academicJournals

Vol. 6(7), pp. 318-337,July, 2014
DOI: 10.5897/JDAE2013.0508
Article Number: 5749ADE45626
ISSN 2006-9774

http://www.academicjournals.org/JDAE

Journal of Development and Agricultural Economics

Full Length Research Paper

Fertilizer adoption in Ethiopia cereal production

Bingxin Yu* and Alejandro Nin-Pratt

International Food Policy Research Institute, United States.

Received 26 September, 2013; Accepted 20 May, 2014

This paper was the first to use nationally representative data from the Agricultural Sample Surveys of Ethiopia to examine the factors affecting the adoption of the fertilizer-seed technology "package" promoted by Ethiopia's government. We used a double hurdle model to analyze fertilizer adoption among four major cereal crops (barley, maize, teff, and wheat). This model allowed us to identify factors affecting farmers' access to fertilizer and factors affecting fertilizer demand conditional to input access. Extension was proven to have the biggest impact on fertilizer adoption. We found that knowledge required to adopt new technology represented a high cost for farmers. In addition to extension, other factors that could reduce the cost to access knowledge include farmers' knowledge and skills in cereal production, risk aversion behavior, household wealth and land fragmentation. Substantial yield gain in maize and teff could be achieved from locally tailored extension packages.

Key words: Technology adoption, double hurdle model, Ethiopia, fertilizer, cereal.
JEL Codes: O33, O38, Q16, Q18.

INTRODUCTION

The economic growth strategy formulated by the Ethiopian government in 1991 places very high priority on accelerating agricultural growth to achieve food security and poverty alleviation. A core goal of this strategy is to increase cereal yields by focusing on technological packages that combined credit, fertilizers, improved seeds and better management practices. The participatory demonstration and training extension system (PADETES), started in 1994 to 1995 and in its early stages focused on cereal crops, but expanded to other crops in later years. This technology-package-driven extension approach has been implemented on a large scale and has reached virtually all farming communities in Ethiopia. It represents a significant public investment ($50 million dollars annually or 2% of agricultural GDP in recent years), four to five times the investment in agricultural research. Extensive data from a large number of demonstrations carried out through PADETES, indicates that the adoption of fertilizer-seed technologies could more than double cereal yields and would be profitable to farmers in moisture-reliant areas (Howard et al., 2003).

However, after nearly a decade of implementation the impacts of the program have been mixed, with increased but still limited use of fertilizer (World Bank, 2006). Byerlee et al. (2007) concluded that some of the major factors affecting the results of PADETES program are poor performance of the extension service, promotion of regionally inefficient allocation of fertilizer, low technical efficiency in the use of fertilizer, no emergence of private

*Corresponding author. E-mail: b.yu@cgiar.org, Tel: +1 202 862 8114. Fax: +1 202 467 4439.

sector retailers whom were negatively affected by the government's input distribution tied to credit, and the generation of an unleveled playing field in the rural finance sector by the guaranteed loan program with below-market interest rates. Among these issues, low adoption of modern inputs, especially chemical fertilizer, deserves more in-depth study as the fertilizer policy represents a substantial portion of public resources going to agriculture.

Several papers have analyzed the factors affecting adoption of chemical fertilizer in Ethiopia's cereal production. Admassie and Ayele (2004) and Beshir et al. (2012) noted that age of household head, farm land size, education, livestock, non-farm income, gender and access to information are major factors affecting technology adoption. Limited knowledge and education are identified as major constraints for technology adoption by Asfaw and Admassie (2004), while Beshir et al. (2012), Carlsson et al. (2005) and Wubeneh and Sanders (2006) highlighted the positive effect of extension services on fertilizer adoption. Liverpool-Tasie and Winter-Nelson (2012) on the other hand, indicate that technology diffusion in Ethiopia is likely to be enhanced if extension can target intentional networks, rather than spatial clusters; and Abebaw and Haile (2013) show that cooperative membership has a strong positive impact on fertilizer adoption. Dercon and Christiaensen (2011) found an important role of risk on fertilizer adoption, showing that the lack of insurance or alternative means of keeping consumption smooth leaves poor households trapped in low return, lower risk agriculture. Croppenstedt et al. (2003) pointed out supply side factors such as credit constraints and untimely fertilizer supply are some of the most important reasons for non-adoption of fertilizer by farmers. Alternatively, Liverpool-Tasie and Winter-Nelson (2009) find no relationship between participation in microfinance programs and the use of technologies and concluded that participation in micro-finance programs increases the likelihood of technology use for the less poor households only.

A major limitation of these studies is that they use a variety of different data sources that are not nationally representative of Ethiopia's agriculture, with some of them not covering the second half of the 2000s when a substantial increase in fertilizer adoption took place. Some of the sources used include the Ethiopia rural household survey (ERHS), which comprises 1,477 households in 15 Peasant Associations across the four major regions in Ethiopia (as in Dercon and Christiaensen, 2011; Liverpool-Tasie and Winter-Nelson, 2009, 2012); a survey conducted in 1994 covering 6,147 cereal-growing farm households, in Amhara, Tigray, Oromia, and SNNP (Croppenstedt et al., 2003), and a survey focusing only in two districts of south Wollo zone (Beshir et al., 2012). The goal of this paper is to look at the extent and determinants of the adoption of the fertilizer promoted in Ethiopia. The study contributes to the literature of technology adoption in Ethiopia's agriculture in several aspects. First, this is the first attempt to analyze technology adoption in Ethiopia using nationally representative data based on agricultural sample surveys from the central statistical agency (CSA, various years). Second, our approach features the sequential process of decision making in technology adoption by separating the decision to adopt fertilizer and the decision about the quantity of input use for each cereal crop, addressing the endogeneity of extension service to improve our understanding of the effectiveness of PADETES. Third, we estimate average partial effects for determinants of technology adoption, allowing us to examine the unconditional effect of factors that influence the adoption process, which is important when there are observations with zero values for input use. Finally, in addition to traditional social economic indicators, we introduce spatial variables obtained through GIS tools in the analysis. The spatial distribution of biophysical constraints and market accessibility are incorporated in the model to take into account the impact of local agronomic and development conditions on technology adoption.

Cereal production and technology adoption in Ethiopia

Table 1 presents a summary of area, production and yields of cereals in main Ethiopian production regions in 2003 to 2004 and 2007 to 2008. Total cereal production was 13.6 million tons in 2007 to 2008, expanded by 27% from 2003 to 2004. Average cereal yield reached 1.6 ton/ha in 2007 to 2008, exhibiting a 22% growth over 5 years. In 2007 to 2008, the main cereal according to land use was teff (30% of total cereal land), followed by maize (20%), sorghum (18%) and wheat (16%). Ethiopia's yield levels are lower than the average yield in least developed countries, although they are higher than the average yield in Eastern Africa.

Between 2003 to 2004 and 2007 to 2008, the area of

Table 1. Area, production and yields of cereals in Ethiopia, 2003 to 2004 and 2007 to 2008.

Variable	2003 to 2004				2007 to 2008				Growth 2003 to 2004 and 2007 to 2008 (%)			
	Area	Production	Yield	Area share	Area	Production	Yield	Area share	Area	Production	Yield	Area share
Cereal crop	000 ha	000 tons	Tons/ha	%	000 ha	000 tons	Tons/ha	%				
Barley	911	1071	1.2	13.4	985	1355	1.4	11.4	8.1	26.5	17.0	-14.9
Maize	1300	2455	1.9	19.1	1767	3750	2.1	20.4	35.9	52.7	12.3	6.8
Millet	303	304	1.0	4.5	399	538	1.3	4.6	31.7	77.0	34.4	2.2
Sorghum	1242	1695	1.4	18.2	1534	2659	1.7	17.7	23.5	56.9	27.0	-2.7
Teff	1985	1672	0.8	29.1	2565	2993	1.2	29.6	29.2	79.0	38.6	1.7
Wheat	1075	1589	1.5	15.8	1425	2314	1.6	16.4	32.6	45.6	10.0	3.8
Other	35	44	1.3	0.5	55	108	2.0	0.6	57.1	145.5	56.1	20.0
Total cereal	6816	8786	1.3	100	8675	13609	1.6	100	27.3	54.9	21.7	

Source: Author's calculation using CSA Agricultural Sample Survey data (various years).

four of the major cereal crops under the promoted technologies (fertilizer and/or seed) increased at 4% annually (Table 2). The adoption of the promoted package of jointly using fertilizer and improved seed has been very limited, accounting for only 6% of cultivatedarea. Traditional farming practice of using local seed but no chemical fertilizer remains the dominant farming system in barley (73% of land), followed by maize (62%), teff (56%), and wheat (43%) in 2007 to 2008.

More than 50% of the area planted with teff and wheat and 38% of the area under maize used fertilizer during the period, regardless of seed type. Barley shows the lowest levels of fertilizer adoption with only 27% of its area cultivated using fertilizer. However, the information available from CSA allows only identifying the use of improved seed varieties if they are purchased on the year of the survey. Because of this, the survey can only capture the systematic use of improved seed varieties if they are hybrids because they need to be purchased every year, underestimating the adoption of open pollinated varieties. Given the importance of hybrids among improved maize varieties and of open pollinated varieties for other crops, CSA data can only capture adoption of improved seed in maize. For this reason, our analysis focuses on fertilizer adoption rather than on the fertilizer-seed package.

Cereal cultivation is highly concentrated geographically (Figure 1). Almost 80% of total area under cereals is in the Amhara and Oromiya regions to the northwest, west, southwest and south of the capital, Addis Ababa. This area includes a diverse set of conditions for agricultural production. Spatial conditions for production and market access have been discussed in detailed by Diao and Nin Pratt (2005) and Tadesse et al. (2006).

