fertiliser early (first third of adopters in the site), in the medium term (second third of adopters in the site) and late (final third of adopters in the site), or never adopting use of fertiliser.[10] We do not estimate equations with education at the site-level as an explanatory variable, since by definition, the dependent variable should be independent of site-level influence, except in terms of the category, 'never adopted', which was considered in Table 7, where the dependent variable was a dichotomous choice of 'adopted' or 'never adopted' fertiliser.

All of the control variables are significant. The signs of the coefficients on age and the square of age indicate that older farmers are more likely to have adopted early than young farmers, though the likelihood of adopting early rises at a decreasing rate. Older farmers have had obvious opportunities to adopt earlier than younger farmers, to the extent that they have been farming for a longer period of time. However, the propensity to take up the opportunity may be somewhat lower for very old farmers, if they are more set in their ways. The effect of the household being headed by a woman is to decrease the likelihood of being an early adopter of fertiliser. If the household head is not primarily engaged in farming, the household is less likely to have adopted early. Since recently formed households were not available to be early adopters, it is necessary to include a variable to control for the number of years that the household has been in existence. The best available proxy is a dummy indicating that the household is at least five years old.[11] The coefficient is significantly positive, suggesting that households established earlier were indeed in a better position to adopt early. Unsurprisingly, the more land devoted to cereal production, the more likely a farmer is to have adopted early.

The most important and interesting finding is that household education is significantly associated with early adoption of fertiliser. Although the size and significance of the coefficient fell slightly when the variable was instrumented to correct for the problem of endogeneity, the coefficient was still significant at the five percent level on a two-tailed t-test (equation 6). The coefficients on education at the neighbourhood-level, controlling for all site fixed effects, are less significant. Nevertheless, the coefficients on neighbourhood-level schooling are large (in comparison with household-level education) and weakly significant on two-tailed t-tests. Thus, living in a neighbourhood where there are high levels of average schooling increases the likelihood that the household has been an early adopter within the site. This is not surprising since households living in neighbourhoods where some households have invested in schooling may be more likely to be exposed to innovations earlier than those living in neighbourhoods where there has been little investment in education.

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[10] Ordered probit estimation is used when the dependent variable is discrete and ordered. That is, occurrence in one category implies a more extreme event than occurrence in the previous category (Maddala 1983, 46-49). A great deal of caution must be used in interpreting marginal effects of explanatory regressors in an ordered probit model. The coefficients first must be transformed using information on the density function and estimates of the 'threshold parameters' (or cumulative probability cut-off points). However, this transformation provides reliable information on the probability of belonging only to the first and last category of response. The precise effects on the probability of belonging to cells in the middle of the range of possible outcomes are ambiguous (Greene 1997, 926-29).

[11] The household was asked whether it existed five years ago.

6. Summary and Conclusions

Previous research on the effects of schooling in rural Ethiopia has been concerned primarily with the private benefits of investment in schooling by individual households engaged in agricultural production (see, for example, Weir 1999). However, one aspect may not be fully captured by examining household-level data. Externality effects of schooling on agricultural production were considered in Weir and Knight (2000), which concluded that externality effects are important, and that the source of externalities was likely to be through the diffusion of innovations rather than through increasing farmer efficiency in the use of a given technology.

We have attempted to test the following hypotheses. Educated farmers tend to be early innovators in a particular area. However, once an innovation has been tried and the results are obvious to others in the site, a farmer need not himself be educated in order to appreciate the possible advantages of new inputs or farming techniques. Social learning may occur. If uneducated farmers learn from the experiences of educated farmers, then part of the effect of schooling includes the external benefits following from the increased opportunities for social learning in the site.

We have provided evidence to suggest that education encourages initial adoption of innovations and that less educated households copy more educated households in a process of social learning. We first estimated the probability of adopting fertiliser and found that the coefficient on education at the household-level was not significant at the ten percent level after instrumentation. We suspect that household education is relevant for early adopters but, as uneducated households copy early adopters, the effect of education is blurred. Evidence to support this hypothesis was provided in the ordered probit analysis of the probability of being an early adopter. Here, we found that, controlling for site fixed effects, education at the household-level did indeed encourage early adoption, a result that was significant at the five-percent level, even after instrumentation. Site- and neighbourhood-level effects of schooling appear to play an important role in both sets of equations. However, education at the neighbourhood-level tends to be only weakly significant. This may be because education externalities are not are not fully internalised at the neighbourhood level, since various types of social network cross neighbourhood boundaries.

