ETHIOPIA
Strategy Support Program

ETHIOPIAN DEVELOPMENT RESEARCH INSTITUTE

EDRI

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

IFPRI

A member of the CGIAR Consortium

ESSP WORKING PAPER 82

Understanding Farmers' Technology Adoption Decisions: Input Complementarity and Heterogeneity

Kibrom A. Abay, Guush Berhane, Alemayehu Seyoum Taffesse, Bethelhem Koru and Kibrewossen Abay

February 2016

TABLE OF CONTENTS

LIST OF TABLES

ABSTRACT

Agriculture growth in Africa is often characterized by low aggregate levels of technology adoption. Recent evidence, however, points to co-existence of substantial adoption heterogeneities across farm households and a lack of a suitable mix of inputs for farmers to take advantage of input complementarities, thereby limiting the potential for learning towards the use of an optimal mix of inputs. We use a detailed large longitudinal dataset from Ethiopia to understand the significance of input complementarities, unobserved heterogeneities, and dynamic learning behavior of farmers facing multiple agricultural technologies. We introduce a random coefficients multivariate probit model, which enables us to quantify the complementarities between agricultural inputs, while also controlling for alternative forms of unobserved heterogeneity effects. The empirical analysis reveals that, conditional on various types of unobserved heterogeneity effects, technology adoption exhibits strong complementarity (about 70 percent) between chemical fertilizers and improved seeds, and relatively weaker complementarity (between 6 and 23 percent) between these two inputs and extension services. Stronger complementarities are observed between specific extension services (advice on land preparation) and improved seed and chemical fertilizers, as opposed to simple visits by extension agents, suggesting that additional benefits can be gained if the extension system is backed by "knowledge" inputs and not just focus on "nudging" of farmers to use these inputs. The analysis also uncovers substantial unobserved heterogeneity effects, which induce heterogeneous impacts in the effect of the explanatory variables among farmers with similar observable characteristics. We also show that ignoring these behavioral features bears important implications in quantifying the effect of some policy interventions which are meant to facilitate technology adoption. For instance, ignoring these features leads to significant overestimation of the effectiveness of extension services in facilitating technology adoption. We also document strong learning behavior, a process that involves learning-by-doing as well as learning from extension agents.

***Key words*:** Technology adoption, input complementarity, unobserved heterogeneity, technology adoption dynamics, random coefficients multivariate probit, maximum simulated likelihood approaches.

JEL code: C35, D01, Q16

1. INTRODUCTION

Increasing agricultural productivity through adoption and diffusion of modern agricultural technologies is one of the key pathways for economic growth and agricultural transformation in developing countries (Evenson and Gollin 2003: Gollin 2010).[1] This is particularly relevant for many sub-Saharan Africa countries where the agricultural sector dominates and is characterized by low productivity. While several African countries have devoted substantial resource to agricultural developments in recent years, aggregate technology adoption trends remain low (Minot and Benson 2009; Byerlee et al. 2007; Rashid et al. 2013; Sheahan and Barrett 2014). A large body of literature points to a wide range of factors limiting technology adoption in Africa. For example, Moser and Barret (2006), Gine and Klonner (2007), Duflo et al. (2011), and Minten et al. (2013) all indicate that credit constraints, transaction costs, and other market imperfections are central to the slow adoption of agricultural technologies.[2]

Despite the substantial research devoted to understanding technology adoption in sub-Saharan Africa and elsewhere, what explains the low adoption levels of seemingly profitable agricultural technologies in many African countries remains an empirical puzzle. A salient feature of recent public agricultural investments in Africa has been the renewed interest and importance placed on public extension systems and providing inputs in packages. The underlying reason for providing packaged inputs is the generic presumption that potential complementarities can be exploited by adopting two or more modern inputs together. For example, most improved seed varieties are expected to provide high yield responses when used with chemical fertilizers (Ellis 1992; Nyangena and Juma 2014). An important step to understanding the low adoption puzzle is quantifying the extent to which packaged inputs can be complementary (both in agronomic responses as well as the

[1] Some studies even attribute the sharp differences in agricultural productivity growth among Asian countries and many African countries to the intensification of modern agricultural inputs, particularly fertilizer use (see Morris et al. 2007).

[2] Many other studies (including Foster and Rosenzweig, 1995; Bandiera and Rasul 2006; Conley and Udry 2010; Foster and Rosenzweig 2010, and Krishnan and Patnam 2014) emphasize the importance of social learning. In the case of Ethiopia, low-levels of chemical fertilizer and improved seed adoptions are commonly attributed to supply-related constraints (Croppenstedt et al. 2003; Byerlee et al. 2007; Dercon and Hill 2009; Davis et al. 2010; Spielman et al. 2011).

perception of these packaged inputs by adopters), and the implication of these complementarities in explaining this puzzle. Clearly, this is an empirical question that varies with contexts, and therefore remains poorly understood in many of the environments where adoption is low.[3] Moreover, even if farmers perceive that a package of technology provides higher rates-of-return than would otherwise be provided when different technologies are used individually, given imperfect input markets and credit constraints, these farmers may be forced to adopt technologies sequentially rather than simultaneously (Feder 1982; Leathers and Smale 1991; Khanna 2001). This implies that the notion and extent of input complementarity may vary (correlate) with intrinsic observed and unobservable heterogeneities among farm households.

Most previous studies to understand technology adoption have focused on explaining single-input adoption decisions and on establishing causal relationships among various input uses and technology adoption decisions with little attention to the complex nature of adoption in the face of complementarities between inputs. Such studies are often prone to methodological challenges related to the nature of adoption decisions, and hence may produce biased estimates. There are at least three potential problems with these univariate approaches. First, these univariate studies often suffer from endogeneity and simultaneity problems, while also providing an incomplete picture of farmers' adoption decisions in the face of a mix of possible inputs. Second, even if multivariate approaches are considered to account for multiple adoption decisions, the presence of (potential) unobserved heterogeneities among farm households confound the estimation of complementarities among various technologies. Some of these unobserved heterogeneities among farmers might be driven by differences in the rates-of-return to technology adoption (Marenya and Barrett 2009; Suri 2011) or differences in (risk) preferences (Isik and Khanna 2003; Liu 2013). Ignoring such unobservable heterogeneities among farmers may lead to inconsistent estimates and biased inferences (Chamberlin 1980; McFadden and Train 2000). Third, most existing studies on technology adoption are based on cross-sectional studies which makes disentangling input complementarities and unobserved heterogeneity effects difficult.

The objective of this paper is to investigate farmers' multidimensional technology adoption decisions in the presence of heterogeneities across households. We aim to quantify potential complementarities among inputs and alternative forms of unobserved heterogeneities among households. Quantifying complementarities among alternative inputs is crucial because these effects are potentially correlated with some other observable and unobservable factors that affect households' adoption decisions.[4] From a policy perspective, quantifying these complementarities while controlling for potential unobserved heterogeneities can provide some input to designing effective technology diffusion strategies. We focus on three agricultural inputs in Ethiopia – chemical fertilizers, improved seeds, and extension services.

Ethiopia provides an interesting context and a typical example of the empirical puzzle described earlier. Ethiopia has consistently invested more than 10 percent of its total budget on agriculture in the last decade and has now one of the largest frontline extension worker-to-farmer-ratio in the world (Davis et al. 2010; Bachewe et al. 2015). Ethiopia's extension system is strongly synchronized with input distribution to households, mainly chemical fertilizers and improved seeds. However, despite such revitalized focus on agriculture and widespread availability of improved technologies, the aggregate adoption rates of these technologies remain low (for example, only 53 percent and 19 percent of households in our sample used fertilizer and improved seeds in 2013, respectively). Moreover, evidence suggests that there exists substantial heterogeneity both in terms of take-up rates as well as in the choice of mix of technologies among households, even within similar biophysical endowments (Sheahan and Barrett 2014). Explaining these heterogeneities in adoption decisions and the nature of the mix of technologies adopted, as well as the implication of such heterogeneities in explaining the empirical puzzle associated with the low adoption of seemingly profitable agricultural technologies, remain crucial for policy makers to explore in Ethiopia.

To address the econometric problems described, we propose a random coefficients multivariate probit model, which accommodates alternative forms of unobserved heterogeneity effects, input complementarities among alternative technologies, and dynamics in technology adoption in a unified framework. We use a large longitudinal dataset that covers the most important crop agricultural zones in Ethiopia. The longitudinal nature of this data enables us to accommodate alternative forms of unobserved heterogeneity effects through random effects and random coefficients specifications in the

[3] Sheahan and Barrett (2014) report invariably "low correlations between commonly paired modern inputs" across six countries – Ethiopia, Malawi, Niger, Nigeria, Tanzania and Uganda.

[4] For instance, one reason why wealthier households, measured in terms of landholding and livestock ownership, are more likely to adopt conventional agricultural technologies is potentially because these households are able to complement their production function with other complementary inputs that may enhance the profitability of a particular technology (Barham et al. 2004; Duflo et al. 2008).

underlying technology adoption propensity equation. Beyond quantifying the extent of input complementarities and alternative forms of unobserved heterogeneities, our stylized model provides several advantages over the univariate studies in the literature. First, the unified modeling framework enables us to uncover some of the behavioral mechanisms that explain adoption decisions in a multi-input framework with potential synergistic advantages. Second, the availability of a large panel data set allows us to account for potential endogeneity of some of the variables of interest, such as the allocation and provisions of extension services, which may be driven by adoption potentials.[5] To minimize some of the endogeneity problems, we employ the lag of extension visits instead of contemporaneous visits, while our multivariate specification also captures common unobserved factors that affect multiple adoption decisions of farmers. Thus, our comprehensive model specification and the longitudinal data we use facilitate causal inference on alternative policy interventions, such as the effectiveness of extension services.