There are substantial regional variations in the adoption of fertilizer (Figure 2). The spatial distribution of fertilizer use varies by crop, although there is also a significant overlap of zones across the different crops. In general, most of the area under fertilizer is concentrated in areas with suitable natural resources for production and roads access.

METHODOLOGY

Conceptual framework

One of the most used methods for modeling technology adoption behavior is the censored regression model, also called the Tobit model (Wubeneh and Sanders, 2006). The key underlying assumption for a Tobit specification is that farmers demanding modern inputs have unconstrained access to the technology. However, in situations where input supply systems are underdeveloped this is often untenable, as farmers wanting to adopt a new technology, fertilizer in this study, often face input access constraints. The Tobit specification has no mechanism to distinguish households with a constrained positive demand for the new technology from those with unconstrained positive demand, and assumes that a household not adopting the technology is making a rational decision. Hence, in the case of access constraints to access inputs, the Tobit model yields inconsistent parameter estimates (Croppenstedt et al., 2003).

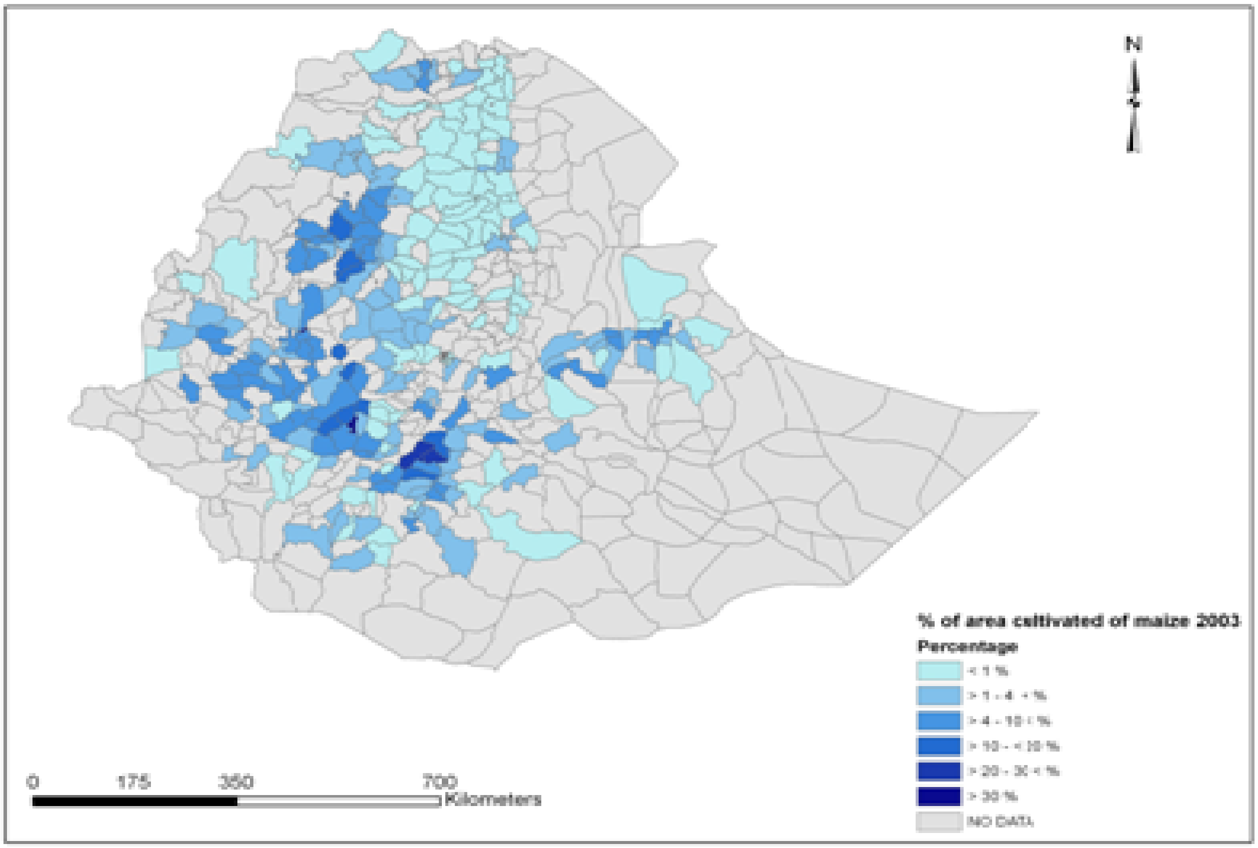
Evidence from previous studies shows the critical role that underdeveloped input supply and marketing systems play on input choices and technology adoption in smallholder agriculture (Shiferaw et al., 2008). Smallholder farmers in many rural areas are semi-subsistence producers and consumers who are partially integrated into imperfect rural markets. Factor markets for labor, land, traction power, and credit in rural areas of developing

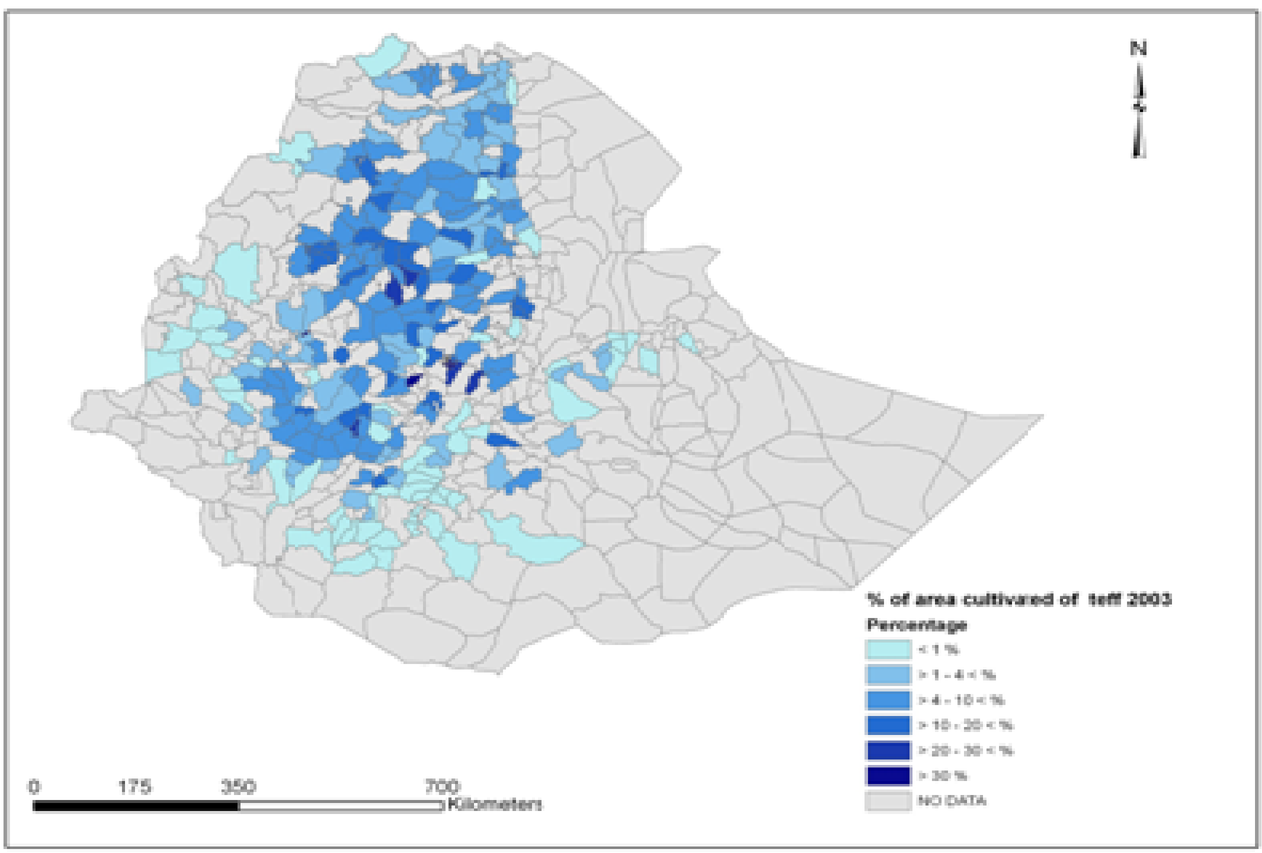
Table 2. Cereal area under modern and traditional technology.

