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A Conceptual Model of Incomplete Markets and the Consequences for Technology Adoption Policies in Ethiopia

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Abstract

In Africa, farmers have been reluctant to take up new varieties of staple crops developed to boost smallholder yields and rural incomes. Low fertilizer use is often mentioned as a proximate cause, but some believe the problem originates with incomplete input markets. As a remedy, African governments have introduced technology adoption programs with fertilizer subsidies as a core component. Still, the links between market performance and choices about using fertilizer are poorly articulated in empirical studies and policy discussions, making it difficult to judge whether the programs are expected to generate lasting benefits or to simply offset high fertilizer prices. This paper develops a conceptual model to show how choices made by agents supplying input services combine with household livelihood settings to generate heterogeneous decisions about fertilizer use. An applied model is estimated with data from a panel survey in rural Ethiopia. The results suggest that adverse market conditions limit the adoption of fertilizer-based technologies, especially among resource-poor households. Farmers appear to respond to market signals in the aggregate and this provides a pathway for subsidies to stimulate demand. However, the research suggests that lowering transaction costs, through investments in infrastructure and market institutions, can generate deeper effects by expanding the technologies available to farmers across all pricing outcomes.

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A conceptual model of incomplete markets and the consequences for technology adoption policies in Ethiopia

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Introduction

In Africa, boosting productivity on smallholder farms is a central component of most rural development strategies, and promoting greater use of chemical fertilizers is often a key element of that strategy. There is a broad consensus that greater fertilizer use is needed to sustain the fertility of African soils and that fertilizers are crucial to productivity-enhancing technologies developed to improve smallholder incomes. Compared to Asia, where smallholder agriculture is also predominant, the spread of higher-yielding varieties of staple crops in Africa has been limited. Fertilizer application rates are also low in comparison to other regions and weak fertilizer markets are often cited as a hurdle to the widespread adoption of superior technologies. These weaknesses are thought to originate in the structure of fertilizer markets themselves. As a remedy, many African governments have instituted fertilizer promotion programs that lower the price of fertilizer on smallholder farms through subsidies.

Still, in most discussions, the notions of market failure, weak markets, incomplete markets and poor market access are not fully conceptualized, which makes it difficult to identify causal determinants. This matters since the policy instruments for improving markets may be different from those used to directly compensate farmers for fertilizer that is expensive, and the lasting consequences of the alternative policies may differ as well. Fully articulating the role played by markets in limiting the adoption of promoted agricultural technologies is also important for applied studies, since the practical indicators used to empirically measure market performance are varied and often uncorrelated (Chamberlin and Jayne, 2012).

In this paper, we develop a conceptual model that characterizes the decisions of agents to provide inputs and related services and show how this affects the range of technologies available locally to farming households. We show how this, in turn, shapes the contours of choices farming households make about livelihood strategies, including the choice about whether to employ fertilizer-using technologies. Because of differences in household resources, not all farmers will be equally affected by agent-driven market outcomes and we show how this also affects choices about using fertilizer.

We then derive an applied model and show that it is possible to represent the combined effects of the business environment affecting agent choice and the decision environment affecting farmer choice in a reduced form that resembles models commonly used in applied settings. However, we also explore how reduced form models are subject to selection bias, since some of the factors that determine the availability of technologies can go unmeasured, resulting in a non-random sample of observed applied technologies. We argue that using an unpacked model of the type we estimate is better for policy research as well, since the approach forces a distinction between market performance and other factors affecting farmers' choices, thereby making it possible to explore multiple policy pathways.

Our applied model takes the form of a panel-selection model, which we estimate using rural household survey data from Ethiopia. Our findings are consistent with the prediction of the conceptual model that heterogeneous market performance and heterogeneous household circumstances combine to generate heterogeneous choices about using fertilizer-based technologies. We find that incomplete markets limit technology adoption by limiting choice, especially for resource poor households who are least able to cope with the hurdles raised by poorly performing markets.

Literature background

The idea that markets do not always work well is a reappearing theme, especially in development economics. It is different from the classic notion of market failure in which phenomena such as externalities can lead to sub-optimal outcomes even when markets are complete and efficient. It is also a broader concept than the idea of non-competitive markets, although a lack of competition can be an element of poorly performing markets. The notion of what constitutes incomplete markets has evolved over time, but it is largely a relative concept. For our purposes, we use the term to imply that locally available goods and services are fewer or more expensive than they would be under optimal public policy, for example, policies that support efficient transportation systems, reliable contract enforcement, or unobstructed information flows.