We have provided descriptive evidence to suggest that the operation of social networks is crucial in the spread of innovations. The strong coefficients on site- and neighbourhood-level education in the probit results offer further support for this proposition. It is difficult to envisage policy interventions to promote this type of informal learning. However, insofar as social networks linking farmers serve to spread innovations that have been sparked by farmers with formal or non-formal education, allowing whole sites to benefit from the education of a few farmers, policy-makers have a persuasive argument, beyond that pertaining to the conventionally measured benefits of schooling, to increase education budgets.

References

Banerjee, Abhijit V. (1992) A simple model of herd behaviour, *The Quarterly Journal of Economics*, **107**, 797-817.

Basu, Kaushik and James E. Foster (1998) On measuring literacy, *The Economic Journal*, **108**, 1733-1749.

Besley, Timothy and Anne Case (1993) Modeling technology adoption in developing countries, *AER (AEA Papers and Proceedings)*, **83**, 396-402.

Choi, Jay Pil (1997) Herd behaviour, the 'penguin effect,' and the suppression of informational diffusion: an analysis of informational externalities and payoff interdependency, *The Rand Journal of Economics*, **28**, 407-25.

Kees Burger, Paul Collier and Jan Willem Gunning (1993) Social learning: an application to Kenyan agriculture, CSAE Working Paper Series 93-5 (Oxford: Centre for the Study of African Economies).

Cotlear, Daniel (1986) Technological and Institutional Change Among the Peruvian Peasantry : A Comparison of Three Regions at Different Levels of Agricultural Development (Oxford: D. Phil. Thesis).

Cotlear, Daniel (1990) The effects of education on farm productivity, in Keith Griffin and John Knight, eds., *Human Development and the International Development Strategy for the 1990s* (London: MacMillan).

Croppenstedt, Andre, Mulat Demeke and Meloria M. Meschi (1998) Technology adoption in the presence of constraints: the case of fertiliser demand in Ethiopia, mimeo (Oxford: Centre for the Study of African Economies).

Davidson, R. and J. MacKinnon (1993) *Estimation and Inference in Econometrics* (New York: Oxford University Press).

Deaton, Angus (1997) *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy* (Baltimore: Johns Hopkins University Press for the World Bank).

Dercon, Stefan, and Pramila Krishnan (1994) Ethiopia Rural Household Survey: Questionnaire for the First, Second and Third Rounds (Oxford: Centre for the Study of African Economies).

Ellison, Glenn and Drew Fudenberg (1993) Rules of thumb for social learning, *Journal of Political Economy*, **101**, 612-43.

Farrell, J. and G. Saloner (1986) Installed base and compatibility: innovation, product preannouncements and predation, *American Economic Review*, **76**, 940-55.

Feder, Gershon, Richard E. Just and David Zilberman (1985) Adoption of agricultural innovations: a survey, *Economic Development and Cultural Change*, **33**, 255-298.

Foster, Andrew D. and Mark R. Rosenzweig (1996) Technical change and human capital returns and investments: evidence from the green revolution, *American Economic Review*, **86:4**, 931-53.

Foster, Andrew D. and Mark R. Rosenzweig (1995) Learning by doing and learning from others: human capital and technical change in agriculture, *Journal of Political Economy*, **103:6**, 1176-1209.

Green, S. E., T. A. Rich, and E. G. Nesman (1985) Beyond individual literacy: the role of shared literacy for innovation in Guatemala, *Human Organization*, **44**, 313-321.

Greene, William H. (1997) *Econometric Analysis*, 3rd ed. (Upper Saddle River, NJ: Prentice-Hall, Inc.).

Jamison, Dean T. and Peter R. Moock (1984) Farmer education and farm efficiency in Nepal: the role of schooling, extension services and cognitive skills, *World Development*, **12**, 67-86.

Lucas, Robert E. (1988) On the mechanics of economic development, *Journal of Monetary Economics*, **21**, 3-42.

Maddala, G. S. (1983) *Limited-Dependent and Qualitative Variables in Econometrics* (Cambridge: Cambridge University Press).

Nelson, Richard R. and Edmund S. Phelps (1966) Investing in humans, technological diffusion and economic growth, *American Economic Review*, **61**, 69-75.

Rogers, Everett M. (1995) *Diffusion of Innovations*, 4th ed. (New York, NY: The Free Press).

Romer, Paul M. (1986) Increasing returns to long run growth, *Journal of Political Economy*, **94:5**, 1002-1035.

Weir, Sharada and John Knight (2000) Education externalities in rural Ethiopia: evidence from average and stochastic frontier production functions (Oxford: Centre for the Study of African Economies, mimeo).

Weir, Sharada (1999) The Effects of Education on Farmer Productivity in Rural Ethiopia, CSAE Working Paper Series 99-7 (Oxford: Centre for the Study of African Economies).