Crop and technology	Total area (000 ha)				Share in crop area (%)				Annual growth rate (%)
	2003	2004	2006	2007	2003	2004	2006	2007	
Barley									
Fertilizer + improved seed	0.8	1.8	0.9	1.2	0.1	0.3	0.1	0.2	10.7
Fertilizer + local seed	145.6	164.4	173	140.6	25.8	25.6	27.3	26.6	-0.9
No fertilizer + improved seed	1.2	2.1	0.1	0.2	0.2	0.3	0	0	-36.1
No fertilizer + local seed	415.6	474.2	459	386.8	73.8	73.8	72.5	73.1	-1.8
Total	563.1	642.5	632.9	528.9	100	100	100	100	-1.6
Maize									
Fertilizer + improved seed	197.2	158.1	188.9	192.2	23.4	17.7	17.7	21.6	-0.6
Fertilizer + local seed	99.5	124.6	211.2	146.3	11.8	13.9	19.7	16.4	10.1
No fertilizer + improved seed	10.7	9.5	9.9	5	1.3	1.1	0.9	0.6	-17.3
No fertilizer + local seed	536.1	601.6	660.1	547.9	63.6	67.3	61.7	61.5	0.5
Total	843.5	893.8	1070.2	891.3	100	100	100	100	1.4
Teff									
Fertilizer + improved seed	3.7	7.7	8.2	9.7	0.3	0.5	0.5	0.6	27.2
Fertilizer + local seed	634.2	705	902.2	821.4	45.2	47.2	54.4	53.5	6.7
No fertilizer + improved seed	4.7	3.7	2.1	2.2	0.3	0.2	0.1	0.1	-17.3
No fertilizer + local seed	761.4	778.7	745.8	701.7	54.2	52.1	45	45.7	-2.0
Total	1,404	1,495	16,58.3	1,535	100	100	100	100	2.3
Wheat									
Fertilizer + improved seed	24.9	28.3	22.5	14.1	3.7	3.4	2.6	2	-13.3
Fertilizer + local seed	341.6	418.7	533	379.9	50.1	50.4	60.6	53.8	2.7
No fertilizer + improved seed	5.8	5.3	4.2	6.1	0.9	0.6	0.5	0.9	1.3
No fertilizer + local seed	308.9	379	320.3	305.5	45.4	45.6	36.4	43.3	-0.3
Total	681.2	831.3	880	705.7	100	100	100	100	0.9
Major Cereals									
Fertilizer + improved seed	227	196	221	217	6.5	5.1	5.2	5.9	-1.1
Fertilizer + local seed	1,221	1,413	1,819	1,488	35.0	36.6	42.9	40.7	5.1
No fertilizer + improved seed	22	21	16	14	0.6	0.5	0.4	0.4	-11.9
No fertilizer + local seed	2,022	2,234	2,185	1,942	57.9	57.8	51.5	53.0	-1.0
Total	3,492	3,863	4,241	3,661	100.0	100.0	100.0	100.0	1.2

Source: Author's calculation using CSA Agricultural Sample Survey data (various years).

countries are often imperfect and/or even missing in some cases (Holden et al., 2001; Pender and Kerr, 1998). In these cases, access to fertilizer is the key threshold that farmers with positive desired demand for the new technology have to overcome. The double hurdle (DH) model (Cragg, 1971) is a useful and proper approach to analyze technology adoption under constrained access to inputs, as many Ethiopian households face constraints in accessing inputs like fertilizer (Noltze, Schwarze and Qaim, 2012). This paper also adopts the DH model to examine technology adoption in two stages. In the first stage, the farmer decides


N
% of area cultivated of maize 2003
Percentage
< 1 %
> 1 - 4 < %
> 4 - 10 < %
> 10 - < 20 %
> 20 - 30 < %
> 30 %
NO DATA
0
175
350
700
Kilometers


N
% of area cultivared of teff 2003
Percentage
< 1 %
> 1 - 4 < %
> 4 - 10 < %
> 10 - 20 < %
> 20 - 30 < %
> 30 %
NO DATA
0
175
350
700
Kilometers

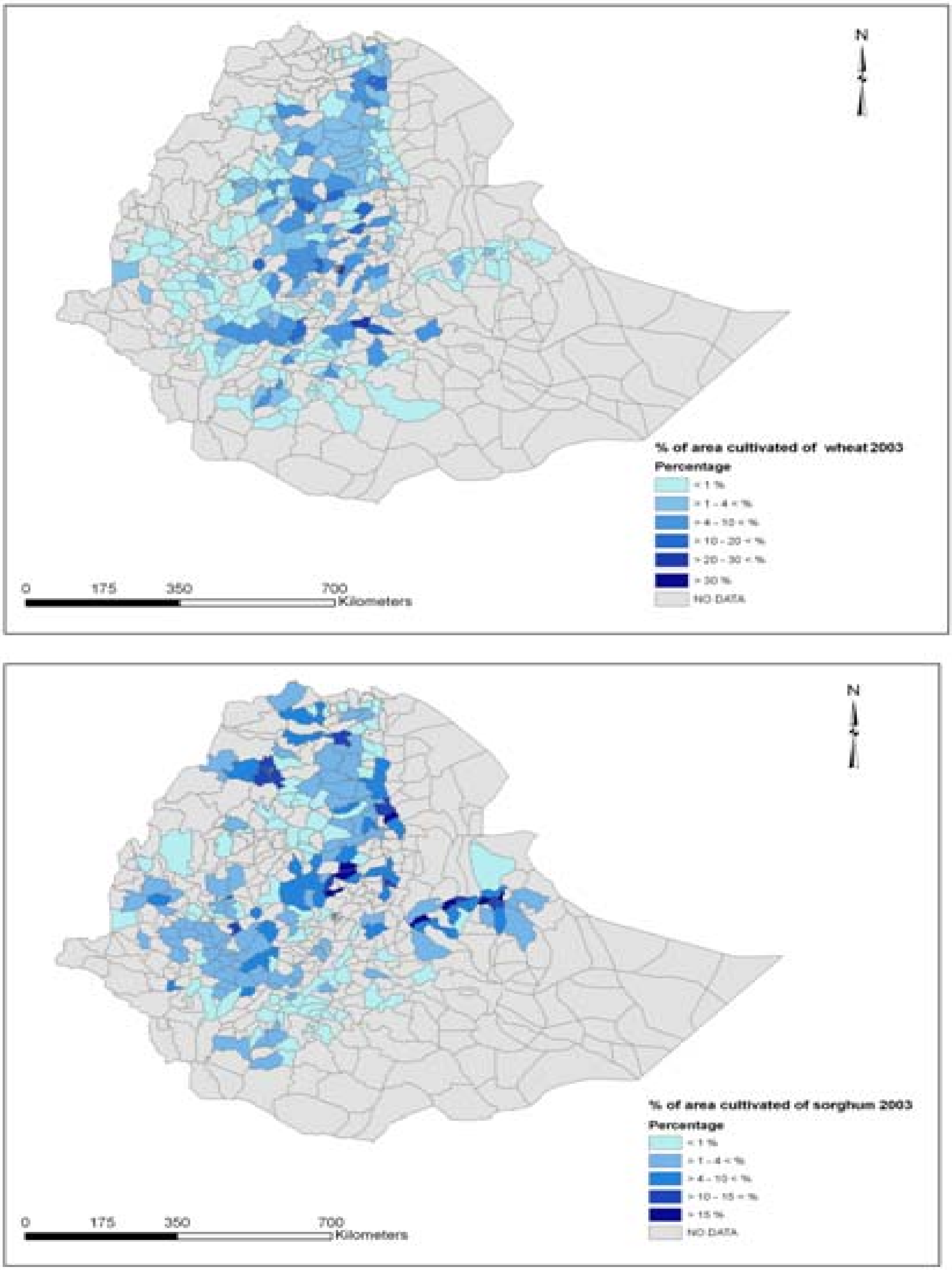
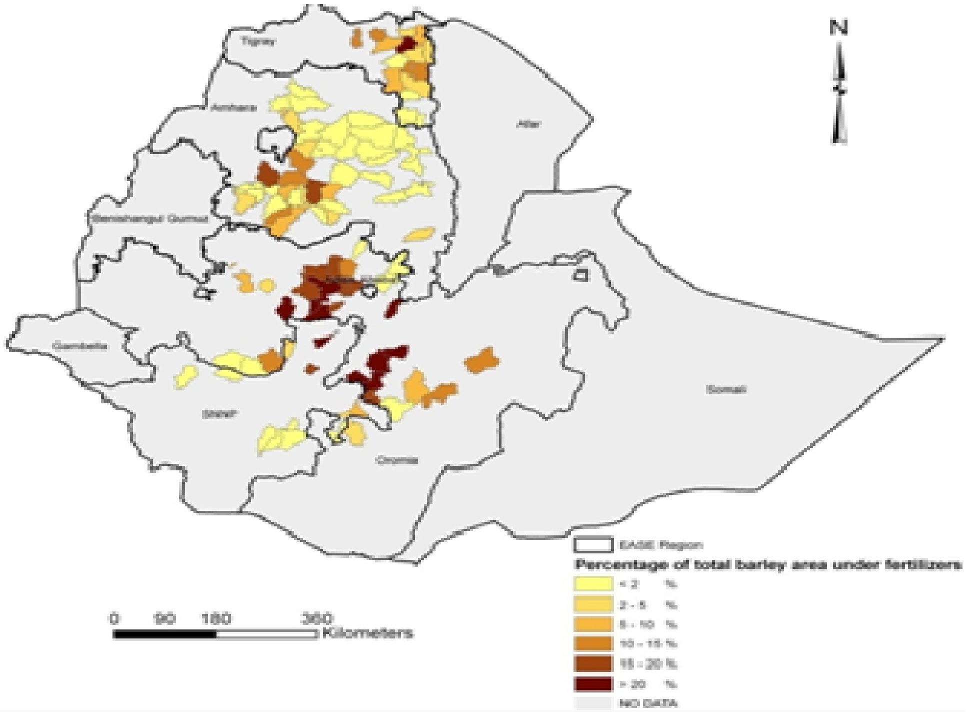
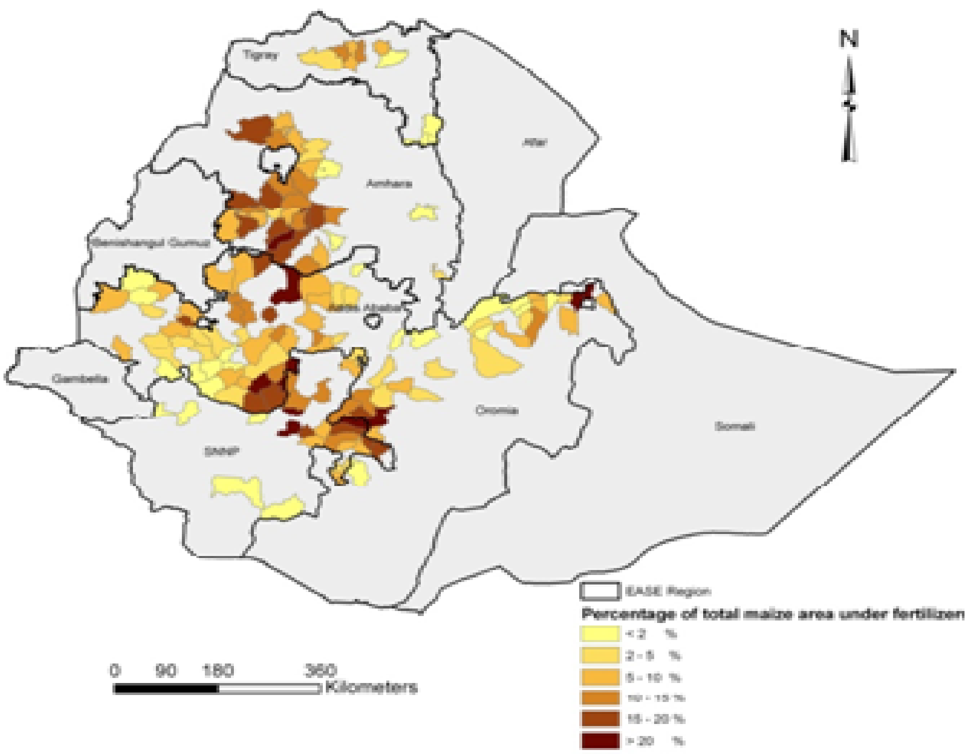