A number of interrelated terms such as incomplete markets, imperfect markets, weak markets and poor market access are often used to convey market limitations. Early on, the term "incomplete markets" was closely associated with missing contracts, especially contracts for risk. The idea was important in early studies that examined the consequences of using commodity-exchange- contracts to hedge price risks on commodity exchanges for farmers who were ultimately concerned with income risks. See, for example, Dillon and Anderson (1971), Myers (1988), and Moschini and Hennessy's (2001) review. Later, missing markets for risk, together with liquidity and credit constraints, would become a central feature of finance models developed to explain how risky assets are priced (Mehra and Prescott 1985; Mankiw 1986; Lucas 1993; Heaton and Lucas 1996).

In the development literature, the pervasive presence of uninsurable risk, poorly functioning labor and credit markets, and high transaction costs were used to explain the diverse livelihood strategies of rural households, including choices about production technologies (for example, Norman 1974; Morrison 1980; Lipton and Lipton 1993; Rosenzweig and Binswanger 1993). Market imperfections were also used to explain the prevalence of small scale farming in Africa and Asia (Feder 1980, 1985)[1]; migration patterns (Masset et al. 1993); seasonal price swings (Saha and Stroud 1994; Stephens and Barrett 2011); and the loss of traditional sources of protection for crop genetic resources (Van Dusen and Taylor 2005). Of course, as many

[1] See also the references in Lipton (2006) and Larson et al. (2013).

writers point out, markets are not static institutions. For example, shifting demographics, new technologies and public policy can induce new markets and affect the efficiency of existing markets (Krugman 1991; Wanmali 1992; Haggblad, Hazell and Reardon 2007; Mu and van de Walle 2011).

A related literature centers on how households, individually and collectively, compensated for incomplete markets. For example, a series of articles provided evidence that informal practices to manage and pool risks are often present in rural economies (for example, Paxson and Alderman 1992; Udry 1994; Morduch 1999; Larson, Anderson, and Varangis 2004; Dercon 2005); that informal land markets and credit markets work in limited ways to fill the void left by missing formal institutions (Lipton 1976; Feder and Onchan 1987; Atwood 1990; Hoff and Stiglitz 1990; Teklu and Lemi 2005); and that, when contract enforcement is weak, personal trade based on reputation, friendship or kinship can facilitate the types of transactions that take place in more competitive formal markets (Cooter and Landa 1984). Indeed, as Woolcock and Narayan (2000) point out in their survey, social capital and informal institutions are often used to compensate for weak markets and poorly functioning formal institutions. At the same time, informal arrangements often have limited geographic reach, since they are based on various forms of personal trade and social capital. As a consequence, they have limited scope for diversifying risks and attracting investments. Informal markets are also plagued by information hurdles and other entry barriers, which means that ethnicity, gender and social position can stand in the way of market participation. Consequently, informal arrangements only partly substitute for formal markets. Conversely, it also means that, as a practical matter, not all households were equally affected by incomplete markets.

In the early development literature on new technology adoption, incomplete markets for labor, land and credit were emphasized as limiting factors rather than weak private fertilizer markets.[2] As the focus shifted from Asia's Green Revolution to stalled productivity in Africa, several factors fed a growing concern about the performance of fertilizer markets. For one, soil scientists became increasingly alarmed about declining soil fertility in Africa and the implications for sustaining African agriculture. [3] Strong evidence also emerged that costs were high along the fertilizer market chain in several African countries, a significant portion of which seemed to arise from market structure rather than costly transport.[4] This was seen as a key obstacle to adoption, since it lowered the economic attractiveness of many of the high-yielding varieties of maize and other staple crops, which depended on purchased fertilizers. The performance of fertilizer markets also moved to the center of a debate about the role of the state in agricultural markets and the consequences of earlier market reforms that eliminated several fertilizer parastals and subsidy programs (Lele, Christiansen, and Kadiresan 1989; Akiyama et al. 2001; Johnson, Hazell and Gulati 2003; Crawford et al. 2003; Jayne et al.,

[2] Feder et. al (1985) provide an excellent review of the literature at that time. Also see Lamb (2003) and references therein.
[3] See, for example, the collection of essays in Buresh et al. (1997).
[4] Based on their study of fertilizer markets in Ghana, Mali, Senegal and Nigeria, Bumb et al. (2012) argue that fertilizer supply chains in Africa are often oligopolistic at the import level and more competitive at the retail level. Still they conclude that financing, transportation and distribution costs account for 74-80 percent of supply-chain costs.