Weir, Sharada (1998) The Determinants of School Enrolment in Rural Ethiopia: Attitudes, Returns and Resources (Oxford: D. Phil. Thesis).

Woldehanna, Tassew, Sharada Weir and John Knight (2000) The role of education in facilitating risk-taking in agriculture: evidence from rural Ethiopia (Oxford: Centre for the Study of African Economies, mimeo).

Yao, Shujie (1996) The determinants of cereal crop productivity of the peasant farm sector in Ethiopia, 1981-87, *Journal of International Development*, **8:1**, 69-82.

Table 1: Variable Definitions and Mean Values

Variable Name	Definition	Mean
Dependent Variables:		
ADOPT_FERT	Dummy: 1 if household adopted fertiliser	0.46
ADOPT_CAT	Categorical Variable (0-3): 0 if never adopted fertiliser; 1 if adopted in last 30 percent of sampled households in site; 2 if adopted in middle 30 percent; 3 if adopted in first 30 percent of households.	0.84
Farm and Household Variables		
LAND	Land used to grow cereals (ha)	1.03
AGE_HHH	Age of household head (years)	45.90
AGESQ_HHH	Square of age of household head (years)	2354.84
FEMALE_HEAD	Dummy: 1 if household head is female	0.21
NON_FARM_HH	Dummy: 1 if household head is not primarily a farmer	0.08
HHGTE5YR	Dummy: 1 if household existed more than five years ago	0.90
Education Variables		
ED_AD_AVG	Average years of schooling of all adults (aged >15 yrs) in the household	1.47
ED_SITE_AVG	Average years of schooling in the site	1.46
ED_NEIGH_AVG	Average years of schooling in neighbourhood (excluding education within the household)	1.38
Site Dummy Variables		
Site_1	Dummy: Household lives in Site 1	0.04
Site_2	Dummy: Household lives in Site 2	0.04
Site_3	Dummy: Household lives in Site 3	0.06
Site_4	Dummy: Household lives in Site 4	0.14
Site_5	Dummy: Household lives in Site 5	0.05
Site_6	Dummy: Household lives in Site 6	0.10
Site_7	Dummy: Household lives in Site 7	0.07
Site_8	Dummy: Household lives in Site 8	0.07
Site_9	Dummy: Household lives in Site 9	0.07
Site_10	Dummy: Household lives in Site 10	0.05
Site_12	Dummy: Household lives in Site 12	0.05
Site_13	Dummy: Household lives in Site 13	0.06
Site_14	Dummy: Household lives in Site 14	0.09
Site_15	Dummy: Household lives in Site 15	0.06
Site_16	Dummy: Household lives in Site 16	0.05

Note: Means are based on the 1191 observations (out of 1477 observations in total) used in the analysis.

Table 2
Influence in Adoption of Input, and Teacher of Input Use, by Category of Education of the Household Head (Percent)

REASON FOR ADOPTION	NO ED	1-3 YRS	4-6 YRS	>6 YRS	ALL
Extension services	50	53	51	35	52
Neighbours/relatives	30	27	36	40	30
High profits or price observed	14	14	8	21	13
Many others adopted	4	3	3	3	3
Number of observations	570	264	99	75	1155

TEACHER	NO ED	1-3 YRS	4-6 YRS	>6 YRS	ALL
Extension services	48	52	40	26	49
Neighbours/relatives	34	27	53	42	34
Observed others	11	11	2	25	10
Self-taught	1	2	1	0	1
Training course	0	0	1	0	0
School	0	0	0	1	0
Number of observations	569	263	98	72	1145

Note: Percentages may not add to 100 owing to other responses not recorded here. 'All' includes households where information on education was missing. Each respondent may respond more than once if using more than one input.

Table 3
Influence in Adoption of Input, and Teacher of Input Use, by Site (Percent)

REASON FOR ADOPTION	Site 8	Site 9	Site 5	Site15	Site 7	Site 4	Site10	Site13	ALL
Ext. services	34	67	27	52	64	63	67	6	52
Neigh/relatives	38	32	17	44	19	33	24	61	30
High profits or price	23	2	41	4	13	1	8	20	13
Others adopted	3	0	9	0	1	0	0	13	3
Num. obs.	154	66	110	89	135	152	195	118	1155
TEACHER	Site 8	Site 9	Site 5	Site15	Site 7	Site 4	Site10	Site13	ALL
Ext. services	25	71	33	35	67	55	65	9	49
Neigh/relatives	37	26	29	62	20	34	28	69	34
Observed others	28	3	14	3	10	2	6	19	10
Self-taught	3	0	3	0	2	1	0	0	1
Training course	0	0	0	0	0	1	0	0	0
School	0	0	0	0	0	0	1	0	0
Num. obs.	154	66	109	89	135	150	191	118	1145

Note: Percentages may not add to 100 owing to other responses not recorded here. Sites are ordered from the lowest average site education to the highest. Only those sites where modern inputs were adopted by more than a few households are included. Each respondent may respond more than once if using more than one input.