The estimation results reveal several important findings. First, we find that adoption decisions exhibit strong complementarity between fertilizer and improved seeds, but relatively weaker complementarities between extension services and the other two inputs. Second, the analysis uncovers substantial unobserved heterogeneity effects which are correlated with the commonly observable characteristics of farm households that affect technology adoption decisions, suggesting heterogeneous effects of these explanatory variables on adoption decisions of farmers. Finally, we show that ignoring these unobserved heterogeneities and complementarity effects leads to significant biases in estimates with implications for policy and program design. For example, ignoring these behavioral effects leads to substantial overestimation of the effectiveness of extension services in facilitating technology adoption. In sum, our results suggest that the conventional technology diffusion and extension systems based on a single production function might not explain farmers' technology adoption process.

The rest of the paper is organized as follows. Section 2 provides a brief discussion on input complementarities, unobserved heterogeneity effects, dynamics in technology adoption, and their implications. Section 3 discusses the institutional context of the study area and the data used for the analysis. In Section 4 we present the empirical model and its specifications, while Section 5 discusses the empirical findings. Section 6 demonstrates the implications of ignoring the behavioral features and specification issues that we address in this article. Section 7 provides concluding remarks and policy implications.

2. MULTIPLE TECHNOLOGY ADOPTION DECISIONS AND UNOBSERVED HETEROGENEITY

Increasing agricultural productivity requires multiple inputs and technologies, placing farm households in a multidimensional adoption decision problem. Understanding the complex behavioral patterns underlying the use of these inputs can help policy makers adopt better designs. There are some theoretical foundations explaining how and why farm households choose among available sets of technologies. For instance, assuming that farm households are rational (Schultz 1964; Duflo 2003), they are expected to choose a combination of inputs (or technologies) that maximize their expected profits.[6] This gives rise to the commonly assumed input complementarity argument, a package of technologies may provide higher productivity than would otherwise be provided when different pieces of technology are used individually (Feder 1982). However, Feder (1982) also emphasizes that pervasive uncertainty about a new technology, as well as binding credit constraints, may confound this notion of complementarity. This leads to another type of explanation, namely ''sequential learning'', advanced by Leathers and Smale (1991), and Khanna (2001). This is also consistent with the notion of learning-by-doing, described in Beseley and Case (1993), and Ma and Shi (2014).

The above arguments imply at least two important points: first, farmers' multiple adoption decisions should be considered jointly since they are inter-related. Dorfman (1996) is probably the first to propose joint modeling of multiple technology adoption decisions. Second, even with joint models, unobserved heterogeneity may confound the identification of these complementarities and learning processes. This implies that quantifying input complementarity may require richer (longitudinal) data and innovative approaches, while most existing studies on technology adoption in developing countries

[5] See some discussion on this in Dercon et al. (2009) and Ragasa et al. (2013). These studies emphasize that it is even difficult to predict the direction of bias associated with the endogeneity of extension services. This implies that the existing studies who attempt to quantify the impact of extensions services on fertilizer and improved seed adoption may provide biased estimates on the effectiveness of extension services.

[6] The view that farmers are ''poor but efficient'' is not uncontested. Duflo (2003) argues that the existing low level of adoption of seemingly profitable agricultural technologies in Africa is not consistent with this view.

are based on cross-sectional data. These cross-sectional studies conceal important unobserved heterogeneity effects in farmers' technology adoption decisions, while also ignoring important dynamics in technology adoption. More specifically, most studies typically make an *a priori* assumption that the effects of explanatory variables do not vary across farm households. However, household-specific unobserved factors related to the explanatory variables considered in the empirical analysis may induce heterogeneous effects across households (Holden 2014). Some of these household-specific unobserved factors may include differences in returns to a specific technology adoption or households' risk-taking behavior (or taste) for a new agricultural technology. For instance, Suri (2011) finds that the rate-of-return to hybrid maize adoption significantly varies across Kenyan farm households and shows that those households with low returns do not adopt it. Using Kenyan data, Marenya and Barrett (2009) also find that, while the average rates-of-return to fertilizer application is positive, fertilizer application is not profitable for around 30 percent of farm plots with low carbon content.

Furthermore, the adoption of a new technology involves some risk and uncertainty about its productivity. This is particularly plausible given that rural livelihoods in Ethiopia involve substantial risk and uncertainties due to adverse weather conditions (Dercon and Christiaensen 2011). Thus, households' preferences and risk taking behavior, which are commonly unobserved (or difficult to measure) but potentially correlated with other observable characteristics of households, can affect their adoption decisions (Knight et al. 2003; Isik and Khanna 2003; Liu 2013). For instance, Feder et al. (1985) argue that the effect of farm size on technology adoption is expected to vary with risk aversion, which is commonly unobserved and difficult to properly capture in surveys. This suggests that the effect of land size on technology adoption could be heterogeneous across households with heterogeneous risk aversion. More generally, these heterogeneities, which are unobservable by the analyst (or difficult to measure), are expected to be correlated with some of the observable characteristics that affect adoption decisions. This implies that these observable factors induce heterogeneous impacts on households' technology adoption decisions.

Methodologically, pervasiveness of such sources of heterogeneity naturally calls for a flexible empirical model that allows for various forms of heterogeneities across farm households. This is particularly appealing given that the sources of the above heterogeneities are not always clear, and hence, as discussed above, cannot be captured in observational datasets. Longitudinal datasets are more suited to address such type of unobserved heterogeneity effects as they allow for accommodating random effects and random coefficients in the underlying technology adoption propensity equation. This study builds an empirical model that accounts for three related concepts in the dynamics of technology adoption processes: (a) input complementarity, (b) unobserved heterogeneity and (c) dynamics in technology adoption decisions. The proposed random coefficients multivariate probit model encompasses these three effects in a unified framework. The longitudinal nature of the data enables us to estimate households' dynamics (learning behavior) in technology adoption by including cross-input lags of adoption decisions. Thus, our comprehensive specification provides interesting insights that would otherwise be impossible to extract from existing univariate studies, while also facilitating causal inference on alternative policy interventions.

3. INSTITUTIONAL CONTEXT, SAMPLING DESIGN, AND THE DATA

The empirical analysis in this article focuses on multiple input adoption decisions of farm households in Ethiopia. Ethiopia provides an interesting context in which to understand this question. The Government of Ethiopia has implemented consecutive growth plans that prioritized agriculture as a fundamental springboard to ignite economic growth in the country. At the center of these agricultural growth plans is the development agent (DA) -led public extension system that stretches from federal to *kebele* levels, deploying about three DAs in each of Ethiopia's approximately 15 thousand *kebeles*. [7] The extension system is also strongly synchronized with input distribution parastatals, mainly chemical fertilizers and improved seeds. DAs deliver a package of extension services ranging from land preparation to fertilizer and improved seed. However, the system is best known for its primary focus on input distribution and for persuading farmers to adopt these technologies, rather than on knowledge transfer through extension. Overall, despite visible progresses in recent years, Ethiopia's agricultural intensification measured in terms of fertilizer and improved seed use remains one of the lowest (Byerlee et al. 2007; Minot and Benson 2009; Rashid et al. 2013). Explaining the low levels of agricultural intensification, the substantial heterogeneities in adoption decisions, and the nature of the mixes of technologies adopted requires further research.

[7] *Kebele* is the smallest administrative unit in Ethiopia and it corresponds to peasant association or village.

Similarly, while the government continues to invest substantial resource on agricultural extension services, there is limited evidence on the effectiveness of extension services on technology adoption.[8]

The empirical analysis in this study is based on a large longitudinal dataset collected for evaluating Ethiopia's Agricultural Growth Program (AGP). This data was collected by the Central Statistical Agency (CSA) of Ethiopia and the International Food Policy Research Institute (IFPRI), and covers around 7500 farm households visited twice in two rounds (2011 and 2013). The AGP, for which the first five-year program ran between 2010-2015, focuses on Ethiopia's high agricultural potential zones in 83 targeted *woredas* with a primary objective of increasing agricultural productivity and market access for key crops and livestock products.[9] The survey sampling design involved three steps. First, 61 *woredas* were randomly selected from among the 83 AGP *woredas* in the four main regions of the country, namely Amhara, Oromiya, Southern Nations, Nationalities and Peoples (SNNP), and Tigray. Similarly, 32 *woredas* were randomly selected from among non-AGP high potential *woredas* in the same regions comparable to the AGP-*woredas.* Second, three Enumeration Areas (EAs) were randomly chosen from among all EAs in each *woreda*. The third step involved a random selection of 26 households from each EA. This was done based on a fresh listing of households residing within each selected EA and then selecting households randomly until the desired number and composition of households was obtained.

The AGP data has interesting features that are well-suited for pursuing rigorous investigation on the dynamics of households' agricultural technology adoption decisions. The survey covers the most important agricultural areas in the country, giving us a unique opportunity to analyze the issue at hand.[10] It contains detailed household-level information on household characteristics, endowments, and access to and use of extension services and inputs. It also contains plot-level information on soil quality, topography, cropping patterns, and input use. These data also bring a wealth of detailed community-level information, such as the extent to which extension services are spread in localities, access to input and output markets, and agro-climatic conditions. Unlike many other studies in the literature which are based on small scale interventions, the AGP data cover a large sample and a wide geographical area, which are essential for providing substantial variation in input use and adoption decisions.

In this article we are interested in investigating how farm households make their adoption decisions when multiple technologies or inputs are available. We specifically focus on three inter-related agricultural inputs: chemical fertilizer, improved seed, and extension services. We measure extension services in two ways. First, as is commonly used in such studies, we use development agents' visits, represented by an indicator variable showing whether a household has been visited by extension agents. As a second indicator, we use households' use of extension services outside the scope of technology adoption, by using an indicator variable for households receiving advice on land preparation from DAs. Using both measures of extension service enables us to triangulate the estimation of complementarity effects driven by the extension system, as well as the complementarity effects driven by households' choice of production technology.

Table 3.1: Technology adoption rates in the sample

Input (technology type)	2011	2013
Chemical fertilizer use (%)	56.9	53.3
Improved seed (%)	23.2	19.1
Extension visit (%)	33.3	42.3
Household received advice from DAs on: land preparation (%)	41.4	38.2
Planting seed (%)	42.4	39.4
Chemical fertilizer application (%)	42.8	40.2
Correlation between fertilizer and improved seed use	0.41***	0.33***
Correlation between fertilizer and extension service (DA visit)	0.21***	0.18***
Correlation between improved seed use and extension service (DA visit)	0.20***	0.14***
Correlation between fertilizer and extension service (advice on land preparation)	0.24***	0.31***
Correlation between improved seed and extension (advice on land preparation)	0.24***	0.23***
Number of observations (households)	*7,381*	*7,381*

Notes: Tabulated cell values are adoption rates given in percentages.*** indicates that pairwise correlations are statistically significant at 1 percent.