2003; Morris et al. 2007). Some argued that private market agents had failed to fill the void left by market reforms and called for greater state intervention (Winter-Nelson and Temu 2005; Poulton, Kydd, and Dorward 2006; Mosely, Carney and Becker 2010). When food prices surged in 2008 and again in 2010, governments in Africa and elsewhere intervened in a variety of ways, and some instituted fertilizer promotion programs that included subsidies (Chamberlin and Jayne 2013; Shively and Ricker-Gilbert 2013).[5]

Farming methods and fertilizer demand

One unambiguous finding from the many household-based studies cited above is that African farmers use a mix of applied technologies, including those that do not rely on chemical fertilizer. Consequently, applied papers on fertilizer demand in Africa must reconcile the heterogeneous choices about farming practices. In many studies, the mixed outcomes are viewed in terms of a constant sample-wide production function, and zero-valued observations of fertilizer demand are implicitly treated as corner-solutions that are optimal from the household's perspective and randomly observed from a statistical perspective.

In a subset of papers however, the adoption decision is distinguished from the intensification decision, at least in the econometric sense. Implicitly or explicitly, market performance is also a consideration in these models, and proxies for high transaction costs or poor market access are included to explain choices about using fertilizer. While the root causes of market performance are not necessarily explicit, the applied models contain a mix of variables related to transportation costs, market organization and household characteristics.[6] Consequently, these models are closest in spirit to ours and share some structural components. What's more, their results are consistent with our conceptual starting point that heterogeneous decision environments result in heterogeneous fertilizer adoption rates.

Using cross-sectional household data from Eastern Zambia, Jha and Hojjati (1993) estimated a two-stage Heckman (1979) model of fertilizer adoption and intensity. They found that the distance traveled to obtain fertilizer was a barrier to adoption and that membership in a cooperative facilitated adoption. Regional dummies, meant to capture differences in markets and agro-ecological conditions, mattered as well. Using a 1994 representative cross-section of farmers in Ethiopia, Croppenstedt et al. (2003) found significant regional effects in their double hurdle model of fertilizer adoption, which they attributed to differing marketing conditions. Winter-Nelson and Temu (2005) employed a two-stage selection model to examine input expenditure levels among 250 coffee-growing households in Tanzania. They found that fertilizer adoption rates fell as the distance traveled to input markets increased. The same was true for their indicator of remoteness, the time it took to travel to the nearest cooperative office or commercial center. Membership in producer associations and spatial dummies were significant as well. Alene et al. (2008) also used a similar model to look at market participation and fertilizer use among 802 maize producers in Kenya. They found

[5] A literature on the costs and efficacy of the programs is beginning to emerge, for example, Ricker-Gilbert et al. (2013) provide a recent review.

[6] For early discussion on how transaction costs affect household choices see Pollak (1985), Binswanger and McIntire (1987), Rosenzweig (1988), Bromley and Cavas (1989) and Goetz (1992).

that remoteness (being farther than 15 kilometers from a fertilizer market), the availability of extension services, and off-farm earnings affected the adoption of fertilizers in expected ways.

Conceptual model

To start the derivation of the conceptual model, we define agents as businesses that sell goods or services used as inputs in other economic endeavors, including farming. We say that markets are weak or incomplete when the agents are too few to generate competitive prices, or when agents providing some types of inputs are absent altogether. It is important to note that not all economic activities and not all market participants are equally affected by incomplete markets. This is because other agents may provide near substitutes and because households and firms may be self-sufficient in some inputs. For example, when lending and insurance markets are weak, some households may be sufficiently wealthy to self-finance or self-insure. And trust based on social capital, including kinship and reputation, can be the basis of forward and contingent contracts when agents offering formal contract-based services are absent. Consequently, the absence of agents does not mean that markets are fully missing, but rather that they are incomplete in the sense that some potential economic activities are precluded or made more costly than would be the case were markets stronger.

Conversely, while it is indicative, the absence of types of economic activity common elsewhere does not imply that local markets are incomplete. Moreover, weak markets do not, in general, imply intrinsic market failures. Differences in exogenous factors, such as endowments, physical infrastructure, and agglomeration effects make some activities, including agent activity, profitable in one place but not in another. From a development policy perspective, the completeness of markets in the long-term depends on the notion that further investments in the institutions and other public goods that support markets would result in greater economic activity.

Outcomes related to market performance are expected to influence household livelihood strategies. Agent activity determines the goods and services available as inputs to farming and non-farming activities, and influences the prices farmers pay and receive. However, farm and household characteristics, such as soil quality, farm size and human capital endowments matter as well. Consequently, farmers facing the same market conditions may still face differing circumstances. When this is the case, farming households might rationally make different decisions about how they farm, including whether or not they use fertilizers. And, as mentioned, farming households differ in their capacity to provide for themselves what agents are unable to provide. Consequently, differences in agent activity will have unequal impacts on farmers' choices about the technologies they employ and, as a consequence, the inputs they use.