Table 4
Characteristics of Those Who Influenced Adoption of Input by Category of Education of the Household Head (Percent)

CHARACTERISTICS	NO ED	1-3 YRS	4-6 YRS	>6 YRS	ALL
Same gender	84	92	93	95	88
Same age	40	30	28	15	34
Younger	45	33	20	27	38
Older	14	36	52	56	27
Same income level	37	34	26	26	33
Richer	58	59	73	69	62
Poorer	2	5	1	5	3
Num. observations	133	526	218	66	1035

Note: Percentages may not add to 100 owing to other responses not recorded here. 'All' includes households where information on education was missing. The number of observations is approximate, since some households were unable to provide responses to all questions. In each case, percentages are calculated based on the actual number of reported observations in each category. Each respondent may respond more than once if using more than one input.

Table 5
Years of Schooling of Household Head, by Reasons for Adoption of Fertiliser and by Who Taught Use of Fertiliser

REASON FOR ADOPTION	ED YEARS	TEACHER	ED YEARS
Extension services	1.4 (280)	Extension services	1.2 (255)
Neighbours/relatives	2.0 (200)	Neighbours/relatives	2.0 (231)
High profits or price observed	1.9 (71)	Observed others	2.0 (58)
Many others adopted	1.6 (13)	Self-taught	1.8 (6)
		Training course	4.0 (1)
		School	6.0 (2)
Do not use fertiliser	1.2 (706)	Do not use fertiliser	1.2 (706)

Note: Number of observations is given in parentheses. Other responses given are not recorded here.

Table 6
Characteristics of the Diffusion of Fertiliser and Correlation with Average Education in the Site

	Site 8	Site 9	Site 5	Site15	Site 7	Site 4	Site10	Site13	CORR
Start Year	1970	1978	1980	1965	1958	1964	1958	1964	
Years adopted	26	18	16	31	38	32	38	32	0.57
% Adopted - 5 yrs	10.6	2.0	3.8	6.3	5.8	1.5	3.9	3.6	-0.46
% Adopted - 10 yrs	23.9	2.8	57.6	52.7	13.1	3.3	4.9	7.6	-0.37
% Adopted - 15 yrs	22.9	46.3	86.4	50.6	19.1	45.7	13.0	26.5	-0.37
% Adopted - 20 yrs	36.5			53.9	59.2	59.1	51.9	40.5	0.08
% Adopted - 25 yrs	55.2			74.4	57.6	67.6	62.0	73.3	0.48
% Adopted by 1995	55.2	55.6	86.4	91.1	83.9	86.9	89.2	97.3	0.74 **
ED_SITE_AVG	0.35	1.15	1.26	1.56	1.66	1.67	3.11	3.29	

Note: CORR = Correlation coefficient between 'X' and ED_SITE_AVG; In all cases, percentage adopted is in relation to the number of households in existence at the time (i.e., households where the oldest household member was at least aged 15 at the time); * = Significant at the 10 % level on a two-tailed t-test; ** = Significant at the 5% level on a two-tailed t-test; Sites are ordered from the lowest average site education to the highest; only those sites where fertiliser has been adopted by more than a few households are included.

Table 7
Marginal Effects Derived from Probit Estimation
of the Probability of Adoption of Fertiliser
Dependent Variable: Adopt (1 if fertiliser adopted; 0 otherwise)

	Eqn. 1	Eqn. 2	Eqn. 3	Eqn. 4
AGE_HHH	-0.001	-0.000	-0.001	-0.001
FEMALE_HEAD	-0.070	-0.119 **	-0.072 ✔	-0.123 **
NON_FARM_HH	-0.180 ***	-0.212 **	-0.175 ***	-0.204 **
LAND	0.171 ***	0.128 ***	0.172 ***	0.131 ***
ED_AD_AVG	0.013 *	0.026 *		
ED_AD_AVG‡			0.012 ✔	0.021 ✔
ED_SITE_AVG	0.217 *		0.230 *	
ED_NEIGH_AVG		0.150 ✔		0.163 ✔
SITE DUMMIES?	NO	YES	NO	YES
SITE VARIABLES?	YES	NO	YES	NO
NUM OBS	1191	1191	1191	1191
PEUSDO_R2	0.31	0.48	0.31	0.47
LOG_LIKELIHOOD	-562.91	-430.36	-563.07	-431.53