[8] The impact of extension services on technology adoption and productivity is generally mixed (see Davis 2008; Benin et al. 2011; Krishnan and Patnam 2014).

[9] *Woreda* is the administrative unit in Ethiopia that corresponds to district. The EA is a statistical area that is representative of the *kebele*.

[10] Not represented in the data used for this analysis are those collected from farm households in drought-prone, low-potential areas, or with unique agro-climatic conditions often unsuitable for agriculture and technology adoption?

In Table 3.1 we present the adoption rates of the three inputs for both rounds (2011 and 2013) of the AGP data. Around 57 percent of farm households applied chemical fertilizer in the first survey while the corresponding figure for the second survey is around 53 percent.[11] The adoption of the other inputs, improved seed and extension services, are rather low compared to the fertilizer adoption rate. But these figures are consistent with adoption rates reported in other studies on Ethiopia (Krishnan and Patnam 2014). It is interesting to note also that the results in Table 3.1 are fairly stable across both rounds. The slight reduction in fertilizer and improved seed adoption in the second round might be attributable to some localized droughts observed in some parts of Ethiopia in 2012. Table 3.1 shows that between 38 and 41 percent of households received DA advice on land preparation. Similarly, between 39 and 42 percent of households received advice on fertilizer application. These simple figures suggest that fertilizer and improved seed applications may also trigger the use of extension services, a problem that plagues the identification of the causal effect of extension services on technology adoption. Our survey provides a wealth of detailed information on households' past and current input use and technology adoption decisions, which enables us to effectively quantify the dynamics of learning effects within a panel structure.

As discussed in Section 2, the notion of complementarity among alternative technologies implies that the profitability of a specific agricultural technology (or a perception of it) depends on the adoption of another technology (Barham et al. 2004). Assuming that adoption rates are ''revealed'' decisions driven by the profitability of a specific agricultural technology or a perception of it, we provide bivariate adoption rates for fertilizer and improved seed use in Table 3.2. These descriptive bivariate adoption rates show that around 36 percent of households applied chemical fertilizer without using improved seed, while the reverse amounts only to 2 percent. These unconditional bivariate adoption decisions may suggest that using improved seed without chemical fertilizer is probably not profitable (or at least not perceived to be profitable by farmers) in the Ethiopian context.

Table 3.2: Bivariate adoption rates of chemical fertilizer and improved seed, %

Chemical fertilizer	Improved Seed		
	No	Yes	Total
No	42.9	2.0	44.9
Yes	35.9	19.2	55.1
Total	78.8	21.2	100.0

Source: Authors' analysis of AGP survey data. Observations = 14,762.

Previous studies have shown that demographic characteristics of households, including gender and education of household heads, have important implications on households' technology adoption decisions. Hence, we include detailed demographic characteristics of households in our empirical specification. Similarly, we consider socio-economic indicators of households measured in terms of livestock holding, landholding, and self-reported wealth statuses. These attributes have implications for technology adoption decisions which involve some financial cost. For instance, livestock holding serves as a buffer stock in the livelihood of rural farm households, and livestock and livestock products sales could finance inputs purchases. Similarly, households with limited land size may need technology-intensive farming practices to augment income through high productivity. On the other hand, small land size may also mean limited financial resource to pay for inputs. We also consider some measures that capture the quality of land owned by a household. The crop choice of a household may also influence technology adoption decisions, because some crops might be more profitable with fertilizer application than others. We finally include some village level factors that may provide crucial information on households' access to alternative agricultural technologies. Table 3.3 presents a description of the explanatory variables considered and their definitions.

Table 3.3: Description of the explanatory variables and their definitions

	Variable description	Mean	SD
Input use and technology adoption (outcome variables)			
Chemical fertilizer use	Dummy=1 if HH adopt chemical fertilizer	0.55	0.50
Improved seed	Dummy=1 if HH adopt improved seed	0.21	0.41
Extension visit	Dummy=1 if HH visited by extension agents	0.38	0.48
Advice on land preparation	Dummy=1 if HH received advice on land preparation	0.39	0.49
Past adoption decisions			
Past (lagged) fertilizer use	Dummy=1 if HH adopt chemical fertilizer last year	0.54	0.50
Past (lagged) extension visit	Dummy=1 if HH visited by extension agents (DAs) last year	0.30	0.46

[11] These figures are slightly higher than the national level fertilizer adoption rates which lie around 45 percent. These slight differences are anticipated because the AGP data oversamples *woredas* with high agricultural potential.

	Variable description	Mean	SD
Household characteristics			
Age of HHH	Age of the household head	43.8	15.07
Gender of HHH	Gender of the household head (1=male)	0.70	0.46
Education of HHH:	Household head has no education	0.62	0.49
	Household head has primary education	0.35	0.48
	Household head has secondary education	0.02	0.15
	Household head has higher education	0.01	0.07
Household size	Number of household members	4.76	2.13
Socio-economic standing of households			
Total land size (ha)	Size of total landholding of the household	1.58	2.00
Tropical livestock units	Tropical livestock units owned by the household	3.26	3.26
Oxen	Number of oxen owned by the household	1.10	1.24
Self-reported wealth status	Dummy =1 if a HH perceive as rich	0.03	0.17
	Dummy =1 if a HH perceive as middle class	0.60	0.49
	Dummy =1 if a HH perceive as poor	0.37	0.48
Plot level characteristics			
Flat sloped	Dummy =1 if flat sloped land	0.67	0.40
Gently slopped	Dummy =1 if gently sloped land	0.30	0.39
Steep sloped	Dummy =1 if steep sloped land	0.02	0.11
Fertile soil	Dummy =1 if land is fertile	0.60	0.41
Semi-fertile soil	Dummy =1 if land is semi-fertile	0.27	0.37
Not fertile	Dummy =1 if land is not fertile	0.10	0.25
Information on crop choice			
Teff is dominant crop	Dummy =1 if HH allocates largest land share to teff	0.15	0.35
Wheat is dominant crop	Dummy =1 if HH allocates largest land share to wheat	0.13	0.34
Barley is dominant crop	Dummy =1 if HH allocates largest land share to barley	0.11	0.31
Maize is dominant crop	Dummy =1 if HH allocates largest land share to maize	0.22	0.41
Village-level factors			
Distance to market	Distance to the nearest market (km)	20.8	61.17
Access to fertilizers	Dummy=1 if chemical fertilizer was available in the village	0.83	0.38
Access to improved seeds	Dummy=1 if improved seed was available in the village	0.60	0.49
DA experience	How many years have they worked in this *kebele*	2.45	1.54
Number of observations	*Number of observations (N*T)*	*14,762*	

Notes: This table provides descriptive statistics of the explanatory variables considered in the analysis. The first column presents mean values, while the second column provides standard deviations. HH stands for household, while HHH stands for household head. SD stands for standard deviation.

4. MODELING HOUSEHOLDS' MULTIPLE ADOPTION DECISIONS IN A UNIFIED FRAMEWORK

Consider the following latent adoption propensities (y_{ntk}^*) as households' expected net benefits of using a specific agricultural technology (k) for a production season (t) . A household adopts a specific agricultural technology if the expected benefit obtained from the new technology exceeds the old one, or the net benefit of using the new technology is greater than zero. Hence, we can link the observed sequence of binary outcome adoption decisions and farmers' expected net benefit from a new technology for a specific production season as:

$$y_{ntk} = \begin{cases} 1 \text{ if } & y_{ntk}^* > 0 \\ 0 \text{ if } & y_{ntk}^* \leq 0 \end{cases} \quad (1)$$

A key contribution of this article centers on the empirical specification of households' expected net benefit (y_{ntk}^*) for a specific technology and how this correlates with the expected net benefit from other agricultural technologies as well as its variations across households. We propose that the profitability of a specific agricultural technology can be correlated to and improved by coupling it with other complementary technologies (Barham et al. 2004; Duflo et al. 2008). Furthermore, we argue that subtle unobserved heterogeneity across farm households may result in substantial variation in the profitability of a specific agricultural technology, and hence households' adoption decisions. To address these key econometric challenges we propose a random coefficients multivariate probit model.

Random Coefficients Multivariate Probit Model

Considering the three adoption decisions of interest – chemical fertilizer, improved seed and extension service – we specify a multivariate probit model with a flexible error structure and random coefficients specification. This model encompasses the three empirical concepts discussed in Section 2: input complementarity, unobserved heterogeneity, and dynamics (learning behavior) in technology adoption. More explicitly, we specify households' expected net benefit of using a specific agricultural technology *k* at time *t*, y_{ntk}^*, as:

$$y_{nkt}^* = \alpha_n + \varphi_{nk}' y_{nht-1} + \beta_{nk}' X_{nt} + \varepsilon_{nkt} \qquad (2)$$

where α_n stands for time-invariant household-specific unobserved effects that are common across adoption decision equations. y_{nht-1} stacks lags of (or past) adoption decisions of other technologies as well as lags of extension visits, which are meant to capture potential ''learning-by-doing'' effects and learning from extension agents, respectively. X_{nt} is a (L×1) vector of exogenous variables that explain households' technology adoption decisions. The error terms of the series of equations, $\varepsilon_{nt} = (\varepsilon_{nt1}, \varepsilon_{nt2} \ldots\ldots \varepsilon_{ntK})$, are identically and independently distributed across households, but are allowed to be fully-correlated across equations (adoption decisions). φ_{nk} is a vector of parameters that captures dynamics in technology adoption, effects that may be driven by self-learning or learning from extension agents, while β_{nk} is a similar vector of household-specific and technology-specific coefficients associated with the other explanatory variables of interest. Both the learning effects (φ_{nk}) as well as the effects of the other explanatory variables (β_{nk}) are allowed to vary across farm households to accommodate unobserved heterogeneity that is correlated with the explanatory variables of the system of equations. For instance, the learning effects may vary across households with varying unobserved individual assertiveness, managerial ability, neighborhood adoption rates, and household's ability to learn from own experience and experiences of others. Similarly, the other coefficients associated with the explanatory variables may vary across households due to some unobserved heterogeneity, such as risk taking behavior and preferences for a specific technology. Hence, one can also interpret these parameters, β_{nk}, as household-level ''taste parameters'' for a specific agricultural technology.[12]