Agent activity and the provision of inputs

With this in mind, let $a(\mu)$, which we refer to as agent activity, denote a set of activities that permit the sales of goods and services needed as inputs to other economic activities. The decision to undertake agent activity depends on a set of exogenous state factors μ, which we refer to as the business environment. Agent activity and competition among agents jointly determine the price of those goods and services, $\omega = \omega[a(\mu), \mu]$. The business environment includes public and private components, including infrastructure, trade policy, and institutions to protect property rights, enforce contracts and provide for public safety. It also includes endowments and other aspects of geography, for instance, population density and navigable waterways. Because some components of μ have geographic features, markets have a spatial dimension. However, more broadly we define a given marketplace, composed of multiple markets for individual inputs, in terms of the homogeneous set of input goods and services it provides to a given population of farming households. That is, we define a marketplace by its service feature, such that farmers participating in the same marketplace can potentially access the same range of input goods and services priced in the same way.

Because agent activities depend on the business environment, each unique vector μ engenders its own market with activities $a^m(\mu^m)$ and associated prices $\omega^m = \omega^m[a^m(\mu^m), \mu^m]$, where the superscript m denotes a market. Said differently, heterogeneity in μ gives rise to distinct markets because differences in business environments give rise to differences in agent activity.[7] An important aspect of this is that some goods and services available in one market may be unavailable in another, and vice versa. Moreover, even when the same goods and services are available in more than one market, some components of the associated price vector will likely differ. To summarize, in general, $\mu^0 \neq \mu^1 \rightarrow a^0 \neq a^1$ and $\mu^0 \neq \mu^1 \rightarrow \omega^0 \neq \omega^1$.

As an aside, past and present public activities are expected to be important determinants of the business environment. In particular, the accumulated public and private investments in market-supporting institutions are expected to crucially affect the local availability of goods and services. To say this more formally, partition the determinants of the business environment as $\{I^m, P^m\} \equiv \mu^m$, where I^m represents the strength of local (market-m) institutions and P^m the remaining components, and let N^m equal a "completeness" measure of agent activity, i.e., the dimension of a^m. All things equal, the strengthening of institutions will increase agent activity, $I^0 > I^1 \rightarrow N^0 > N^1$; that is, stronger institutions are expected to increase the list of locally available input goods and services. Still, since exogenous factors matter as well, observing above-average levels of agent activity does not necessarily mean that local institutions are relatively strong, that is $N^0 > N^1 \nrightarrow I^0 > I^1$. From a development perspective this implies that the completeness of markets relies only partly on the strength of local institutions. What's more, the consequences of making additional investments in institutions will have heterogeneous consequences across markets and for agents within a given market.

On-farm technology choices

Associated with each market is a set of farming households that decide whether or not to purchase the inputs that agents provide. Following Mundlak (1988), we characterize a farmer's decisions about which inputs to use and how intensely to use them as an endogenous choice farmers make about which among several

[7] To avoid second-order effects, we also assume that all markets are small so that differences in agent and economic activity, including household choices about farming, in any given market of interest do not generate differences in the business environment of other markets.

available technologies to implement.[8] As mentioned, farmers face a variety of circumstances, which, taken together, shape their respective livelihood strategies. Because their individual decisions about how to farm are based on what technology best suits their individual needs and capacities, they collectively implement a heterogeneous set of applied technologies. Differences in farms and farmers generate some differences in the set of decision environments; however, differences in agent activity matter as well. This is because agent activity affects the set of goods and services available as inputs and, consequently, the set of locally feasible technologies from which farmers must choose. Agent activity influences input prices as well, and thereby also influences the choice of applied technology from any given set of available technologies.[9]

More formally, let $\Phi(s) = max_x\ pf(x,s) - wx$ characterize the full set of optimization problems faced by a given population of farmers conditional on a set of locally available convex technologies, $\mathrm{F(x,s)} \subset \mathrm{F(x,\Omega)}$, where $\mathrm{F(x,\Omega)}$ is the set of all invented technologies, where the set Ω contains all possible combinations of (non-choice) state factors, and where $\mathrm{s} \in \Omega$, is the vector of local state variables that conditions farmers' choices about which applied technology, $\mathrm{f(x,s)} \in \mathrm{F(x,s)} \in \mathrm{F(x,\Omega)}$ to employ. Relevant local state variables include input prices and output prices, $\mathrm{w,p} \in \mathrm{s}$. Standard input demand curves and the supply curve can be recovered from the solution via the envelope theorem, such that $\partial\Phi/\partial\mathrm{w} = -\mathrm{x}^*(\mathrm{y,s})$, and $\partial\Phi/\partial\mathrm{p} = \mathrm{f(x^*,s)} = \mathrm{y}^*$, where $\mathrm{y}^* \geq 0$, and $\mathrm{x}^* \geq 0$ are the solutions to the conditional profit maximization problem.