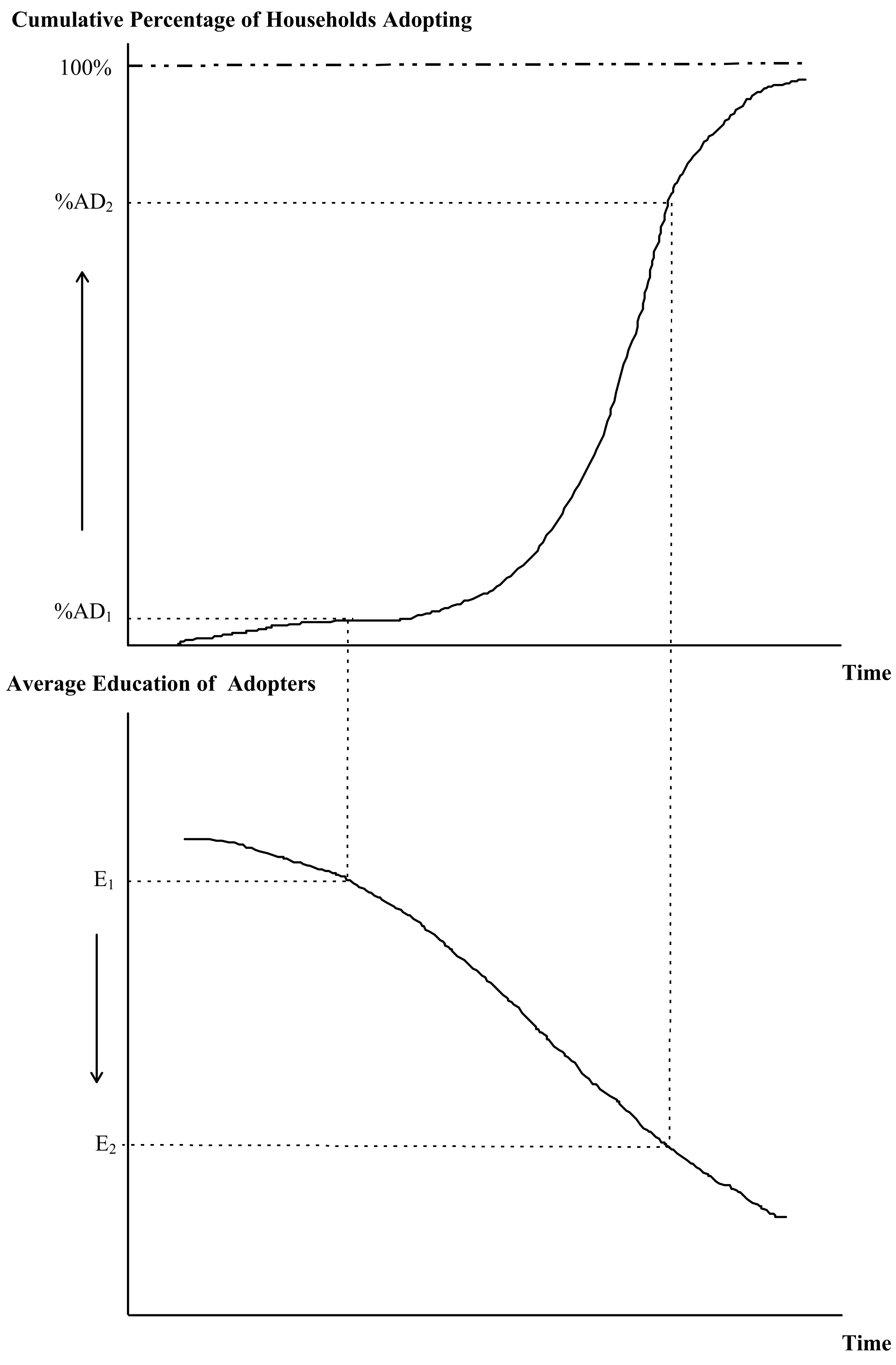
Note: The results shown are not the estimated coefficients but the marginal effects (e.g., in the first equation, the marginal effect of the household being female-headed is to decrease the probability of adopting fertiliser by 7 percent. The effect of an additional year of schooling, on average, in the household is to increase the likelihood of adoption by 1.3 percent). Stars indicate significance using a two tailed t-test: *** = 0.01; ** = 0.05; * = 0.10; ✔ = 0.20. Site variables include distance to the nearest town and distance to the nearest road. The sample size of 1191 households includes everyone in the ERHS who provided full information on the included variables and instruments. ED_AD_AVG‡ is an instrumental variables estimator in which the instrument is average age of all adults in the household. The instrument passed the relevancy test (Davidson and MacKinnon 1993).