Figure 1. Share of cultivated area in total wereda area for four cereal crops, in percentage; Source: Author's computation using CSA data (various years).


N
Tigray
Amhara
Afar
Benishangul Gumuz
Gambella
SNNP
Oromia
Somali
EASE Region
Percentage of total barley area under fertilizers
< 2 %
2 - 5 %
5 - 10 %
10 - 15 %
15 - 20 %
> 20 %
NO DATA
0 90 180 360
Kilometers


N
Tigray
Afar
Amhara
Benishangul Gumuz
Addis Ababa
Gambella
SNNP
Oromia
Somali
EASE Region
Percentage of total maize area under fertilizers
< 2 %
2 - 5 %
5 - 10 %
10 - 15 %
15 - 20 %
> 20 %
NO DATA
0 90 180 360
Kilometers

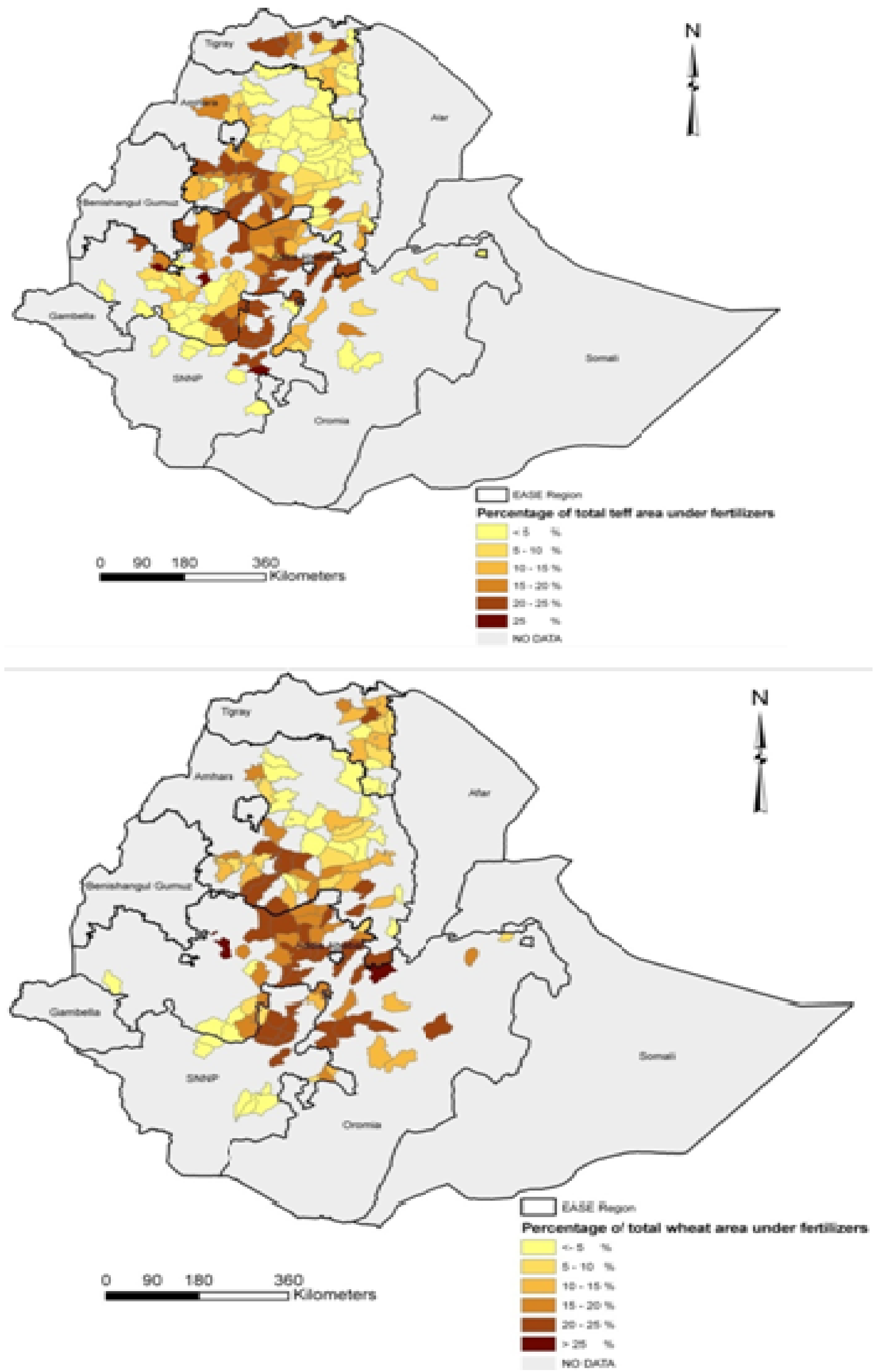


Figure 2. Spatial distribution of fertilizer use in cereal production; Source: Author's calculation using CSA data (various years).

whether or not to participate in the fertilizer market. If he/she chooses to participate, the next step is to decide the quantity to purchase. Through this procedure, the DH model allows separation of the sample of farming households into three groups: households adopting fertilizer, households wanting to adopt but reporting no positive application, and households choosing not to adopt. We incorporate this additional information to the DH model to obtain more efficient and consistent estimates of technology adoption. Similar DH model is adopted by Asfaw et al. (2011) to examine the adoption of chickpea seed variety in Ethiopia.

The DH model used in this study has two equations, one explaining access to fertilizer, and the other one explaining the level of application once access to inputs is granted. First, the latent but unobservable variable underlying an individual farmer's access to fertilizer A^* can be modeled as:

$$A^* = x_1\gamma + e, \tag{1}$$

where x_1 is a vector of variables that affect access, γ is the parameter vector, and *e* is random variable distributed as normal with mean 0 and variance 1. The unobserved demand for fertilizer of farmers (Y^*) can be modeled as:

$$Y^* = x_2\beta + u, \tag{2}$$

where x_2 is a vector of variables that determine the demand function, β is parameter vector, and *u* is normal random variable with mean 0 and variance σ_u^2. The observed input demand (Y) is characterized by the interaction of Equations (1) and (2). A positive use of input like fertilizer is observed only if two thresholds are passed in the decision making process. Hence the farming households are separated into three groups. Group 1 represents the adopters as the farmer has passed the positive demand threshold (Y^* >0) and has access to input (A^* > 0). Group 2 in the sample includes farmers who want input (Y^* >0) but cannot because of some constraints like lack of access (A^* ≤ 0). Group 3 consists of farmers who do not want to use input (Y^* < 0) whether they have access to it or not (A^* > 0 or A^*≤ 0).

We assume that the access and demand equations are independent and that the log likelihood function for the sample-separated data can be expressed as:

$$\ln L = \sum_{G1=1} \ln\left[\Phi(x_1\gamma) \times \left(\frac{1}{\sigma_u}\right) \times \phi\left(\frac{Y - x_2\beta}{\sigma_u}\right)\right] + \sum_{G2=1} \ln\left[\Phi(x_2\beta/\sigma_u) \times (1 - \phi(x_1\gamma)\right] + \sum_{G3=1} \ln\left[1 - \Phi(x_2\beta/\sigma_u\right), \tag{3}$$

where φ and Φ are the probability density and cumulative distribution function of the standard normal variable, respectively; 1, 2 and G3 are indicator functions showing whether a given observation belongs to group 1, 2 or 3, respectively. Equation (3) can be estimated using maximum likelihood (ML) techniques, which gives consistent estimates of the parameters. If u_i and e_i are independent, the maximum likelihood function can be separated into a probit and a truncated normal regression model. The model specification of the DH estimator can be tested against the Tobit model using a likelihood ratio (LR) test to determine whether the data supports sequential technology adoption decisions or traditional probit and Tobit approaches are sufficient.

We address potential endogeneity of some of the explanatory variables (in particular the variable representing "extension") using the control function (CF) approach of Rivers and Vuong (1988). According to Imbens and Wooldridge (2008), the CF approach offers some distinct advantages for models that are nonlinear in parameters or endogeneity variables because the CF estimator tackles the endogeneity by adding an additional variable to the regression, generating more precise and efficient estimator than the IV estimator.