If, in an applied setting, the decision environment is homogeneous for a given study population, then the expected set of input and output levels $\{\mathrm{y}^*,\mathrm{x}^*\}$ and the chosen applied technology, $\mathrm{f(x^*)}$ are the same for all farms, since all farmers face the same optimization problem and arrive at the same optimal solution. Otherwise, the state-variables of the general function $\Phi(\mathrm{s^i})$ should be scripted to denote the different states, or decision environments, relevant to a particular choice; the same is true for outcomes resulting from that choice, $\{\mathrm{y}^*(\mathrm{s^i}),\mathrm{x}^*(\mathrm{y}^*,\mathrm{s^i})\} \equiv \{\mathrm{y^i},\mathrm{x^i}\}$.[10]

<u>Agent activity, household self-sufficiency and heterogeneity in the decision environment</u>

Except in trivial cases, agents in a given market are expected to offer goods and services across multiple decision environments. This is because some elements of s^i, for example farm soil quality, do not depend on current agent activity. Consequently, heterogeneity in farm and household characteristics will generate heterogeneity in the decision environment within a homogeneous business environment. In contrast, households that participate in different markets and are therefore presented with a different set of options for input goods and services automatically face a different set of state variables.

With this in mind, partition the relevant state variables into those that are independent of current-period agent activity, $\mathrm{s^f}$, and those that depend on current-period agent activity in a given marketplace, $\mathrm{s^m}$,

[8] Mundlak, Butzer and Larson (2012) discuss the implications for panel data.
[9] For example, Melitz and Ottaviano (2008) discuss how changes in trade policy can induce firm productivity gains through competition.
[10] This applies to both primal and dual representations. Consequently, it is not a trivial matter to move from one representation to the other in an applied setting when some state variables can go unobserved (Mundlak 1996).

such that $s = \{s^f, s^m\}$. From this starting point, it is possible to incorporate the role played by agents in establishing the decision making environment by writing s^m as a function of agent activity and an additional set of exogenous factors τ. In particular, consider $s_0 \in s^m \in s^i$, where $s_0 = \gamma_0^i(a^m, \tau)$. Note that differences in either τ or agent activity are sufficient to generate differences in technology choices, since, in general, $\{a^0, \tau^0\} \neq \{a^1, \tau^1\} \rightarrow s^0 \neq s^1 \rightarrow f^0 \neq f^1$.

Due to the topology we have constructed, elements of τ must either affect the decision environment directly or affect the decision environment indirectly via agent behavior. Therefore, it is possible to express the relationships more concisely since each element of τ is either tied to a household or farm (and therefore an element of s^f), or is a factor that conditions agent activity (and is therefore contained in μ). Consequently, it is possible to express a reduced form of the conditioning state variables in a way that identifies those that rely proximately on agent activity and ultimately on the business environment. With this in mind consider the state variable $s_0 \in s^f \in s^i$, which can be written as $s_0 = \gamma_0^i(a^m, \tau) = \gamma_0^i[a^m(\mu), \mu, s^f] = \gamma_0^i(\mu, s^f)$.

At the same time, incomplete markets need not preclude all farmers participating in that marketplace from adopting technologies that depend on inputs that the market fails to provide or provides at high cost. In particular, some farmers may be able to rely on their own resources to make up for market shortfalls. In this case, the conditions that permit households to compensate for weak markets can be written as $s_1 = \tilde{\gamma}_1^i(s^f, \tau) = \tilde{\gamma}_1^i(s^f, \mu^m)$, where $s_1 \in s^f \in s^i$.

<u>Summary and an example</u>

To summarize, the conceptual model states that implemented technologies and the associated set of chosen inputs by households are conditioned by a set of potentially heterogeneous decision environments, which are determined partly by farm and household characteristics and partly by agent activities. Agent activity, in turn, depends on the business environment, which is homogeneous within a given decision environment. This means that the set of locally available technologies can be expressed equivalently as:

$$F(x, s) = F(x, s^f, s^m) = F[x, s^f, \mu^m] \quad (1)$$

where the market-independent characteristics of the decision environment, $s^f \in s^i$, are present in conjunction with the business environment μ^m that conditions agent activity.