Table 8
Ordered Probit: Timing of Adoption of Fertiliser
Dependent Variable: Adopt_Cat. Category of Adopter (0-3) - Never Adopted, Late (last third of adopters in the site), Middle (middle third), Early (first third)

	Eqn. 5	Eqn. 6
AGE_HHH	0.042 **	0.039 **
AGESQ_HHH	-0.000 **	-0.000 **
FEMALE_HEAD	-0.214 *	-0.218 *
NON_FARM_HH	-0.453 ***	-0.431 **
HHGTE5YR	0.331 ***	0.271 **
LAND	0.208 ***	0.220 ***
ED_AD_AVG	0.066 ***	
ED_AD_AVG‡		0.052 **
ED_NEIGH_AVG	0.312 ✔	0.354 ✔
SITE DUMMIES?	YES	YES
SITE VARIABLES?	NO	NO
NUM OBS	1191	1191
PEUSDO_R2	0.24	0.24
LOG_LIKELIHOOD	-1070.78	-1072.64

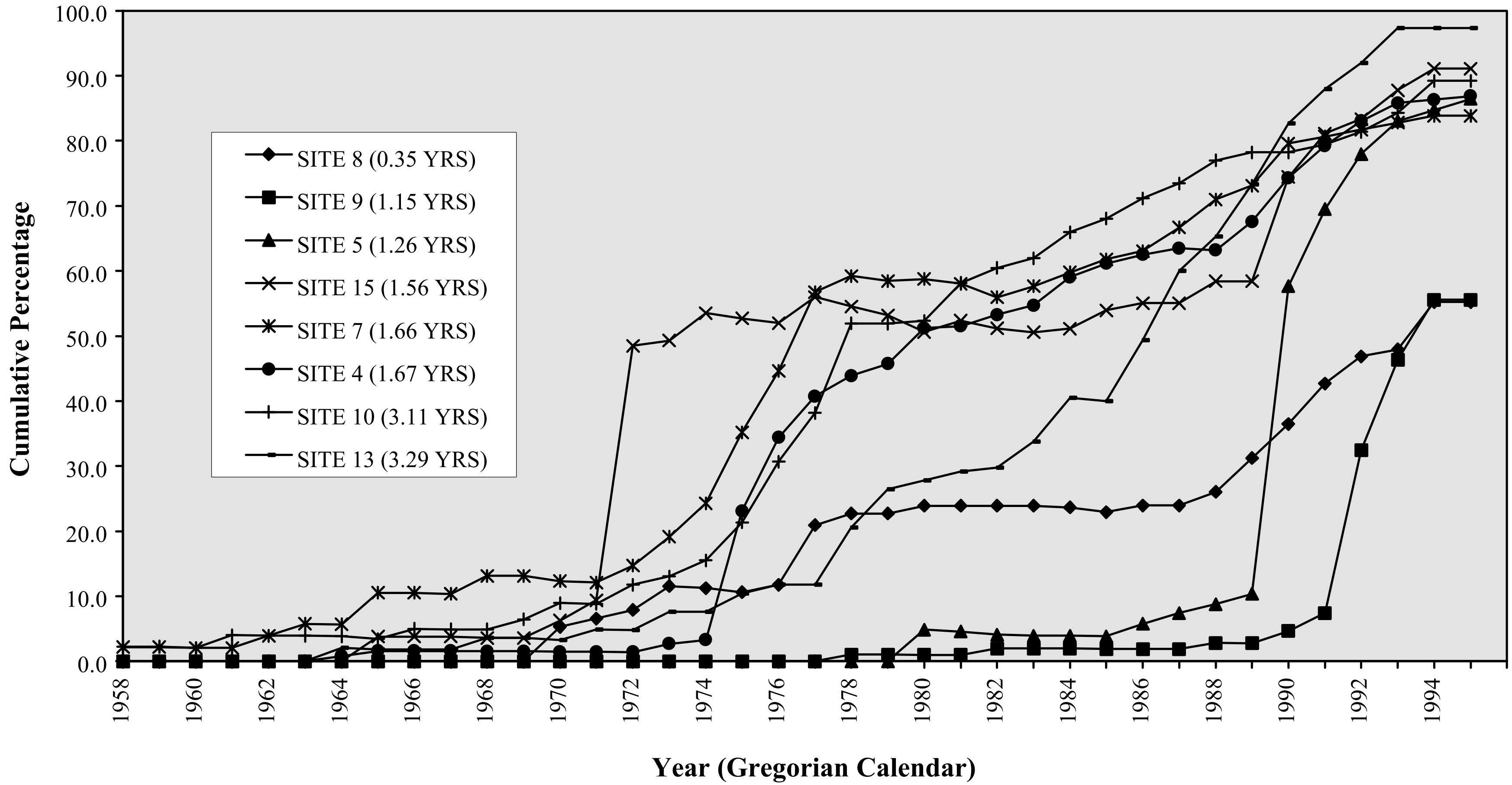
Note: The results presented are the estimated coefficients and not the marginal effects. See footnote 9 in the text. Stars indicate significance using a two tailed t-test: *** = 0.01; ** = 0.05; * = 0.10; ✔ = 0.20. Site variables include distance to the nearest town and distance to the nearest road. The sample size of 1191 households includes everyone in the ERHS who provided full information on the included variables. ED_AD_AVG‡ is an instrumental variables estimator in which the instrument is average age of all adults in the household. The instrument passed the relevancy test (Davidson and MacKinnon 1993).