After obtaining coefficient estimates for parameters of interest, we can derive the average partial effects (APE) of the explanatory variable across plot and time. The APE is the partial effect averaged across the sample. The first step in obtaining the APE is to derive the partial effect for the explanatory variable of interest x_j for each observation in the sample. The partial effect of a variable x_j on the unconditional expected value of *y* depends on whether x_j is an element of access equation (2) or demand equation (1), or both (Burke, 2009). First, if x_j is an element of both equations, the partial effect is:

$$\frac{dE(y)}{dx_j} = \gamma_j * f(x_1\gamma) * \left[x_2\beta + \sigma \times \lambda\left(\frac{x_2\beta}{\sigma}\right)\right] + \beta_j F(x_1\gamma) \times \left\{1 - \lambda\left(\frac{x_2\beta}{\sigma}\right)\left[\left(\frac{x_2\beta}{\sigma} + \lambda\left(\frac{x_2\beta}{\sigma}\right)\right]\right\}. \tag{4}$$

If x_j is only determining the probability of *Y* > 0 in the access Equation (1), then β_j = 0, and the second term on the right-hand side of Equation (4) disappears. If x_j is only determining the value of *Y* in the demand Equation (2), given that *Y* > 0, then γ_j = 0, and the first term on the right-hand side is dropped.

The APE for a continuous variable is then calculated as the average of the partial effects. The APE of a binary explanatory variable is calculated as the mean difference between unconditional expected value, $E(y)$, valued at the binary variable *D*=0 and *D*=1. The APE is generally of greater interest than the partial effect at the average of the sample mean, particularly in nonlinear models and in the case of discrete variables (Imbens and Wooldridge, 2008). However, the APE obtained from the control function approach outlined above cannot be used for statistical inference. Therefore the bootstrap method is used to obtain the variances of APE and their associated significance levels.

Data and descriptive statistics

The model in Equation (3) is estimated empirically using data from CSA annual agricultural sample surveys conducted in four years: 2003 to 2004, 2004 to 2005, 2006 to 2007, 2007 to 2008, covering all crop production regions of Ethiopia. More recent years are not included in the analysis because administrative border shifts substantially due to government reconstruction. The surveys are nationally representative under a stratified two-stage cluster sample design. First enumeration areas (EAs) were selected using probability proportional to the number of agricultural households from the census and adjusted for the sub-sampling effect (with the caveat that the survey does not cover the non-sedentary population in some zones). At the second stage, 25 agricultural households, households with at least one member engaged in growing crops and/or raising livestock, from each sample EA were systematically selected at the second stage. Each year more than 2,000 enumeration areas (EAs) were selected, resulting in about 50,000 agricultural households growing cereals and other annual and permanent (perennial) crops. The exact number of EAs and agricultural households covered in the survey varies slightly each year due to cost and other considerations. In the selected rural peasant households the agricultural data were collected from sedentary agricultural holders, who operate the land that is used wholly or partly for agricultural production. Unfortunately due to the nature of the survey, it is impossible to build a panel of households for analysis.

Data on crop production and agricultural practice are recorded at plot level. Information on farming practice of irrigation, using agricultural chemicals, growing a single crop (mono-cropping) and land rental access are binary variables. Extension access is defined as whether the plot under government extension programs. At holder level, variables about access to credit and advisory services are binary variables defined as whether the holder benefit from credit service and agricultural advisory services in the locality. Agricultural advisory service is related with extension but not the same because a holder can have plots not under government extension programs but still receiving advisory service from other organizations like NGOs and vice versa. Land fragmentation is represented by the number of plots operated by the holder, and crop rotation refers to whether the holder practices crop rotation or not. Gender, age, and education grade refer to the holder's demographic characteristics.

At household level, household size and total cereal area are included to capture household labor and land resources. At community level, having experience with fertilizer is defined as the share of crop area using fertilizer in total cereal area, while the importance of a particular crop is the proportion of the crop area in total cereal area. Knowledge availability in community is captured by the area share of crop land using fertilizer in the wereda (districts in Ethiopia).

Location affects technology adoption through social and agro-climatic effects, and measures of location and spatially-differentiated variables can explicitly quantify effects of spatial factors on technology uptake and land use. This survey database is complemented by spatial information, incorporating variables that reflect heterogeneity in the quality and availability of natural resources, demographic distribution, and infrastructure and market access.

The spatial variables include market access, population density, road density and land productivity at wereda level. Market access is defined as average travel time in minutes to reach a market of 50,000 or more people (CSA, EDRI and IFPRI, 2007). Road density is the ratio of the length of total road network to land area in the wereda, measured in kilometers per square kilometer (CSA, EDRI and IFPRI, 2007). The road network includes all roads in the country: motorways, highways, main or national roads, and secondary or regional roads. Population density measures the number of persons per square kilometer (CSA, 2010). Crop suitability is calculated based on agro-ecological zones to capture the quality of natural resources for production of the different crops at wereda level. It evaluates land resources and biophysical limitations and potentials for each crop, hence provides the distribution of land, classified into five suitability classes: very suitable, suitable, moderately suitable, marginally suitable and not suitable. Two variables are used to capture suitability for each of the four cereal crops. One variable is area share of highly suitable land, which is the ratio of total very suitable and suitable land in the wereda to total wereda area (EDRI, 2009). The other variable is area share of moderately to marginally suitable land, defined as the ratio of total moderately and marginally suitable land to total wereda area (EDRI, 2009).

Based on Just and Zilberman (1983), we classify explanatory variables for fertilizer access Equation (1) in the DH model and available from CSA data as follows: a) financial constraints -- access to credit; b) fixed costs of adopting the technology; and c) spatial constraints and supply-side effects. Similarly, we group variables affecting the demand of fertilizer (Equation 2) in: a) variables affecting productivity in the use of fertilizer; b) resource availability and risk related variables; and c) spatial variables affecting prices and profitability. Table 3 summarizes the variables used in the analysis.

Variables in the dataset assumed to affect access to inputs (Equation 1) include farmer's access to extension services, farmers' characteristics like gender, age and education, and the level of adoption in the district where the farmer is located (measured as the share of the crop using improved technology in total area of that crop in the district). Most of these variables are related to fixed costs incurred when adopting the new technology and result from the farmer's need to access to knowledge that would allow him/her to implement the new technology We expect a positive relationship between access to fertilizer and access to extension services, education and the level of adoption at the district level. Supply-side effects such as lack of supply, late delivery and inadequate infrastructure are captured by variables representing market access, population and road density and zonal dummies.

Variables explaining demand of fertilizer are irrigation and the use of pesticide and herbicide which we consider respectively as complementary investments and inputs that can increase

Table 3. Factors used to determine fertilizer adoption.

Type	Variable	Plot	Holder	Household	Wereda
Access to fertilizer					
Financial constraints	Access to credit		X		
Fixed costs of adoption	Access to extension	X			
	Access to advisory service		X		
	Gender		X		
	Age		X		
	Education grade		X		
	Area share of crop land using fertilizer			X	X
Spatial constraints, supply-side effects	Market access				X
	Population density				X
	Road density				X
	Zonal dummies				
	Year dummies	X			
Use of fertilizer					
Variables affecting productivity in the use of fertilizer	Irrigation	X			
	Use of pesticide and herbicide	X			
	Mono-crop in the particular plot	X			
	Crop rotation		X		
	Access to extension	X			
	Access to advisory service		X		
	Gender		X		
	Age		X		
	Education grade		X		
	Area share of crop land using fertilizer			X	X
	Area share of highly suitable land				X
	Area share of moderately to marginally suitable land				X
Resource availability and risk related variables	Household size			X	
	Total cereal area			X	
	Area share of the crop in total cereal area			X	
	Number of plots		X		
	Access to land (plot is rented)	X			
Spatial constraints, supply-side effects	Market access				X
	Population density				X
	Road density				X
	Zonal dummies				X
	Year dummies	X			

Source: Variables from CSA Agricultural Sample Survey data (various years).

productivity of fertilizer. Farmer's characteristics like gender, age and education can also affect demand of fertilizer use. Quality of natural resources measured as suitable area in the district where the farmer is located is used as an indicator of expected crop response to fertilizer. Finally, specialization in a particular crop can facilitate use and improve efficiency in the use of fertilizer. Resource availability and risk related variables are also key determinants in the adoption decision and intensity of fertilizer use. According to Coady (1995), a wealthy farmer usually exhibits decreasing absolute risk aversion but increasing relative risk aversion, meaning that the farmer will tend to use higher absolute levels of inputs but less inputs per hectare than less wealthier producers. We expect variables indicating wealth and capital availability as total area and access to additional land (renting land), to be positively related to fertilizer use, with estimated coefficients smaller than 1 if households are relative risk averse. The share of the crop in total area reflects the importance of the crop in the production system, and we expect this variable to be positively related to fertilizer use. The correlation between household size and fertilizer use should be positive for two reasons. First, we assume that fertilizer application is a labor intensive task, and with the cost of family labor being lower than that of hired labor, a positive coefficient for this variable captures this lower cost of applying fertilizer (Coady, 1995). A second explanation for a positive coefficient of household size is related to risk. With labor being a "safe" asset, compared to crop production, more family labor is equivalent to a higher level of non-stochastic assets, allowing for higher use of fertilizer.

Spatial variables like market access, population density and road density affect the level of fertilizer use through marketing and transportation margins affecting the prices that farmers pay for fertilizer and eventually also the price they receive for their products. Zonal dummies capture other specific spatial effects not captured by other variables.

Descriptive statistics

Table 4 presents descriptive statistics of explanatory variables in the DH model by group of fertilizer usage for four major cereal crops (barley, maize, teff, and wheat). The table shows substantial differences between technology adopters and non-adopters. Compared to non-adopters, adopters report larger plot size, higher yields, they are more specialized, they show higher use of pesticides and herbicides, they are younger, more educated, more experienced and wealthier than non-adopters (more oxen, crop fields and larger cereal area), and they have better access to extension, credit, advisory services, larger household size. There are also differences in the spatial location of adopters and non-adopters. Adopters tend to have better market access, improved infrastructure (higher road density), they are located in regions with higher population density, better natural endowments (crop suitability), and live in weredas where technology has disseminated broadly.