To provide an example of how agent activity might influence a decision environment, consider farmgate prices $\rho_h^i \equiv [p^i, w^i] \in s^i$ where household h participates in marketplace m. Now write the farmgate prices as a function of agent activity and an additional set of exogenous factors, τ_h, specific to the farm so that $\rho_h^m = \rho^m[a^m, \tau_h^m]$. This relationship need not be complex. For example, it could be that merchants are willing to sell inputs and purchase output at prices ρ_h^i based on border prices, $\rho^b \in \mu^m$, plus mark-ups $\lambda^m(t_h)$, based on the cost of transport from the market border to the farm, $t_h \in \tau_h$. For example, in the case where the transport and transaction costs associated with providing fertilizer at the farmgate is a linear function of the distance, d, from the border to a farm in market m, then $w_h^m(a^m, s^f) = \rho^b + \lambda_0^m(a^m)d_h$, where λ_0^m is a constant market-specific parameter that depends on agent activity and $d \in s^f$ is a characteristic of the farm belonging to household h. All else equal, higher transport prices will raise input prices and lower output prices at the farmgate, which in turn might encourage the farmer to produce less and to use inputs less intensely. To continue the example, less competition among agents might lead to higher mark-ups, exacerbating the effects of high transport costs.

In extreme cases, perhaps because the farm is located in a remote or unsafe place, no agent will be willing to travel to the farm and the farmer will be unable to purchase inputs or sell outputs at the farmgate. However, the farmer may choose to travel to the market border to purchase inputs and sell outputs. In this case, the farmer faces an implicit set of farmgate prices based on the opportunity costs of the resources the farmer puts to this task To continue the example above, the implicit farmgate price for fertilizer can be written as $w_h^m(\mu^m, s^f) = \rho^b + \lambda^h(s^f)d_h$, where λ^h is a now a constant household-specific parameter. In a general sense, the transportation of fertilizer to the farm becomes another household activity, potentially drawing on limited household labor resources and household-specific capital. All things equal, differences in λ^h increase the number of decision environments in a given market. This in turn implies that observed differences in farming practices, including the decision to adopt fertilizer-using technologies, depend not only on agent activity (market performance), but also on the capacity of households to substitute household activity for agent activity.

The applied model

In this section, we use results from the conceptual model to build an applied model that examines the specific choice of whether or not to use a technology that relies on chemical fertilizer, $z \in x$, as an input. As an intuitive introduction to the applied model, imagine the farmer's problem as one of sorting among technologies to find one that solves the marginal value condition $p^h \frac{\partial f^h}{\partial z} \geq w_z^h$, where p^h and w_z^h are the farmgate prices, market-based or implicit, for output and for fertilizer respectively. The set of technologies available to the farmer are contained in $F(x, s^h)$, a subset of which, $F^z|_{z>0} \subset F(x, s^h)$, includes those that require using fertilizer. A lack of local agents providing key services shrinks both F and F^z relative to corresponding sets available under a better business environment. As a consequence, some farmers may be unable to find a technology in F^z that solves the marginal value condition. In consequence, they will choose non-fertilizer using technologies if they decide to produce at all. Other farmers with more abundant resources search a different set of available technologies and may find one that solves the marginal-value condition despite poorly performing markets.

To develop an applied model in which decisions to adopt fertilizer-using technologies are modeled separately from the intensity of fertilizer use, we adopt what has become a common practice of asserting a two-stage decision process in which a farmer first allocates land among activities and then chooses the rates of application for the remaining inputs.[11] To start, partition the vector of inputs so that $x(s) \equiv [x_a, \hat{x}]$, where x_a is harvested area and $\hat{x}$ is a vector of the remaining N inputs contained in x. The production identity can be written as $f^i = \widehat{Y}(\hat{x}^i)x_a^i$. Dividing through by land gives $y = f/x_a = Y(z)$ so that planned yields are a function of factor intensity, where $z_n(s) = \hat{x}_n(s)/x_a(s)$ for $n = 1, 2, 3 \ldots N$.. Associated with each input is a factor-intensity schedule associated with the corresponding input demand schedule. We focus specifically on a model of fertilizer intensity, so that $\eta_h^i = \beta_i' s_h^i + \varepsilon_h^i$, where $\eta(s^i) \in z(s^i) \geq 0$, where η_h^i denotes the observed intensity of chemical fertilizer use per hectare by household h at time t associated with applied technology i, where β_i is a vector of fixed parameters associated with technology i; s^i is a vector of state variables that describes the relevant household decision environment, and ε_h^i are residual values also associated with technology i.