Note that Equation (2) has two parameters that capture unobserved heterogeneity effects of different nature:
(a) unobserved heterogeneity that is time-invariant and independent of the explanatory variables, captured by α_n; and
(b) unobserved heterogeneity that might be correlated with the explanatory variables of interest, captured by the household-specific parameters β_{nk}. Specifically, the random effects (time-invariant household-specific unobserved effects) capture unobserved factors that are common to decisions on adoption of the three technologies considered. These may include behavioral traits, such as innate ability to process information and assertiveness that shape decision making, risk-taking and preferences towards new technologies; or physical factors commonly limiting adoption of the three technologies, e.g., access to these technologies and credit. Our specification allows the time-invariant unobserved effects to correlate across (adoption) equations, as this enables us to control for time-invariant common unobservable factors that would otherwise confound the size of complementarity effects captured by the contemporaneous correlation in the error terms of the equations. Such a specification is plausible given that we are modeling decisions that can be driven by similar behavioral and biophysical attributes. On the other hand, the unobserved heterogeneity that is allowed to correlate with the explanatory variables of interest may include unobserved factors that might be correlated with the observable explanatory variables of interest. For instance, previous studies have shown that risk aversion is a crucial behavioral attribute that affects technology adoption (Knight et al. 2003; Isik and Khanna 2003; Liu 2013) and it is potentially correlated with some observable characteristics of households, including gender, landholding, and wealth endowments (Feder 1982). Thus, if these commonly unobserved attributes of households are independent of the covariates, X_{nt}, then they will appear in α_n; on the other hand, if these attributes are correlated with other observable covariates in X_{nt} they will appear in β_{nk}.

[12] Since we have longitudinal data we assume that households' tastes, as represented by β_{nk}, does not vary across time. We believe that this is a reasonable assumption and it facilitates empirical identification of the parameters of the model.

To complete the model structure, we need to be explicit about the distribution and structure of the time-invariant random effects, household-level random coefficients, and the *K-variate* error terms of the equations. The first term is assumed to be normally distributed as $\alpha_n \sim N(0, \delta^2)$, while the random coefficients, $\theta_{nk} = \begin{pmatrix} \varphi_{nk}' \\ \beta_{nk}' \end{pmatrix}$, are assumed to be realizations from a multivariate normal distribution with mean vector θ_k and covariance matrix Ω_k, implying $\theta_{nk} = \theta_k + \tilde{\theta}_{nk}$, where $\tilde{\theta}_{nk} \sim MVN_L(0, \Omega_L)$ (in which MVN_L represents the multivariate normal distribution of dimension *L*).[13] These specifications accommodate unobserved heterogeneity correlated with the explanatory variables, as well as unobserved heterogeneity that is independent of the explanatory variables.[14] For simplicity, the covariance matrix Ω_K holds only diagonal elements that stand for the variances of the parameters to capture heterogeneity effects.

Given the above specification of unobserved heterogeneity effects, the joint error terms of the equations capture input complementarities and are assumed to be distributed multivariate normal as $\varepsilon_{nt} \sim MVN_K(0, \Sigma_K)$, with Σ_K assuming the following covariance structure:

$$\mathbf{\Sigma}_K = \begin{bmatrix} 1 & \rho_{12} & \rho_{13}\ldots\ldots & \rho_{1K} \\ \rho_{21} & 1 & \rho_{23}\ldots\ldots & \rho_{2K} \\ . & . & .. & .. \\ . & . & .. & .. \\ \rho_{K1} & \rho_{K2} & \rho_{K3}\ldots\ldots & 1 \end{bmatrix} \tag{3}$$

The diagonal elements in the above matrix are normalized to 1 for identification purpose, which, consequently, yield that the off-diagonal elements of the covariance matrix ($\sum_K$) hold the correlation matrix of the shared unobserved factors associated with households' latent propensities to adopt a package of agricultural technology.

We have considerable parametric assumptions in our empirical model specification. However, there are at least two reasons that justify such parametric formulation: (a) the longitudinal nature of the data provides some time-variation that may help to empirically identify the parameters in order to disentangle functional form assumptions and heterogeneity; and (b) we think that these parametric assumptions are less restrictive than ignoring unobserved heterogeneity effects or assuming these to be independent of the explanatory variables. Furthermore, we are applying these functional form assumptions to a large dataset for which the normality assumptions may not be too strong to dictate the empirical results (Baltagi 2001:15).

With the above specification, three important points should be noted. First, the random effects that enter all equations generate a correlation (across adoption decisions and across time) that amounts to $\frac{\delta^2}{1+\delta^2}$. This is a time-invariant correlation in unobserved factors that affect farm households' multiple adoption decisions. Thus, we are not attributing every correlation in unobserved effects as manifestations of input complementarity. Second, the contemporaneous correlations of the error terms of the sequence of equations capture remaining unobserved factors that affect farm households' propensity to adopt the three agricultural technologies considered. We attribute this contemporaneous correlation as complementarity effects. Attributing these contemporaneous correlations as complementarity effects instead of error correlation enables us to circumvent spurious correlation that is driven by other factors than input complementarity. Third, the three concepts we introduce here are related to each other and, we argue, an empirical adoption model should explicitly consider three of them simultaneously to make an inference on either of them. For instance, an empirical model that ignores alternative forms of heterogeneity effects may attribute these factors to complementarity effects because they create some correlation among alternative technology adoption decisions.

[13] For ease in presentation, we treat all elements of θ_{nk} as random parameters, but one can fix some elements of θ_{nk} and let the remaining elements be random.

[14] Substituting $\theta_{nk} = \theta_k + \tilde{\theta}_{nk}$ in equation (1) shows that the unobserved heterogeneity correlated with the explanatory variables of interest enters farm households' adoption propensity equation through $\tilde{\theta}_{nk}' X_{nt}$.

Given the above structure, the likelihood function can be constructed for all possible adoption decisions of a household. For instance, the probability that a household adopts all the agricultural technologies considered here can be written as:

$$\Pr(y_{n1t}=1,.....y_{nKt}=1)=\int_{\theta_{nk}=-\infty}^{\infty}\left\{\int_{\ell_1=-\infty}^{\theta_{nk}'X_{n1t}}\int_{\ell_2=-\infty}^{\theta_{nk}'X_{n2t}}...\int_{\ell_K=-\infty}^{\theta_{nk}X_{nKt}}\phi_K(\ell_1,\ell_2,..\ell_K\,|\,\Sigma_K)d\ell_1,d\ell_2...d\ell_K\right\}f(\theta_{nk}\,|\,\theta_k,\Omega)d\theta_{nk} \quad (4)$$

where $\phi_K(.)$ stands for a *K-variate* standard normal density function, θ_{nk} now stacks all household- specific parameters (including the random effects and random coefficients) and follow a probability density function $f(.)$. Similarly, in this notation X_{nt} includes all lagged outcomes and other explanatory variables of the system of equations.

The above probability for a sequence of adoption decisions entails double-nested multi-dimensional integration for each household. The inner integrand involves a three dimensional integration problem, while the outer involves a dimension of integration equivalent to the number of random parameters specified. Both integrals can be evaluated using Maximum Simulated Likelihood (MSL) approaches (Revelt and Train 1998; Train 2009). For efficiency gains, we particularly approximate the inner integrand using the Geweke-Hajivassiliou-Keane (GHK) simulator(Geweke 1991; Hajivassiliou and McFadden 1998; Keane 1994).[15] The GHK simulator works on recursive conditioning of multivariate outcomes or sequence of outcomes.[16]

5. ESTIMATION RESULTS AND DISCUSSION

In this section, we discuss key empirical results and their implications. As a benchmark and to evaluate the performance of our preferred model specification, we first estimate the independently formulated probit models commonly used in modeling single technology adoption decisions, which is nested in our preferred model. This model ignores unobserved heterogeneity and input complementarity. We refer to this as the independent probit (IP) model. We compare the performance of the IP model with the preferred random coefficients multivariate probit (RCMVP) model, which accounts for input complementarity as well as unobserved heterogeneity effects. In both models, the empirical specification and choice of explanatory variables builds on previous research and theoretical considerations.[17] We initially allow for every coefficient to vary across households, and later restrict it to be fixed if the estimated standard deviation of the coefficient is not statistically significant.[18]

Table 5.1 provides the RCMVP model estimates for the first case where we measure extension service using DA visits, while Table 5.2 presents corresponding estimates using our second measure of extension service of whether the household has received advice on land preparation. In both cases, likelihood ratio tests for comparing the RCMVP specification and IP model can be decisively rejected. This suggests that the RCMP model fits the data better and captures technology adoption process much better than the independently formulated probit models. This is also partly evident from the significant error correlation parameters as well as from the significant standard deviations of the random coefficients. More concisely, the RCMVP model outperforms the standard univariate probit model commonly employed in the technology adoption research, indicating the presence of input complementarity and substantial unobserved heterogeneity effects. For the focus of this research, we present only the results of the RCMVP models.

[15] The GHK simulator is found to be the most efficient approach to approximate multidimensional integrals of the form in equation (4) (Geweke et al. 1994; Hajivassiliou et al. 1996; Abay 2015).

[16] Within the Maximum Simulated Likelihood (MSL) framework, we employ quasi-Monte Carlo draws from Halton sequences in evaluating the inner and outer integrals of equation (3). Considering the potential noise we might have brought through the simulation process, robust standard errors are computed (McFadden and Train 2000). Train (2009) provides a detailed guide for implementing the GHK simulator. A Matlab program for estimating this model is available from the authors upon request.