RESULTS AND DISCUSSION

Following the framework outlined in the previous section, the endogeneity of extension is addressed by a control function at plot level. The reduced form equation of endogenous explanatory variable, extension access, is regressed over exogenous variables including land rental, farming practice (mono-crop, chemical use, crop rotation, damage control and irrigation), holder characteristics (gender, age, education grade), access to credit and advisory services, household characteristics (household size, farm size, experience in fertilizer, importance of crop) and wereda fertilizer adoption level. Year dummies are used to control time variations and the error term incorporated cluster effect at EA level.

Determinants of fertilizer access

Treating extension as endogenous variable, Table 5 reports results of the econometric estimation of the DH model for fertilizer access at plot level. The first result to be noted is that of the Wald test for independent equations at the bottom of the table indicating that the extension service is endogenous in the decision making process of fertilizer adoption. Compared to the coefficients obtained under the assumption of exogenous extension, the coefficients estimated using the CF approach is smaller in the access function, but larger in the demand function. It suggests that extension service boosts the probability of having fertilizer access but does not affect the amount of fertilizer used among users. We also tested the model by checking the hypothesis that farmers make input decisions simultaneously instead of sequentially as assumed by the DH model. To do this we estimated the Tobit and the DH model separately and compared their log-likelihoods (LR test at the bottom of Table 5). We found that the log-likelihood of the DH model is significantly larger than that of the Tobit model, confirming the relative superiority of the DH specification for this dataset over the Tobit model.

Looking at the main results of the model explaining access to chemical fertilizer we find that the main explanation of access to fertilizer is the possibility of reducing the fixed knowledge cost related to adoption of the new technology, mainly through access to extension services. Also important in explaining access to fertilizer is the share of total cereal land under fertilizer both at household level and at the wereda level where the household is located, suggesting that fertilizer is more likely to be adopted in households who have already used this input in other crops, and in districts with better

Table 4. Descriptive statistics of adopters and non-adopters of fertilizer by crop and input use.

Variable	Barley		Teff		Wheat		Maize	
	Non-adopter	Adopter	Non-adopter	Adopter	Non-adopter	Adopter	Non-adopter	Adopter
Plot level								
Plot area (ha)	0.12	0.16	0.21	0.27	0.14	0.24	0.10	0.18
Plot yield (ton/ha)	1.09	1.27	0.90	1.00	1.25	1.60	1.66	2.05
Extension (yes = 1)	0.08	0.31	0.07	0.27	0.10	0.29	0.05	0.55
Irrigation (yes = 1)	0.01	0.01	0.01	0.00	0.01	0.01	0.03	0.02
Improved seed (yes = 1)	0.00	0.01	0.00	0.01	0.01	0.05	0.01	0.44
Pest. and herbicide (yes = 1)	0.02	0.12	0.06	0.14	0.05	0.18	0.01	0.02
Holder level								
Gender (male = 1)	0.85	0.84	0.88	0.87	0.86	0.85	0.83	0.87
Age	45.5	44.7	43.3	42.9	45.1	43.7	43.3	41.3
Education grade	2.1	2.8	2.2	2.8	2.3	3.0	2.4	2.8
Credit (yes = 1)	0.21	0.41	0.18	0.39	0.21	0.38	0.18	0.37
Advisory service (yes = 1)	0.47	0.51	0.45	0.54	0.47	0.50	0.38	0.58
Number of oxen	1.2	1.3	1.3	1.5	1.2	1.4	1.1	1.2
Household level								
Household size	5.37	5.82	5.31	5.66	5.36	5.76	5.28	5.68
Cereal area (ha)	0.82	1.03	0.93	1.19	0.86	1.14	0.78	0.95
Crop land using fertilizer (%)	15.5	84.0	8.9	76.7	12.7	81.8	18.8	74.6
Wereda level								
Market access (minutes)	258	230	261	239	257	233	263	248
Road density (km/km^2)	30.8	34.8	29.5	31.6	30.5	34.2	29.3	32.4
Population density (persons/km^2)	199	221	177	194	193	223	193	213
Area share of highly suitable land (%)	0.13	0.19	0.29	0.32	0.2	0.2	0.25	0.29
Crop land using fertilizer (%)	20.3	37.2	39.2	51.7	36.3	55.4	22.0	31.2

Source: Author's calculation using CSA agricultural sample survey data (various years).

access to inputs and knowledge on the new technology.

Holder's characteristics also affect household's access to fertilizer. In particular, age has a significant and negative effect on the likelihood of fertilizer adoption in the case of maize, wheat and barley, supporting the hypothesis that older holders are less likely to access the modern technology than younger holders. Accessibility is better in male-headed households than their female-headed counterparts among teff and barley farmers. No relation between access to

Table 5. Double hurdle regression estimates for fertilizer access.[a]

Variable	Maize		Teff		Wheat		Barley	
	Coefficient	P > z	Coefficient	P > z	Coefficient	P > z	Coefficient	P > z
Fertilizer access (yes=1)								
Credit (yes = 1)	-0.094	0.000	0.027	0.185	0.067	0.002	-0.115	0.000
Extension (yes = 1)	2.646	0.000	0.014	0.902	0.231	0.059	1.611	0.000
Advisory service (yes = 1)	-0.299	0.000	0.012	0.677	0.070	0.083	-0.263	0.000
Gender (male = 1)	0.013	0.527	0.093	0.000	-0.000	0.987	0.067	0.024
Age	-0.002	0.000	0.001	0.306	-0.003	0.000	-0.004	0.000
Education grade	0.004	0.173	-0.003	0.440	0.001	0.828	0.000	0.997
Area share of total crop land using fertilizer (household)	0.022	0.000	0.040	0.000	0.035	0.000	0.031	0.000
Area share of total crop land using fertilizer (wereda)	0.010	0.000	0.012	0.000	0.013	0.000	0.013	0.000
Market access (wereda)	-0.000	0.000	0.000	0.001	-0.001	0.000	-0.000	0.000
Population density (wereda)	0.000	0.048	-0.000	0.037	0.000	0.162	-0.000	0.854
Road density (wereda)	-0.001	0.000	-0.001	0.000	-0.001	0.001	-0.001	0.007
Generalized residual	-0.477	0.000	0.497	0.000	0.383	0.000	-0.449	0.000
Constant	-2.652	0.000	-2.450	0.000	-2.322	0.001	-3.827	0.000
Observations	110162		89533		60228		62026	
Log likelihood	-167.6		4820		7412		3635	
P-value of Wald test of indep. eqns. (rho = 0)	0.274	0.000	0.290	0.000	0.257	0.000	0.259	0.000
P-value of LR test of Tobit model	19983	0.000	25783	0.000	21405	0.000	12830	0.000

Note: [a] Extension is treated as an endogenous variable; Source: Author's calculation using CSA data (various years).

fertilizer and education was found.

The spatial variables included to explain access do not appear to have major impact as their coefficients are quite small. In the case of maize, the spatial effects are better captured by the zonal dummies (not reported). Access to fertilizer in maize production is more likely in the south and southwest, around Awasa and Jimma, in West Oromia, and in the zones crossed by the major road going east to Djibouti: West and East Hararge, West Arsi and Harari). Coefficients of the dummy variables in the case of teff show that farmers of some zones in SNNP and in particular in Amhara with high teff production have difficulties to access the technology. In the case of wheat, none of the coefficients of the zonal dummy variables is significant, indicating that only variables related to fix costs of the technology are relevant explaining access to fertilizer.

Determinants of fertilizer demand

Results for the estimation of the model explaining area planted using fertilizer conditional on access to fertilizer at plot level are presented in Table 6. The conditional area under fertilizer is mainly explained by: specialization in the particular crop (mono crop production at the plot level); access to inputs through extension specialist; previous knowledge and experience in cereal production (crop rotation); access to land rental market and land fragmentation; total cereal area; share of the crop in total household cultivated cereal area; and the area under fertilizer in the wereda.

The area under cereal production is positively

Table 6. Double hurdle regression estimates for fertilizer use.

Variable	Maize		Teff		Wheat		Barley	
	Coefficient	P>z	Coefficient	P>z	Coefficient	P>z	Coefficient	P>z
Area under chemical fertilizer								
Irrigation (yes = 1)	-0.049	0.216	-0.208	0.000	-0.136	0.003	-0.044	0.561
Pesticides and herbicides (yes = 1)	0.019	0.547	0.053	0.000	0.055	0.000	0.089	0.000
Mono-crop (yes = 1)	0.243	0.000	0.132	0.000	0.514	0.000	0.157	0.000
Crop rotation (yes = 1)	0.039	0.008	0.034	0.004	0.055	0.000	0.006	0.769
Extension (yes = 1)	0.187	0.005	0.102	0.005	0.071	0.097	0.148	0.017
Advisory service (yes = 1)	-0.015	0.505	-0.024	0.037	-0.014	0.363	-0.026	0.237
Gender (male = 1)	0.076	0.000	0.029	0.000	0.020	0.014	0.020	0.182
Age	0.001	0.000	0.003	0.000	0.003	0.000	0.002	0.000
Education grade	-0.007	0.000	0.001	0.114	-0.000	0.813	0.004	0.046
Area share of total crop land using fertilizer	0.000	0.525	0.000	0.045	-0.000	0.135	-0.000	0.142
Area share of total crop land using fertilizer (wereda)	0.001	0.043	-0.001	0.000	0.001	0.007	0.002	0.000
Share of highly suitable land	0.025	0.160	0.005	0.785	0.018	0.378	-0.062	0.019
Share of moderately to marginally suitable land	-0.018	0.542	-7.185	0.024	0.573	0.000	-0.098	0.082
Household size	0.000	0.783	-0.001	0.217	0.004	0.002	0.002	0.347
Cereal area of household	0.317	0.000	0.182	0.000	0.155	0.000	0.281	0.000
Share of the crop in total cereal area	0.006	0.000	0.004	0.000	0.004	0.000	0.007	0.000
Number of plots under holder	-0.047	0.000	-0.044	0.000	-0.038	0.000	-0.057	0.000
Plot is rent (yes = 1)	0.050	0.001	0.000	0.992	0.038	0.000	0.105	0.000
Market access	0.000	0.000	0.000	0.000	0.000	0.411	0.000	0.449
Population density	-0.000	0.000	-0.000	0.017	-0.000	0.001	-0.000	0.160
Road density	0.000	0.478	-0.000	0.000	-0.001	0.000	-0.001	0.000
Generalized residual	-0.041	0.290	-0.054	0.011	-0.020	0.419	-0.076	0.026
Constant	-0.676	0.000	-0.420	0.000	-0.443	0.551	-1.626	0.005
Log-likelihood	-10040.9		71.4		-30098		-16162	