Note that the fertilizer intensity function is written as if the underlying technology were known. In most empirical settings, this is not the case and the data contain a mix of outcomes from multiple applied technologies. Including observed state variables helps with the identification problem, since the decision framework drives technology choice.[12] To proceed, we make the assumption that this is sufficient to capture behaviors across technologies, an assumption implicit in most applied models, and write the fertilizer intensity equation as:

$$z_h = \beta' s_h^\beta + \varepsilon_h, \ \eta_h \geq 0 \tag{2a}$$

Note that equation (2a) is constructed as the joint outcome of the technology choice and the subsequent fertilizer intensification choice. Conceptually, this is not problematic since it is possible to depict the implemented technologies as $f_h \in F[x, s^f, \mu^m]$ via equation (1). However, for interpretation purposes, it is useful to model the two decisions in an unreduced form and there are econometric reasons for doing so as well.

As discussed, African farmers frequently adopt technologies that use no fertilizer, and this is potentially due to weak and incomplete markets. In applied settings, it is difficult to observe the full set of variables that determine the set of production technologies that are available to all farmers in a given sample. If, as a consequence, the sets of available technologies differ among farmers due to unobserved or omitted variables, then the sample of fertilizer-using technologies used to estimate (2a) is not random. More importantly, if the effects of the unobserved factors are correlated with the intensification determinants given in (2a), the estimated values for β will be biased (Heckman 1979).

To account for this, consider a second component to the model, based on the implicit function:

$$z_h^* = \alpha' s_h^\alpha + v_h; \ z_{ht} = 1\,(z_h^* > 0) \tag{2b}$$

[11] See Antle (1983) and the related discussion in Kimhi (2006).
[12] See Mundlak, Butzer and Larson (2012) for a discussion in the context of panel data.

where the value of z^* is unobserved; α is a vector of fixed parameters; and v are residual values.[13] The equation is meant to capture the selection process underlying household choices about taking up fertilizer-using technologies. In keeping with the conceptual model, $s^{\alpha} \subset (s^f, \mu)$ is a vector that contains variables describing the business environment that supports agent activity and variables that are expected to capture a household's capacity to compensate for missing agent activity. Said in broader terms, the selection equation is designed to capture the consequences of incomplete markets for the take-up of the technologies underlying observed fertilizer use, recognizing that not all households are equally reliant on markets. From the applied economist's perspective, the additional equation compensates for the fact that imprecisely measured variations in the decision environments faced by agents and by households combine to exscind the visible portion of the fertilizer demand function.

<u>Basic statistical model</u>

With this as preface, we place the fertilizer adoption and demand equations into the context of a panel selection model, which provides estimates of the demand for fertilizer, adjusted for selection bias. In particular, the residual e_h.in the fertilizer demand equation (2a) is expanded so that

$$\eta_{ht} = \beta' s^{\beta}_{ht} + \varepsilon_{ht} + c_h \quad (3a)$$

where c_h is a random effect associated with farming household h, and $\varepsilon_{ht} \sim N(0, \sigma^2)$. The residual in the selection equation (2b), v_{ht}, is expanded in a similar way so that

$$z^*_{ht} = \alpha' s^{\alpha}_{ht} + u_{ht} + d_h; \; z_{ht} = 1\,(z^*_{ht} > 0) \quad (3b)$$

where d_h is a random effect also associated with farm h, and where $u_{ht} \sim N(0,1)$. The two random errors are potentially correlated, with $\text{corr}(\varepsilon, u) = \rho$. The random effects, c_i and d_i, are assumed to be bivariate-normally distributed with zero means and standard deviations, σ_c and σ_d, respectively. The random effects are also potentially correlated, with $\text{corr}(c, d) = \theta$.

<u>Augmented statistical model</u>

Selectivity comes in two forms: through the correlation of ε_{ht} and u_{ht}, and the correlation of the group specific components, c_h and d_h. Potentially these later components are correlated with the included variables, and we estimated an augmented version of the model to account for this possibility.[14] In particular, we follow a

[13] For example, by expanding the set of available technologies for a given household, unmeasured agent activity (market performance) or abundant unmeasured social capital (farm household characteristics) may lead the farming household to use fertilizer (chose a fertilizer-using applied technology). Farming in a market rich in agent services or abundant social capital might also lead to a reduction in unmeasured transaction costs, which leads the farmer to use fertilizer more intensely. In terms of the applied model, the some of the effect of the unobserved state variables winds up in the residual of equation 2b). If the fertilizer intensity equation 2a) were estimated without taking this into account, a portion of the effect associated the omitted variables would be attributed to any correlated observed state variables, and results from the reduced-form censured regression would be biased as a consequence.