[17] Before arriving at the preferred empirical specification, we experimented with various functional forms for the variables and with the choice of sets of variables. We had some non-linear effects on some the variables, e.g., age of household head, as well as some interactions terms and other agro-ecological and community-level dummies. But these non-linear effects were statistically insignificant and inclusion (exclusion) of the large set of geographic and community-level dummies did not matter for the main parameters in which we are interested.

[18] Note that if the off-diagonal elements of the error structure and all the standard deviations of the random coefficients in the RCMVP model are not statistically significant, the RCMVP model collapses to the IP model.

Table 5.1: Random coefficients multivariate probit (RCMVP) estimates of joint technology adoption decisions, with extension services measured by whether Development Agent visited farm household

	Technology (or input) type		
Explanatory variables considered	**Chemical fertilizer**	**Improved seed**	**Extension service (DA visit)**
Learning effects:			
Lagged extension visit	0.258 (0.039) ***	0.239 (0.036) ***	
Standard deviation	0.301 (0.202)		
Lagged chemical fertilizer use		0.319 (0.038) ***	
Household demographics:			
Gender of HHH (1=male)	0.038 (0.030)	0.036 (0.039)	0.123 (0.027) ***
Standard deviation	0.744 (0.129) ***	0.211 (0.077) ***	
Age of HHH	0.001 (0.001)	-0.003 (0.001) ***	0.003 (0.001) ***
Education	0.265 (0.031) ***	0.143 (0.028) ***	0.138 (0.021) ***
Household size	0.060 (0.008) ***	0.029 (0.008) ***	0.057 (0.006) ***
Standard deviation	0.055 (0.020) ***		
Socio-economic standing of households:			
Tropical livestock units (TLU)	0.032 (0.003) ***	0.005 (0.004)	0.013 (0.002) ***
Number of oxen owned	0.163 (0.017) ***	0.085 (0.014) ***	0.044 (0.01) ***
Self-reported wealth status: medium or rich	0.121 (0.093)	0.316 (0.086) ***	0.218 (0.071) ***
Standard deviation	0.484 (0.493)		0.484 (0.493)
Log (total land size)	0.126 (0.014) ***	0.136 (0.018) ***	0.049 (0.010) ***
Plot level characteristics:			
Proportion of fertile land	-0.355 (0.039) ***	-0.014 (0.039)	0.027 (0.027)
Proportion of flat-sloped land	0.337 (0.038) ***	0.184 (0.050) ***	0.018 (0.029)
Standard deviation	0.712 (0.137) ***	0.435 (0.099) ***	0.146 (0.059) **
Information on crop choice:			
Teff is dominant crop	0.673 (0.072) ***	0.236 (0.041) ***	-0.011 (0.031)
Standard deviation	0.553 (0.188) ***		
Constant	-0.550 (0.068) ***	-1.686 (0.085) ***	-0.927 (0.053) ***
δ	0.053 (0.284)		
ρ_{12}	0.704 (0.071) ***		
ρ_{13}	0.227 (0.043) ***		
ρ_{23}	0.056 (0.026) **		
Log-likelihood value for the IP model	-25410		
Log-likelihood value for the RCMVP model	-24779		
Likelihood ratio test for comparing the IP and RCMVP models	$X^2 = -2(LL_{IP} - LL_{RCMVP}) = 1262$		
Number of observations	14,762		

Notes: This table presents the estimates of the RCMVP model. The first column of results presents estimates for the chemical fertilizer application component of the model, while the second and third columns provide estimates for improved seed and extension service use propensities, respectively. Standard deviations are estimated "dispersion" parameters for the random coefficients. Robust standard errors are in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent, respectively.

Table 5.2: Random coefficients multivariate probit (RCMVP) estimates of joint technology adoption decisions, with extension services measured by whether the household has received advice on land preparation

	Technology (or input) type		
Explanatory variables considered	**Chemical fertilizer**	**Improved seed**	**Extension service (advice on land preparation)**
Dynamics (learning effects):			
Lagged extension visit	0.229 (0.035) ***	0.213 (0.032) ***	
Standard deviation	0.261 (0.210)		
Lagged chemical fertilizer use		0.324 (0.037) ***	
Household demographics:			
Gender of HHH (1=male)	0.040 (0.030)	0.045 (0.039)	0.205 (0.028) ***
Standard deviation	0.534 (0.146) ***	0.128 (0.106)	
Age of HHH	0.001 (0.001)	-0.003 (0.001) ***	0.001 (0.001)
Education	0.265 (0.031) ***	0.146 (0.028) ***	0.116 (0.022) ***
Household size	0.061 (0.008) ***	0.029 (0.008) ***	0.057 (0.006) ***
Standard deviation	0.066 (0.017) ***		
Socio-economic standing of households:			
Tropical livestock units (TLU)	0.033 (0.003) ***	0.006 (0.004)	0.013 (0.003) ***
Number of oxen owned	0.162 (0.017) ***	0.083 (0.014) ***	0.059 (0.011) ***
Self-reported wealth status: medium or rich	0.110 (0.092)	0.315 (0.087) ***	0.055 (0.072)
Standard deviation	0.305 (0.521)		0.305 (0.521)
Log (total land size)	0.123 (0.014) ***	0.139 (0.018) ***	0.084 (0.011) ***
Plot level characteristics:			
Proportion of fertile land	-0.363 (0.041) ***	-0.019 (0.04)	-0.128 (0.029) ***
Proportion of flat-sloped land	0.341 (0.040) ***	0.169 (0.049) ***	0.101 (0.03) ***
Standard deviation	0.828 (0.133) ***	0.485 (0.084) ***	0.253 (0.054) ***
Information on crop choice:			
Teff is a dominant crop	0.750 (0.086) ***	0.242 (0.041) ***	0.091 (0.033) ***
Standard deviation	0.851 (0.167) ***		
Constant	-0.554 (0.07) ***	-1.681 (0.086) ***	-0.866 (0.056) ***
δ	0.149 (0.257)		
ρ_{12}	0.700 (0.085) ***		
ρ_{13}	0.367 (0.068) ***		
ρ_{23}	0.121 (0.030) ***		
Log-likelihood value for the IP model	-25445		
Log-likelihood value for the RCMVP model	-24513		
Likelihood ratio test for comparing the IP and RCMVP models	$X^2 = -2(LL_{IP} - LL_{RCMVP}) = 1864$		
Number of observations	14,762		

Notes: This table presents the estimates of the RCMVP model. The first column of results presents estimates for the chemical fertilizer application component of the model, while the second and third columns provide estimates for improved seed and extension service use propensities, respectively. Standard deviations are estimated "dispersion" parameters for the random coefficients. Robust standard errors are in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent, respectively.

The contemporaneous error correlations of the joint model are all positive and statistically significant in both Table 5.1 and Table 5.2. Given that we controlled for a rich set of unobserved heterogeneity effects, captured by the common random effects (α_n) and the random coefficients (β_{nk}), we interpret these parameters as estimates of input complementarities among the alternative agricultural technologies considered. As expected, there is very strong complementarity between chemical fertilizer use and improved seed adoption (a correlation of 0.7).[19] This is consistent in both Table 5.1 and Table 5.2. Although relatively weaker, the results also indicate some complementarity between chemical fertilizer use and extension services, as well as between improved seed and extension services. The sizes of these complementarities are comparable to the unconditional correlations in adoption of alternative agricultural inputs reported by Sheahan and Barrett (2014). Given

[19] Recalling the bivariate correlations in Table 3.2, one could loosely argue that much of these associations are unidirectional as we can observe quite a small share of households (2%) using improved seed without fertilizer.

that our empirical specification controls for a number of factors, including direct effects of extension services, we argue that there is substantial complementarity observed in our dataset, particularly between fertilizer and improved seeds. The relatively weaker complementarity observed between extension services and the other two inputs considered here is not surprising, given the quality limitations in the Ethiopian extension system in terms of providing tangible technical (“knowledge”) support on fertilizer or improved seed uses (e.g., Davis et al. 2010). Previous studies indicate that agricultural research is poorly embedded into the Ethiopian extension system, and that knowledge inputs from additional training to the DAs is also limited (Davis et al. 2010; Krishnan and Patnam 2014). This leaves the system with limited capacity to provide much desired agronomic and other technical support to farmers. Instead, Ethiopia’s extension system devotes considerable amount of effort on supplying and persuading farmers to adopt new technologies, mainly fertilizer and improved seeds (Davis et al. 2010; Ragas a et al. 2013). Clearly, the complementarities captured between extension service and the two other inputs have to do with the “nudging” effect of the extension system to promote these inputs, rather than being driven by the ‘‘knowledge’’ effect. This therefore suggests that part of the empirical adoption puzzle, at least in the context of this study, is explained by the existing weak extension system.

The fact that the size of complementarity captured between extension service and the other two inputs is relatively larger when ‘‘advice on land preparation’’ is used to proxy extension service, rather than simple ‘‘DA visit’’, is indicative of the potential gains to be exploited by improving the capacity of the extension system to provide instruction on simple agronomic techniques such as land preparation and improved planting practices, e.g., row planting. Although attributing these complementarities requires further research, the differences in the size of complementarities between the alternative measure of extension services may also imply that part of the complementarities are driven by farmers’ choice of production function, which in turn might be driven by households’ profit (or perception of profit) motive.

The estimation results also reveal substantial unobserved heterogeneities among farm households in our sample. The significant standard deviation estimates for the random coefficients of the model imply that unobserved heterogeneity, which is correlated with the explanatory variables, is pervasive in households’ technology adoption process. This indicates that ignoring this type of heterogeneity may entail severe consequences on empirical inferences. From a slightly different perspective, one could also interpret this finding as evidence for the fact that farm households exhibit heterogeneous tastes or preferences for a specific agricultural technology. The standard deviation estimates and detected heterogeneity appear to be consistent for both measures of extension service (Table 5.1 and Table 5.2), evidence that suggests our results are robust to different empirical specifications.[20] Overall, our results suggest that a single production function may not explain the complicated technology adoption process among households. This would necessitate adapting policy interventions by integrating households’ preferences and other attributes. This, in turn, implies that existing technology diffusion programs in sub-Saharan Africa, which commonly assume a uniform production function among households, might have been partially responsible for the observed generally low adoption of agricultural technologies. In Section 6, we show the implication of ignoring these behavioral features, input complementarities, and unobserved heterogeneity effects on policy inferences.