Note: [a] Extension is treated as an endogenous variable; Source: Author's calculation using CSA data (various years).

associated with area using fertilizer. The coefficients of advisory services are far smaller and can be insignificant, suggesting extension is the dominants source of knowledge for holders. In addition, farmers increase fertilizer application of a particular cereal crop if the crop is important in the production system (captured by the crop's area share). Households that rent land for crop production tend to have larger area under fertilizer than those without access to land. Similar to total land under cereal production, having access to land rental market results in an increase in the area using fertilizer but a reduced share of fertilized area in total cereal land. Coefficients obtained for land rental in different crops support the hypothesis that households compensate forthe additional risk of increasing area of a crop by reducing input intensity for that crop.

In contrast with other studies (e.g. Croppenstedt et al., 2003), family size does not play a significant role determining fertilizer use. As fertilizer is assumed to be a labor intensive technology, it is expected that availability of family labor would result in higher fertilizer use. Only in the case of wheat we find that household size is positively and significantly related to area under fertilizer. A possible explanation for our results is that farmers make their decisions of the area applied fertilizer mainly based on the crop growing in the plot, and the availability of labor is not a constraint yet given the relatively low adoption rate of fertilizer.

Among holder characteristics we find that age has a positive and statistically significant effect on fertilizer demand in all crops suggesting that among adopters, farming experience is related to efficiency and adoption in the use of fertilizer, at both household and wereda level. We also find a significant effect of gender in conditioning fertilizer demand and households with more educated head exhibit higher fertilizer adoption in barley production but not in the case maize. With the exception of market access for maize and teff, the coefficients of spatial variables (crop suitability, population and road density) are negligible, indicating that biophysical and demographic conditions are not the major constraints in fertilizer adoption in Ethiopia.

Average partial effects

As identification and estimation of average effects become more complicated in the case of nonlinear models with discrete variables, as in this study, it is not easy to examine and compare the effect on fertilizer adoption from different influencing factors. The average partial effect (APE) is hence introduced to measure the average change in technology adoption due to a change in the variables of interest. We obtained average partial effects by bootstrapping the estimated model and results after 500 iterations are reported in Table 7. These results show that extension has a significant positive effect on fertilizer adoption. For example, households having access to extension can increase the average maize area under fertilizer by 0.1 ha.

The higher the share of crop area under fertilizer at household and district level the higher fertilizer use. Farmers' own skills and knowledge, represented by mono crop, crop rotation, and uses of chemicals, all contribute to the quantity of fertilizer used. APEs of variables associated with household wealth confirm that households have exhibited decreasing absolute risk aversion but increasing relative risk aversion. Fragmented land plots prevent wide adoption of technology, while on average a plot managed by a male holder tends to show higher fertilizer use, than those managed by younger female holders. APE results also suggest that although infrastructure related factors like market access, and population and road density do have an impact on fertilizer adoption, their effects are small and not comparable with the agroecological constraints defined by crop suitability.

Ranked by APE, the top three factors affecting average change in area using fertilizer are extension, mono-crop and total area for cereal production. Similarly, Extension, cereal area and mono-crop are found major contributors in changes in fertilizer adoption. Our results are consistent with previous studies on fertilizer adoption in Ethiopia, especially in the role of extension and farmers' experience.

Conclusion

Extension services have played a central role in facilitating access to the promoted technology, as it is the instrument to disseminate new technology package including seed, fertilizer and new farming practice. Ethiopia's agricultural extension system is one of the largest in the world, with over 60,000 development agents working in nearly 10,000 farmer training centers throughout the country. This paper aims to understand the extent and determinants of fertilizer adoption in the country. A double hurdle model is chosen, which allows us to analyze separately the factors affecting access of farmers to the new technology and demand for fertilizer conditional to access in a sequential approach, addressing the endogeneity of extension service. Built on the framework of Asfaw et al. (2011), the study is the first to estimate fertilizer adoption using nationally representative data from Ethiopia Agricultural Sample

Table 7. Average partial effects of factors on chemical fertilizer adoption.

Average increase in area under fertilizer (ha)	Maize		Teff		Wheat		Barley	
	APE	t-value	APE	t-value	APE	t-value	APE	t-value
Variables in both demand and access equations								
Extension (yes = 1)	0.1007	7.9	0.0209	2.6	0.0184	2.2	0.0342	5.4
Advisory service (yes = 1)	-0.0056	-4.0	-0.0043	-2.0	-0.0012	-0.4	-0.0046	-3.7
Gender (male = 1)	0.0040	5.5	0.0072	4.7	0.0034	0.9	0.0017	1.9
Age	0.0000	0.9	0.0005	8.4	0.0004	6.9	0.0001	3.3
Education grade	-0.0003	-3.2	0.0002	0.9	-0.0001	-0.2	0.0002	1.6
Area share of total crop land using fertilizer (household)	0.0004	22.6	0.0010	36.4	0.0007	22.5	0.0004	22.1
Area share of total crop land using fertilizer (wereda)	0.0002	11.8	0.0001	4.9	0.0003	10.7	0.0003	16.4
Market access	0.0000	1.1	0.0000	10.8	0.0000	-1.1	0.0000	-1.2
Population density	0.0000	-2.2	0.0000	-3.0	0.0000	-0.4	0.0000	-1.0
Road density	0.0000	-0.7	-0.0001	-5.6	-0.0002	-3.8	-0.0001	-5.7
Variables in demand equation only								
Irrigation (yes = 1)	-0.0024	-1.1	-0.0319	-5.9	-0.0212	-3.4	-0.0019	-0.6
Pesticides & herbicides (yes = 1)	0.0010	0.5	0.0099	6.1	0.0092	5.8	0.0043	5.3
Mono-crop (yes = 1)	0.0135	12.6	0.0243	3.5	0.0928	9.7	0.0074	4.0
Crop rotation (yes = 1)	0.0020	1.8	0.0060	2.2	0.0085	2.4	0.0003	0.3
Share of highly suitable land	0.0013	1.3	0.0009	0.3	0.0035	0.9	-0.0028	-2.1
Share of moderately to marginally suitable land	-0.0009	-0.5	-1.3125	-2.5	0.0876	4.4	-0.0045	-1.6
Household size	0.0000	0.2	-0.0002	-1.1	0.0006	1.5	0.0001	0.8
Cereal area of household	0.0166	18.4	0.0332	33.5	0.0267	30.8	0.0129	24.1
Share of the crop in total cereal area	0.0003	29.7	0.0008	34.5	0.0008	31.8	0.0003	28.1
Number of plots under holder	-0.0025	-16.7	-0.0081	-18.7	-0.0065	-25.1	-0.0026	-19.4
Plot is rent (yes = 1)	0.0027	3.1	0.0000	0.0	0.0067	4.6	0.0052	6.1

Source: Author's calculation using CSA data (various years).

Surveys while considering model endogeneity using a control function approach.

The major findings are presented below, centered on the impact of extension. First, statistical tests allow us to examine several theoretical and methodological assumptions laid out at the start of the study. The studyconfirms the endogeneity of extension service in the decision making process of fertilizer adoption. Log-likelihood test also indicates that farmers make input decisions sequentially, not simultaneously, highlighting the relative superiority of the DH specification for this analysis. Average partial effect from bootstrapping process is appropriate in inspecting the unconditional effects of factors that influence the adoption process because it is especially helpful in cases when there are observations with zero values for input use.

Second, extension service boosts fertilizer use, which corroborates with many other studies on fertilizer adoption in Ethiopia (Beshir et al., 2012; Carlsson et al., 2005; Wubeneh and Sanders, 2006; Noltze et al., 2012). Extension not only increases the probability of adoption fertilizer but

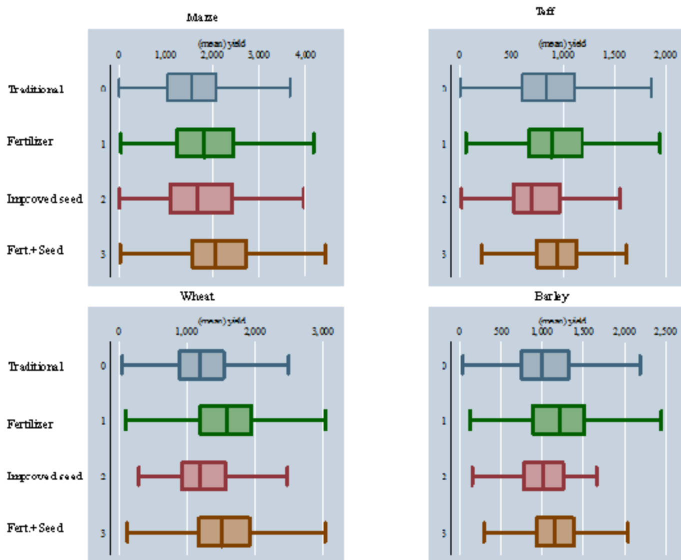


Figure 3. Yield distributions of cereals at the plot level different input combinations (average values 2003-2007 in kilograms per hectare); Source: Author's computation using CSA agricultural sample survey data.

expand the area planted using fertilizer conditional on access to fertilizer. Farmers face a high "knowledge" cost related to adoption of new technology and extension services helps cut the adoption cost (Asfaw and Admassie, 2004). Education and past experience can also effectively lower the adoption barrier and hence promote the diffusion of new technology, which were also identified in earlier studies by Admassie and Ayele (2004) and Beshir et al. (2012). Other factors affects fertilizer use includes household wealth, access to land rental market, land fragmentation and the importance of the crop in the production system.