Figure 1
Average Education of Adopters and the Diffusion Path of Innovations: A Hypothetical Example

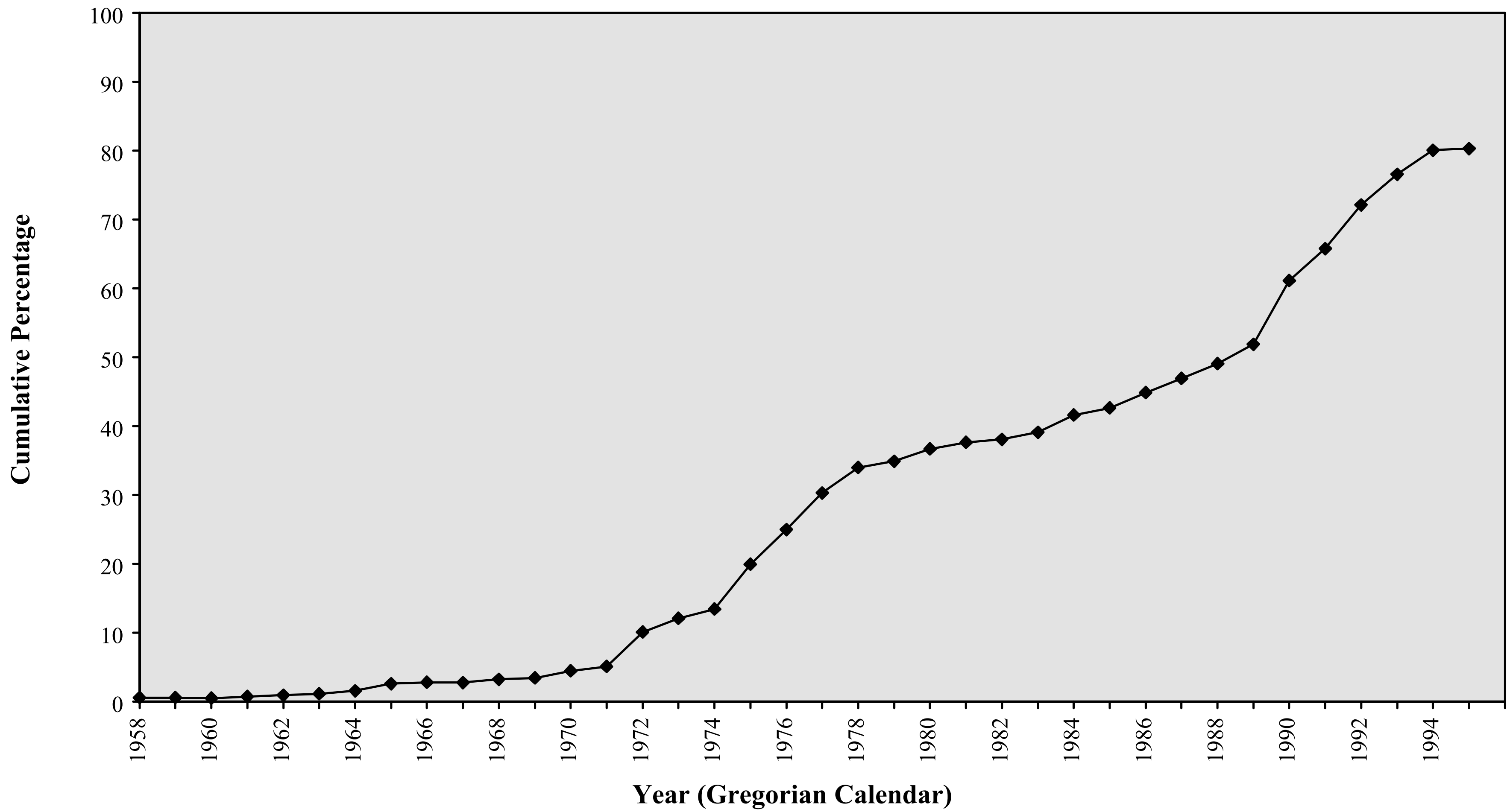


APPENDIX: GRAPHS

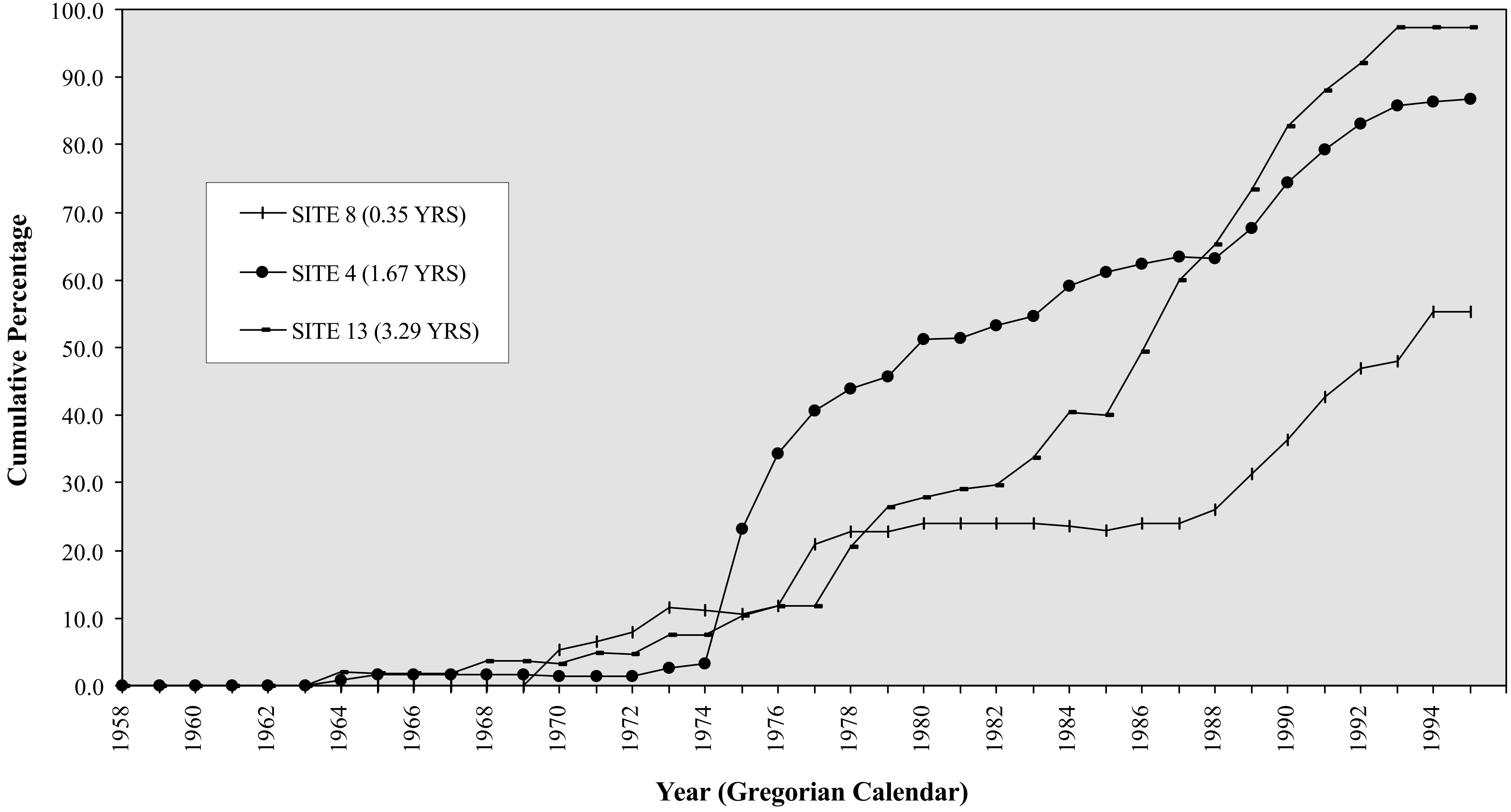
GRAPH 1
Cumulative Percentage of Available Households Adopting Fertiliser in Each Year by Site (Average Years of Schooling in the Site Given in Parentheses)



GRAPH 2
Cumulative Percentage of Households Adopting Fertiliser in Each Year
All Sites, by Year



GRAPH 3
Cumulative Percentage of Available Households Adopting Fertiliser in Each Year
Selected Sites (Average Years of Schooling in the Site Given in Parentheses)



GRAPH 4
Cumulative Percentage of Households Adopting Fertiliser by Year from Start Year
Selected Sites (Average Years of Schooilng in the Site Given in Parentheses)