The results in Tables 5.1 and 5.2 also provide some evidence of learning and dynamics in the choice of technological mix. For instance, we can see that those households that had been visited by extension agents last year are more likely to use fertilizer in one or more of their plots the following year. We may interpret this as households’ learning behavior from extension agents. The marginal effects in Table 6.1 show that this is a quantitatively strong and a relatively ‘‘clean’’ effect of extension services on fertilizer use, given that we are using lags of extension services. Using the lag of extension visits instead of contemporaneous visits reduces some concerns regarding the endogeneity of extension services by avoiding reverse causality effects, while our multivariate specification also captures contemporaneous common unobserved factors that affect both outcomes. These two problems may confound the identification of the causal effect of extension services on technology adoption and explain the mixed evidence that has been presented on the effectiveness of extension services in sub-Saharan Africa (Davis 2008; Davis et al. 2010; Benin et al. 2011; Krishnan and Patnam 2014). Thus, our results provide interesting insights to many sub-Saharan African countries, including Ethiopia, who are investing a good share of their public agriculture budget on agricultural extension services.[21]

[20] Besides using alternative measures for extension service, we also assess the robustness and stability of our estimates using several empirical exercises. Due to the size of the sample we are able to make several sample splits that can help us to uncover some heterogeneity non-parametrically. For instance, to assess the differential effect of gender of the household head on technology adoption non-parametrically, we estimate this effect for the four main regions of Ethiopia separately, and we can see that the gender effect is statistically significant only for Amhara and Tigray regions.

[21] These results are consistent with the goals of the Ethiopian extension system, a policy package that generally entrust extension services to facilitate technology adoption (Ministry of Agriculture 2011).

The estimation results also show that households' past fertilizer use is associated with higher propensity to use improved seed in one or more of their plots. This might be attributed to the dynamic learning behavior discussed in Beseley and Case (1993) or the sequential adoption of agricultural technologies described in Leathers and Smale (1991) and Khanna (2001). We cannot infer whether the former or the latter is driving the results, but, either way, we can argue that there is some ''self-learning''. Both arguments justify that, in the presence of uncertainty about the profitability of a new technology, along with the pervasive credit constraints that smallholder households face, farmers are more likely to rely on learning-by-doing to experiment on the profitability of a specific technology. Tables 5.1 and 5.2 also show that extension visits have significant impact on adoption of improved seed, perhaps due to DAs' relentless efforts to promote modern inputs.

The estimation results associated with the remaining explanatory variables in the three technology adoption propensity equations are generally consistent with previous evidence. For instance, the results show that male-headed households, those households headed by literate individuals, and those with larger family size are more likely to adopt all the technologies considered. A new piece of evidence in this regard relates to the heterogeneity in the impacts of some of the demographic characteristics of households. For instance, there exists strong heterogeneity in the effect of gender of the household head on fertilizer and improved seed adoption. This is anticipated in the Ethiopian context where husbands commonly assume family headship regardless of their participation in agricultural activities and decisions. Male-headed households with those male heads having differential roles in agricultural activities and decisions on those activities are expected to exhibit differential propensity to adopt a specific agricultural technology. A more behavioral explanation of such heterogeneities might be related to differential (within the same gender) risk aversion (preference) for a particular technology. Based on our estimations and parametric assumptions, the estimated mean and standard deviation associated with the gender effect on fertilizer use show that the gender effect is positive for only around 52 percent of the sample and negative for the remaining 48 percent. Similarly, the effect of household size on fertilizer use is heterogeneous across households, potentially because of the differential composition of households.[22]

Those households with better socio-economic standing, measured by landholdings, livestock ownership, and self-reported wealth status, have higher propensity to adopt fertilizer, improved seed, and extension services, potentially because of economies of scale and risk aversion (Knight et al. 2003; Khanna 2001). This might also be attributed to the fact that these households have less liquidity constraints and are less likely to seek absolute risk aversion (Gine and Klonner 2005; Zerfu and Larsen 2010). The estimation results in Tables 5.1 and 5.2 point to the fact that more fertile land may require less technological input (chemical fertilizer, improved seed, and extension services) for achieving a specific level of production and productivity, while a higher ''proportion of flat plots'' encourages further investment in terms of fertilizer, improved seeds and extension service use. However, there exists strong heterogeneity in the latter's effect, indicating that this positive association may not always be the case due to some unobserved heterogeneity, potentially associated with this measure of ''quality'' of land. As for crop choice, those households allocating a larger share of their land to teff production are more likely to use fertilizer (Sheahan and Barrett 2014). However, as detected by the significant standard deviation parameter associated with the crop choice effect, we can see some heterogeneity in the effect of crop choice on fertilizer adoption.

In summary, the estimation results suggest that and households with larger family sizes, educated heads, male heads, and larger land and livestock ownership are more likely to adopt agricultural technologies. This is consistently observed in both measures of extension service use considered in this study. These results insinuate that poorer and marginalized households may not be enjoying the benefits of the existing technology diffusion strategies of the government of Ethiopia. This necessitates more institutional investment and the removal of physical barriers that may hinder agricultural intensification by these poorer households. Otherwise, poorer and marginalized households may remain trapped in poverty. These pieces of evidence necessitate designing pro-poor technology diffusion policies, perhaps by expanding the availability of credit and other institutional facilities that serve the poor. Overall, this evidence reinforces the argument by Marenya and Barrett (2009) that existing technology adoption strategies may not be ''pro-poor''.

More generally, many observable characteristics associated with higher (lower) propensity of fertilizer use induce higher (lower) improved seed use as well as extension service use. This evidence makes it plausible to expect unobserved factors that affect all these adoption decisions simultaneously. Intuitively, this implies that the productivity and profitability of a specific agricultural technology may depend on the adoption of other technologies, hence, suggesting that these inputs might be complementary to each other. However, care must be taken not to attribute every association in the adoption of

[22] For instance, among households with a similar family size, those with more working adult members might be more likely to adopt a specific agricultural technology.

alternative technologies as manifestations of input or technological complementarities. The next section provides a thorough discussion on the implications and consequences of ignoring such effects.

6. IMPLICATIONS OF IGNORING INPUT COMPLEMENTARITY AND UNOBSERVED HETEROGENEITY

To evaluate the impact of ignoring the aforementioned specification issues, unobserved heterogeneity and input complementarities, we conduct two empirical exercises. First, we compute marginal effects of the explanatory variables for the model that ignores unobserved heterogeneity and input complementarity (the Independent Probit (IP) model) and compare these with the marginal effects from the more comprehensive RCMVP model.[23] This is equivalent to comparing unconditional marginal effects from the commonly used univariate probit models and conditional marginal effects from the RCMVP model. For simplicity, we only compute marginal effects for the fertilizer adoption equation and only focus on the direct effect of the explanatory variables. The marginal effects given in Table 6.1 measure average (percentage point) change in the probability of adoption when the value of the explanatory variable of interest changes by one unit (for continuous variables) or switches from 0 to 1 for indicator variables. For the RCMVP model, this is done by integrating both types of unobserved heterogeneity effects within the model, conditional on the other adoption decisions. Standard errors for the marginal effects are computed using 200 bootstrap draws taken from the sampling distribution of the estimated parameters of the model.

Table 6.1: Marginal (average partial) effects for the independent probit (IP) and random coefficients multivariate probit (RCMVP) models for chemical fertilizer use

	Model	
Explanatory variables considered	**Independent Probit (IP)**	**RCMVP**
Dynamics (learning effects)		
Past (lagged) extension visit	23.77 (2.188)	14.84 (2.744)
Household demographics		
Gender HHH (1=male)	2.59 (1.926)	3.33 (2.387)
Age of HHH	0.01 (0.046)	0.04 (0.045)
Education	13.65 (1.534)	15.14 (2.089)
Household size	2.87 (0.354)	3.45 (0.470)
Socio-economic standing of households		
Tropical livestock units	1.83 (0.218)	1.78 (0.261)
Oxen	8.44 (0.914)	9.12 (1.311)
Self-reported wealth status: medium or rich	5.37 (5.321)	7.02 (5.449)
log (total land size)	7.19 (0.915)	7.52 (1.208)
Plot- level characteristics		
Proportion of fertile land	-19.59 (2.584)	-20.44 (3.371)
Proportion of flat-sloped land	18.03 (1.856)	20.91 (2.781)
Information on crop choice		
Teff is a dominant crop	33.72 (3.107)	35.76 (5.495)

Notes: This table presents marginal (average partial) effects for the independent (IP) and our preferred RCMVP model computed only for the chemical fertilizer component of the joint model. Standard errors (in parentheses) are computed using 200 bootstrap draws taken from the distribution of the estimates in Table 5.1. All marginal effects expressed as percentage points.

For instance, the IP model shows that extension visits increase the probability of fertilizer adoption by around 24 percentage points while the RCMVP model quantifies the effect to be 15 percentage points. These are quantitatively large effects and in contrast to the existing mixed evidence on the effectiveness of extension systems in sub-Saharan Africa. As expected, the marginal effects of some of the explanatory variables vary significantly across the IP and the RCMVP models. For instance, the IP model significantly overestimates the effectiveness of extension services and extension visits. Comparing the effects of extension services from both models in Table 6.1 shows that such overestimation is quantitatively important and may amount up to 60 percent of the ‘‘true’’ effect. This is not surprising given that the IP model ignores

[23] The IP and RCMVP model coefficients are not directly comparable due to the presence of random coefficients in the RCMVP model that lead to the normalization of the model coefficients with respect to a smaller overall scale. Thus, we rely on comparing marginal effects to get some idea about the performance of the standard model commonly used in the literature and our preferred model.

household-specific unobserved heterogeneities as well as common unobservable factors that affect fertilizer and extension visits. Such overestimation misleads policy efforts aimed at improving the adoption and diffusion of modern agricultural technologies, which may have contributed to the empirical puzzle related to low adoption. Overall, comparing the marginal effects from the IP and RCMVP models highlight the fact that ignoring these econometric and specification issues may endanger evaluating the effectiveness of alternative policy interventions in technology adoption.