Third, similar to Dercon and Christiaensen (2011), risk aversion behavior can have a considerable impact on farmer's fertilizer adoption decision. Having access to land rental market can increase the area using fertilizer but reduce the share of fertilized area in total cereal land, suggesting that households compensate for the additional risk of increasing area of a crop by reducing input intensity for that crop. In addition, variables associated with household wealth confirm that households have exhibited decreasing absolute risk aversion but increasing relative risk aversion.

Fourth, spatial variables obtained through GIS tools are introduced in the analysis to capture of biophysical constraints and infrastructure factors like crop suitability and market access. Although we find market access and road density do have an impact on fertilizer adoption, their effects are small and not comparable with the agroecological constraints defined by crop suitability and other local agronomic and development conditions (Diao and Nin-Pratt, 2005; Tadesse et al., 2006). Substantial yield gain in maize and teff can be achieved if technology is provided through a locally tailored extension package. This translates into the need of an extension package focusing on improving access to technological packages that are adapted to local agroecological conditions to fully realize the potential.

Although the results of this analysis highlight the important role and great potential of extension in the development of Ethiopia agriculture, the impacts of the strategy to raise cereal production and yields through extension have been mixed, as fertilizer use increased but access to extension and productivity growth remain low among farmers in the country. Some potential constraints could compromise the effectiveness of the extension system, including service mismatching farmers' need, deficiency of resources, low capabilities and knowledge of extension workers and lack of transparency and motivations. Readers can refer to Davis et al. (2010) for detailed discussion on these constraints.

One problem observed from the data and that it is not necessarily captured by the DH model is the great yield variability among producers using fertilizers (Figure 3). First, the median of the yield distribution obtained using fertilizer + seed in maize and wheat is larger than that of the traditional technology but far from the expectations that the authorities had of doubling yields when the program was launched. Second, the highest yields (the 90th percentile of the distribution) are close to those obtained in trials and experiments during the first face of PADETES (3,700 kg/ha in maize and close to 3,000 kilograms per hectare in wheat). Reducing the high variability observed in yields with fertilizer+seed technology should result in movements of the mean and median of the yield distribution closer to what today are "frontier" values (high yield) resulting in improved conditions and incentives to adopt the technology. Third, median yields obtained in teff and barley using fertilizer technology are low and similar to those obtained using the traditional technology, with frontier values in the improved technology being much lower than those obtained with the traditional technology. This suggests that availability of improved varieties in teff and barley is still a major constrain to increase yields and that the only technical alternative to the traditional technology is the use of chemical fertilizer. The possibilities of increasing yields of these crops using fertilizer only are quite limited.

Conflict of Interests

The author(s) have not declared any conflict of interests.

ACKNOWLEDGEMENTS

The authors acknowledge the significant contribution of José Funes and Sinafikeh Asrat Gemessa to an early version of this paper.

REFERENCES

Abebaw D, Haile MG (2013). The impact of cooperatives on agricultural technology adoption: Empirical evidence from Ethiopia. Food Policy 38:82–91. http://dx.doi.org/10.1016/j.foodpol.2012.10.003

Admassie A, Ayele G (2004). Adoption of improved technology in Ethiopia. Addis Ababa, Ethiopia: Ethiopia Development Research Institute. PMid:16895031

Asfaw A, Shiferaw B, Simtowe F, Haile MG (2004). Agricultural technology adoption, seed access constraints and commercialization in Ethiopia. J. Dev. Agric. Econ. 3(9):436-447.

Beshir H, Emana B, Kassa B, Haji J (2012). Determinants of chemical fertilizer technology adoption in North eastern highlands of Ethiopia: the double hurdle approach. J. Res. Econ. Int. Finan. 1(2):39-49.

Burke WJ (2009). Fitting and interpreting Cragg's tobit alternative using Stata. The Stata J. 9(4):584-592.

Byerlee D, Spielman DJ, Alemu D, Gautam M (2007). Policies to promote cereal intensification in Ethiopia: A review of evidence and experience. Discussion Paper 00707. Washington, DC: International Food Policy Research Institute.

Carlsson F, Kohlin G, Mekonnen A, Yesuf M (2005). Are agricultural extension packages what Ethiopian farmers want? A stated preference analysis. Working Papers in Economics. Department of Economics, Goteborg University. P. 172.

Coady DP (1995). An empirical analysis of fertilizer use in Pakistan. Economica 62:213–234. http://dx.doi.org/10.2307/2554904

Cragg JG (1971). Some statistical models for limited dependent variables with applications to the demand for durable goods. Econometrica 39:829–844. http://dx.doi.org/10.2307/1909582

Croppenstedt A, Demeke M, Meschi M (2003). Technology adoption in the presence of constraints: The case of fertilizer demand in Ethiopia. Rev. Dev. Econ. 7(1):58-70. http://dx.doi.org/10.1111/1467-9361.00175

CSA. Various years. Annual agricultural sample survey (database). Central Statistical Agency. Last accessed September 2011, http://www.csa.gov.et/

CSA, EDRI and IFPRI. 2007. Atlas of Ethiopia Population and Housing Census. Central Statistical Agency, Ethiopian Development Research Institute, and International Food Policy Research Institute, Addis Ababa, Ethiopia.

Davis K, Swanson B, Amudavi D, Mekonnen DA, Flohrs A, Riese J, Lamb C, Zerfu E (2010). In-depth assessment of the public agricultural extension system of Ethiopia and recommendations for improvement. Discussion Paper 01041. Washington, DC: International Food Policy Research Institute.

Dercon S, Christiaensen L (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. J. Dev. Econ. 96(2):159-173. http://dx.doi.org/10.1016/j.jdeveco.2010.08.003

Diao X, Nin -Pratt A (2005). Growth options and poverty reduction in Ethiopia: A spatial, economy-wide model analysis for 2004-15. DSGD Discussion, Washington, DC: International Food Policy Research Institute. P. 20.

EDRI (2009). Crop suitability analysis– agroecological zones. Addis Ababa, Ethiopia: Ethiopian Development Research Institute.

Holden ST, Shiferaw B, Pender J (2001). Market imperfections and land productivity in the Ethiopian highland. J. Agric. Econ. 52(3):53–70. http://dx.doi.org/10.1111/j.1477-9552.2001.tb00938.x

Howard J, Crawford E, Kelly V, Demeke M, Jeje JJ (2003). Promoting high-input maize technologies in Africa: The Sasakawa-Global 2000 experience in Ethiopia and Mozambique. Food Policy 28:335–348. http://dx.doi.org/10.1016/j.foodpol.2003.08.008

Imbens G, Wooldridge JM (2008). Control function and related methods. Applied Microeconometrics Workshop Lecture Notes.

Just RE, Zilberman D (1983). Stochastic structure, farm size, and technology adoption in developing agriculture. Oxford Econ. 35(2):307–328.

Liverpool-Tasie LSO, Winter-Nelson A (2009). Poverty Status and the Impact of Formal Credit on Technology Use and Wellbeing among Ethiopian Smallholders. World Dev. 38(4):541–554. http://dx.doi.org/10.1016/j.worlddev.2009.11.006

Liverpool-Tasie LSO, Winter-Nelson A (2012). Social Learning and Farm Technology in Ethiopia: Impacts by Technology, Network Type, and Poverty Status. J. Dev. Stud. 48(10):1505–1521. http://dx.doi.org/10.1080/00220388.2012.693167

Noltze M, Schwarze S, Qaim M (2012). Understanding the adoption of system technologies in smallholder agriculture: The system of rice intensification (SRI) in Timor Leste. Agric. Syst. 108:64-73. http://dx.doi.org/10.1016/j.agsy.2012.01.003

Pender J, Kerr JM (1998). Determinants of farmers' indigenous soil and water conservation investments in semi-arid India. Agri. Econ. 19:113–125.http://dx.doi.org/10.1016/S0169-5150(98)00026-7

Rivers D, Vuong QH (1988). Limited information estimators and exogeneity tests for simultaneous probit models. J. Econometr. 39:347-366. http://dx.doi.org/10.1016/0304-4076(88)90063-2

Shiferaw BA, Kebede TA, You L (2008). Technology adoption under seed access constraints and the economic impacts of improved pigeonpea varieties in Tanzania. Agric. Econ. 39:309-323.

Tadesse M, Alemu B, Bekele G, Tebikew T, Chamberlin J, Benson T (2006). Atlas of the Ethiopian Rural Economy. Addis Ababa, Ethiopia: Ethiopian Development Research Institute.

Wubeneh NG, Sanders JH (2006). Farm-level adoption of sorghum technologies in Tigray, Ethiopia. Agri. Systems 91:122-134. http://dx.doi.org/10.1016/j.agsy.2006.02.002

World Bank (2006). Ethiopia: Policies for pro-poor agricultural growth. Washington, DC.