Second, we compute simple bivariate predictions from the IP and the RCMVP models and then compare them with bivariate distributions from the data. This provides an indication on how well our preferred model fits that specific data and households' technology adoption process, compared to the univariate models in the literature. Table 6.2 presents average predicted probabilities for a bivariate combination of adoption decisions. These predictions are computed assuming independence in the IP model, while the RCMVP model predictions are computed conditional on the other remaining adoption decision.

Table 6.2: Bivariate distributions (percentages) of the AGP survey data and predictions from the independent probit (IP) and random coefficients multivariate probit (RCMVP) models

	AGP Survey Data	IP model	RCMVP model
Technology type	**Improved Seed**	**Improved seed**	**Improved seed**
Chemical fertilizer use	19.21	13.16	17.81
Extension service	11.23	8.68	10.46
	Extension service	**Extension service**	**Extension service**
Chemical fertilizer use	25.44	22.14	25.17

Notes: This table shows bivariate distributions based on actual data and mean predicted probability as per our models. The figures are given in percentages.

Comparing the sample averages in the data with the predicted probabilities from the IP and RCMVP models, we can see that the RCMVP model predicts the overall technology diffusion process seen in the survey data very precisely and indeed better than the IP model. As expected, comparing the predictions from the IP model and the RCMVP model, the latter outperforms the former decisively for bivariate distributions with strong complementarity. Overall, this exercise suggests that the RCMVP model provides a more realistic representation of behavioral features of the data and, hence, realistically approximates the households' technology adoption process. This has crucial implication in terms of forecasting and understanding the overall technology adoption process at national and regional levels.

7. CONCLUDING REMARKS AND IMPLICATIONS

This article investigated farmers' multidimensional technology adoption decisions in the presence of heterogeneities across households. A stylized random coefficients multivariate probit model is introduced to investigate multiple dimensions of households' technology adoption decisions while also quantifying potential complementarities among inputs and alternative forms of unobserved heterogeneities among households. In doing so, this model enables us to account for three key econometric issues in modeling households' technology adoption process: (1) input complementarities among alternative technologies, (2) unobserved heterogeneity effects, which might be independent or correlated with the observable explanatory variables that affect households' technology adoption, and (3) dynamics (learning process) in adoption decisions, a process that may involve learning-by-doing or learning from extension agents. To our knowledge, this is the first study in the technology adoption literature that addresses these econometric issues in a unified framework. We apply this model on a detailed and large longitudinal dataset collected for evaluating the Ethiopian Agricultural Growth Program (AGP). Unlike many previous studies, the longitudinal feature of the AGP data enables us to capture and quantify richer behavioral features in households' technology adoption dynamics.

The empirical analysis in this article provides several interesting findings. First, the results show that households' technology adoption decisions exhibit strong complementarity for some of the agricultural inputs considered. Conditional on various observable characteristics of households and alternative forms of unobserved heterogeneity, we find large correlations in adoption propensities between fertilizer and improved seed while these correlations are weaker for the remaining inputs. Second, there exist strong unobserved heterogeneity effects that induce heterogeneous impacts in the effect of the explanatory variables among farmers with similar observable characteristics. One could also interpret these heterogeneities as differences in ''tastes'' among farmers for a specific agricultural technology which might be driven by heterogeneity in preferences (risk taking behavior) or differences in the rate-of-returns to technology adoption. This implies that conventional technology diffusion strategies based on a single production function may not explain farmers' technology adoption process. This, in turn, implies that the design of existing technology diffusion efforts in sub-Saharan Africa, which commonly assume a uniform production function among households, might have contributed to the existing low take-up (adoption) of agricultural technologies. Third, there exists substantial dynamics (learning behavior) in technology adoption. We find that extension visits are positively associated with fertilizer and improved seed application. Similarly, we find that those households who applied fertilizer in the previous year are more likely to use improved seed in the following year. This is consistent with the dynamic learning behavior discussed in Beseley and Case (1993), as well as the sequential adoption behavior documented in Leathers and Smale (1991) and Khanna (2001). Finally, we show that ignoring the aforementioned specification issues, unobserved heterogeneity, and input complementarity effects, leads to systematic biases in quantifying the effects of some policy interventions which are meant to facilitate technology adoption. For instance, ignoring these econometric issues leads to significant overestimation of the effectiveness of extension services in facilitating technology adoption. We document that such overestimations are quantitatively large and can mislead policy interventions that aim at improving the adoption and diffusion of modern agricultural technologies.

Overall, the findings provide several key insights that may help in facilitating the adoption and diffusion of agricultural technologies in developing countries. The significant complementarities among agricultural technologies established in this study suggest that policy instruments that affect one or more of these technologies are likely to influence the adoption and diffusion of other agricultural technologies. Although the complementarities between the agricultural inputs we considered vary, our results highlight that the diffusion of some of the agricultural technologies can be improved by providing these technologies as a package, especially for those inputs with strong complementarity. But this requires some caveats, as our findings also show that poorer households are less likely to enjoy current technology diffusion strategies. As discussed in Byerlee et al. (2007) ‘‘inflexible input distribution’’ may compromise households’ opportunity to experiment with a technology by increasing the fixed cost of a package of technology if these strategies are not domain-specific.

We find that the extension system in Ethiopia has had a significant effect in terms of helping the diffusion of fertilizers and improved seeds, perhaps directly through DAs’ persistence in promoting these inputs. We also find that wealthier households, measured in terms of landholding, livestock ownership, and self-reported wealth status, are more likely to adopt agricultural technologies. As stressed in Marenya and Barrett (2009), these results suggest that poorer and marginalized households may not be benefiting from existing technology diffusion strategies. These pieces of evidence necessitate designing pro-poor technology diffusion policies, perhaps by improving availability of credit and other institutional facilities that serve the poor. These results, coupled with the substantial heterogeneities documented, reinforce that a single production function and extension service model may not explain the dynamics of technology adoption by farming households. This, in turn, necessitates reconsidering technology adoption programs and adapting policy interventions by integrating households’ preferences, risk taking behavior, and other attributes.

Finally, we note that our article is not without limitations, but we believe that future research can take on some of these shortcomings. First, although our results show some reasonable complementarities among agricultural inputs, we do not explicitly study the sources of these correlations and complementarities. Further research on the sources of these complementarities and their implications on productivity is required. Second, while we account for unobserved heterogeneity of a different nature, we did not explicitly attribute these heterogeneities in our estimation. Future research may focus on disentangling the sources of these heterogeneities and their implications on the productivity and profitability of these technologies. Investigating the implication of these complementarities and attributing the unobserved heterogeneities is crucial for explaining the low adoption rates of agricultural technologies. For instance, evaluating the implication of these complementarities on productivity and rates-of-return can provide input to the existing debate on whether fertilizers should be subsidized or not. Finally, we also are cognizant of the considerable parametric assumptions we impose on the model structure. However, given the large and longitudinal nature of the data, we believe that these parametric assumptions are less restrictive than ignoring the pervasive unobserved heterogeneity effects. However, extending these investigations with similar rigor using non-parametric approaches may yield further insight into this research on technology adoption decisions.

REFERENCES

Abay, K.A. 2015. “Evaluating Simulation-based Approaches and Multivariate Quadrature on Sparse Grids in Estimating Multivariate Binary Probit Models.” *Economics Letters* 126 (1): 51–56.

Bachewe, F., G. Berhane, B. Minten, and A.S. Taffesse. 2015. *Agricultural Growth in Ethiopia (2004-2014): Evidence and Drivers*. ESSP Discussion Paper 81. Addis Ababa: IFPRI-ESSP.

Bandiera, O., and I. Rasul. 2006. “Social Networks and Technology Adoption in Northern Mozambique.” *The Economic Journal* 116 (1): 869–902.

Barham, B., J. Foltz, D. Jackson-Smith, and S. Moon. 2004. “The Dynamics of Agricultural Biotechnology Adoption: Lessons from rBST Use in Wisconsin, 1994- 2001.” *American Journal of Agricultural Economics* 86 (1): 61–72.

Benin, S., E. Nkonya, G. Okecho, J. Randriamamonjy, E. Kato, G. Lubade, and M. Kyotalimye. 2011. “Returns to Spending on Agricultural Extension: The Case of the National Agricultural Advisory Services (NAADS) Program of Uganda.” *Agricultural Economics* 42 (2): 249–267.

Besley, T.J., and A. Case. 1993. “Modeling Technology Adoption in Developing Countries.” *American Economic Review* 83 (2): 396–402.

Baltagi, B. 2001. *Econometric Analysis of Panel Data*. Vol.2, John Wiley & Sons.

Bhat, C. R. 2001. “Quasi-random Maximum Simulated Likelihood Estimation of the Mixed Multinomial Logit Model.” *Transportation Research Part B: Methodological* 35 (7): 677–693.

Bonger, T., G. Ayele, and T. Kuma. 2004. *Agricultural Extension, Adoption and Diffusion in Ethiopia.* Research Report 1. Addis Ababa Ethiopian Development Research Institute,.

Chamberlain, G. 1980. “Analysis of Covariance with Qualitative Data.” *Review of Economic Studies* 47 (1): 225–38.

Conley, T.G., and C.R. Udry. 2010. “Learning about a New Technology: Pineapple in Ghana.” *American Economic Review* 100 (1): 35–69.

Croppenstedt, A., M. Demeke, and M.M. Meschi. 2003. “Technology Adoption in the Presence of Constraints: The Case of Fertilizer Demand in Ethiopia.” *Review of Development Economics* 7 (1): 58–70.

Davis, C. 2008. “Extension in sub-Saharan Africa: Overview and Assessment of Past and Current Models and Future Prospects.” *Journal of International Agricultural and Extension Education* 15:15–28.

Davis, K., B. Swanson, D. Amudavi, D. Mekonnen, A. Flohrs, J. Riese, C. Lamb, and E. Zerfu. 2010. *In-depth Assessment of the Public Agricultural Extension System of Ethiopia and Recommendations for Improvement*. IFPRI Discussion Paper 01041.

Dercon, S., and R.V. Hill. 2009. *Growth from Agriculture in Ethiopia: Identifying Key Constraints*. A paper prepared as part of a study on Agriculture and Growth in Ethiopia.

Dercon, S., Gilligan, D., Hoddinott, J. and Woldehanna, T. 2009. “The Impact of Roads and Agricultural Extension on Consumption Growth and Poverty in Fifteen Ethiopian Villages.” *American Journal of Agricultural Economics* 91(4): 1007–1021.

Dercon, S., and L. Christiaensen. 2011. Consumption Risk, Technology Adoption and Poverty Traps: Evidence from Ethiopia. *Journal of Development Economics* 96: 159-173.

Dorfman, J.H. 1996. “Modeling Multiple Adoption Decisions in a Joint Framework.” *American Journal of Agricultural Economics* 78 (1): 547–57.

Duflo, E. 2003. “Poor but Rational?” Unpublished manuscript.

Duflo, E., M. Kremer, and J. Robinson. 2008. “How High are Rates of Return to Fertilizer? Evidence from Field Experiments in Kenya.” *American Economic Review* 98 (2): 482–488.

Duflo, E., M. Kremer, and J. Robinson. 2011. “Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya.” *American Economic Review* 101 (6): 2350–2390.

Ellis, F. 1992. *Agricultural Policies in Developing Countries*. New York: Cambridge University Press.

Evenson, R.E., and D. Gollin. 2003. “Assessing the Impact of the Green Revolution, 1960 to 2000.” *Science* 300 (5620): 758–62.

Feder, G. 1982. “Adoption of Interrelated Agricultural Innovations: Complementarity and the Impacts of Risk, Scale, and Credit.” *American Journal of Agricultural Economics* 64 (1): 94.

Feder, G., R.E. Just, and D. Zilberman. 1985. “Adoption of Agricultural Innovations in Developing Countries: A Survey.” *Economic Development and Cultural Change* 33 (2): 255–98.

Foster, A.D., and M.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.

Geweke, J. 1991. “Efficient Simulation from the Multivariate Normal and Student-t distributions Subject to Linear Constraints and the Evaluation of Constraint Probabilities.” *Computing Science and Statistics: Proceedings of the 23rd Symposium on the Interface: 571-578*.

Giné, X., and S. Klonner. 2005. *Credit Constraints as a Barrier to Technology Adoption by the Poor: Lessons from South-Indian Small-scale Fishery*. World Bank Policy Research Working Paper 3665.

Gollin, D. 2010. *Agricultural Productivity and Economic Growth*. Handbook of Agricultural Economics Volume 4.

Hajivassiliou, V., D. McFadden, and P. Ruud. 1996. “Simulation of Multivariate Normal Rectangle Probabilities and Their Derivatives Theoretical and Computational Results.” *Journal of Econometrics* 72 (1-2): 85–134.

Hajivassiliou, V.A., and D.L. McFadden. 1998. “The Method of Simulated Scores for the Estimation of ldv Models.” *Econometrica* 66 (4): 863–896.

Holden S.T. 2014. *Agricultural Household Models for Malawi: Household Heterogeneity, Market Characteristics, Agricultural Productivity, Input Subsidies, and Price Shocks: A Baseline Report.* Centre for Land Tenure Studies Working Paper 05/14.

Isik, M., and M. Khanna. 2003. “Stochastic Technology, Risk Preferences, and Adoption of Site-specific Technologies.” *American Journal of Agricultural Economics* 85 (2): 305–317.

Keane, M.P. 1994. “A Computationally Practical Simulation Estimator for Panel Data.” *Econometrica* 62 (1): 95–116.

Krishnan, P., and M. Patnam. 2014. “Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption?” *American Journal of Agricultural Economics* 96 (1): 308–327.

Liu, E.M. 2013. “Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers in China.” *The Review of Economics and Statistics* 95 (4): 1386–1403.

Ma, X., and G. Shi. 2014. “A Dynamic Adoption Model with Bayesian Learning: An Application to U.S. Soybean Farmers.” *Agricultural Economics* 46 (1): 25–38.

Marenya, P.P., and C.B. Barrett. 2009. “State-conditional Fertilizer Yield Response on Western Kenyan Farms.” *American Journal of Agricultural Economics* 91 (4): 991–1006.

McFadden, D., and K. Train. 2000. “Mixed MNL Models for Discrete Response.” *Journal of Applied Econometrics* 15 (5): 447–470.

Ministry of Agriculture . 2011. *Participatory Extension System.* Extension Directorate, Addis Ababa.

Minot, N., and T. Benson. 2009. *Fertilizer Subsidies in Africa: Are Vouchers the Answer?* IFPRI Issue Brief 60. Washington, DC: International Food Policy Research Institute

Minten, B., B. Koru, and D. Stifel. 2013. “The Last Mile(s) in Modern Input Distribution: Pricing, Profitability, and Adoption.” *Agricultural Economics* 44 (6): 629–646.

Morris, M., V.A. Kelly, R.J. Kopicki, and D. Byerlee. 2007. *Fertilizer Use in African Agriculture*. The World Bank.

Moser, C.M., and C.B. Barrett. 2006. “The Complex Dynamics of Smallholder Technology Adoption: The Case of SRI in Madagascar.” *Agricultural Economics* 35 (3): 373–388.

Nyangena, W. and O.M. Juma. 2014. *Impact of Improved Farm Technologies on Yields: The Case of Improved Maize Varieties and Inorganic Fertilizer in Kenya*. Discussion Paper Series 14-02. Environment for Development.

Ragasa, C., G. Berhane, F. Tadesse, and A.S. Taffesse. 2013. “Gender Differences in Access to Extension Services and Agricultural Productivity.” *The Journal of Agricultural Education and Extension* 19 (5): 437–468.

Rashid, S., N. Tefera, N. Minot, and G. Ayele. 2013. “Can Modern Input Use Be Promoted Without Subsidies? An Analysis of Fertilizer in Ethiopia.” *Agricultural Economics* 44 (6): 595–611.

Revelt, D., and K. Train. 1998. “Mixed Logit with Repeated Choices: Households’ Choices of Appliance Efficiency Level.” *The Review of Economics and Statistics* 80 (4): 647–657.

Schultz, T. 1964. *Transforming Traditional Agriculture*. New Haven, CT: Yale University Press.

Sheahan, M., and C.B. Barrett. 2014. *Understanding the Agricultural Input Landscape in sub-Saharan Africa: Recent Plot, Household, and Community-Level Evidence.* World Bank Policy Research Paper 7014. Washington, DC: World Bank.

Spielman, D.J., D. Kelemwork, and D. Alemu. 2011. “Seed, Fertilizer, and Agricultural Extension in Ethiopia.” *ESSP II Working Paper* 20.

Suri, T. 2011. “Selection and Comparative Advantage in Technology Adoption.” *Econometrica* 79 (1): 159–209.

Taffesse, A.S. 2008. *Decomposition of Growth in Cereal Production in Ethiopia. Agriculture and Growth in Ethiopia.* Working paper prepared for a study on agriculture and growth in Ethiopia.

Train, K. 2009. *Discrete Choice Methods with Simulation*. Cambridge University Press, New York, NY.

Zerfu, D., and D.F. Larson. 2010. *Incomplete Markets and Fertilizer Use: Evidence from Ethiopia*. World Bank Policy Research Working Paper 5235.

About the Authors

Kibrom A. Abay is a post-doctoral researcher with the Department of Economics of the University of Copenhagen, Denmark; **Guush Berhane** is a Research Fellow in the Development Strategy and Governance Division of IFPRI, working in the Ethiopia Strategy Support Program (ESSP) with the Ethiopian Development Research Institute (EDRI) in Addis Ababa; **Alemayehu Seyoum Taffesse** is a Senior Research Fellow in the Development Strategy and Governance Division of IFPRI, working in ESSP with EDRI in Addis Ababa; **Bethelhem Koru** and **Kibrewossen Abay** both are Research Officers working in ESSP with EDRI in Addis Ababa.

Acknowledgments:

This paper has benefited from discussions and comments by James Warner and Goytom Abraha Kahsay. All remaining errors are ours.

About ESSP

The Ethiopia Strategy Support Program is an initiative to strengthen evidence-based policymaking in Ethiopia in the areas of rural and agricultural development. Facilitated by the International Food Policy Research Institute (IFPRI), ESSP works closely with the government of Ethiopia, the Ethiopian Development Research Institute (EDRI), and other development partners to provide information relevant for the design and implementation of Ethiopia's agricultural and rural development strategies. For more information, see http://www.ifpri.org/book-757/ourwork/program/ethiopia-strategy-support-program or http://essp.ifpri.info/ or http://www.edri-eth.org/.

About these working papers

The ESSP Working Papers contain preliminary material and research results from IFPRI and/or its partners in Ethiopia. The papers are not subject to a formal peer review. They are circulated in order to stimulate discussion and critical comment.

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

2033 K Street, NW | Washington, DC 20006-1002 USA | T: +1.202.862.5600 | F: +1.202.457.4439 | Skype: ifprihomeoffice | ifpri@cgiar.org | www.ifpri.org

IFPRI–ESSP ADDIS ABABA

P.O. Box 5689, Addis Ababa, Ethiopia | T: +251.11.617.2000 | F: +251.11.646.2318 | mahlet.mekuria@cgiar.org | http://essp.ifpri.info

ETHIOPIAN DEVELOPMENT RESEARCH INSTITUTE

P.O. Box 2479, Addis Ababa, Ethiopia | T: +251.11.550.6066 ; +251.11.553.8633 | F: +251.11.550.5588 | info@edri-eth.org | www.edri-eth.org

The Ethiopia Strategy Support Program (ESSP) is financially supported by the United States Agency for International Development (USAID) and the Department for International Development (DFID) of the United Kingdom. This publication has been prepared as an output of ESSP. It has not been independently peer reviewed. Any opinions stated herein are those of the author(s) and are not necessarily representative of or endorsed by the International Food Policy Re-search Institute or the Ethiopian Development Research Institute.