[14] For example, government programs and private agents providing credit or extension services may prioritize more productive areas. Land titling practices may differ among communities as well. See discussions in Simtowe et al. (2009), Swaninathan et al. (2009) and Deininger and Jina (2006).

suggestion by Zabel (1992) and include group means as additional determinants. Specifically, we estimate the augmented model:

$$z_{ht} = \beta' s_{ht}^{\beta} + \delta' s_{h.}^{\beta} + \varepsilon_{ht} + c_h \tag{4a}$$

$$z_{ht}^{*} = \alpha' s_{ht}^{\alpha} + \gamma' s_{h.}^{\alpha} + u_{ht} + d_h; \; z_{ht} = 1\,(z_{ht}^{*} > 0) \tag{4b}$$

where s_h^{β} and s_h^{α} are the means of s_{ht}^{β} and s_{ht}^{α} over time. Note that the mean effects are a decomposition of fixed household effects. A simulated maximum likelihood method is used to estimate both versions of the model.[15]

Our estimation strategy follows the parametric approach suggested by Greene (2007), based on Verbeek (1990); Zabel (1992); and Verbeek and Nijman (1992), which we prefer to nonparametric approaches.[16] While there is an advantage to the nonparametric estimators, as they are robust to distributional misspecifications of the correlation between the unobserved effects and observed variables, from a practical perspective, the approach is less useful for policy-motivated research. As Greene (2007: E30-2) emphasizes, the parameters of the selection model are not the slopes of the index function, the implicit behavioral component of the model. Consequently, nonparametric models lack the more detailed assumptions about underlying functional form and parametric families are needed to interpret the conditional means and partial effects from the model, which are often key to policy discussions.

Model determinants

Variables used in the selection and input demand equations of the empirical model are listed and described in Table 1; the associated summary statistics are given in Table 2. The determinants of the selection equation are chosen to account for differences in the sets of economic fertilizer-using technologies available to households in the sample. Included in the list are variables directly indicating the provision of market services by agents, specifically whether or not agents are available locally to sell fertilizer, and whether households have access to credit and extension services. The next determinants are measures of production and price risk: average rainfall (climate) and price variability.[17] These variables are included to represent obstacles to agents that might offer services locally and also to account for the hurdles that households face when agents are unwilling to provide risk-mitigating services.[18] The next set of variables is meant to capture the households' capacity to compensate for services that agents do not provide. Three variables are included

[15] LIMDEP 9 is used to estimate the model. See Greene (2007) for greater detail.

[16] See, for example, Kyriazidou (1997), and Honore and Kyriazidou (2000).

[17] The variables may also have non-contemporaneous reinforcing characteristics that work to build household resources. Alem et al. (2010) argue that ample rainfall seasons boost incomes, helping farmers resolve liquidity problems in subsequent seasons. Rosenzweig and Binswanger (1993) also draw the connection between positive climatic environments and wealth.

[18] Spielman et al. (2010) point to some along the fertilizer supply chain that stand in the way of robust markets in Ethiopia, including the high cost of delivering small amounts of fertilizer to a large number of geographically dispersed smallholders with limited cash resources; they note that the 2-3 market window planting for rainfed crops in Ethiopia combined with variable year-to-year rainfall patterns generate high inter-year variability in the demand for fertilizer, increasing the risk to fertilizer dealers that purchased inventories will go unsold or sell at lower than expected prices.

to capture three forms of capital: human, financial and social. Specifically, we include a measure of education, wealth, and involvement in local governance. We also include age of the household head and household size. Age is expected to provide information on the willingness of the household to experiment with newer technologies and take on other types of risk; household size is meant to account for the capacity of the household to manage risks, either by diversifying income, by allocating a portion of labor resources to other income generating tasks, or by better managing production risks through labor-intensive management. The size of the household might also influence choices about technology in the face of incomplete labor markets.

The variables for the conditional demand for fertilizer, measured as fertilizer per unit of land, are standard. We include the relative price of fertilizer and the area cultivated. We also include information related to available family labor and human capital, which are expected to be complementary inputs to fertilizer. We include the livestock density as a proxy for available organic fertilizer. Soil moisture is important to the efficacy of fertilizer use and farmers have some scope for adjusting its use as the growing season progresses (Larson and Plessmann 2009). We therefore include weather outcomes measured relative to long-term averages (climate). We include wealth, which is expected to influence the households' decision about the composition of labor activities in the household. To account for the cumulative effects of technology adoption and broad changes in the economic and policy environments, we include a time effect.[19]

Background on fertilizer use in Ethiopia, data sources and descriptive statistics[20]

The household data used in our analysis come from a countrywide panel household survey conducted in 2004 and 2006 by the Ethiopian Economic Association (EEA) and the World Bank. The survey consists of about 2,300 randomly selected households in 115 villages (kebeles) stratified by agro-ecological zones and regions to ensure coverage of all the agricultural production systems of the country. After adjusting for missing data, there are data on 2,140 matching households. The first round focused on extension services while the second round focused on land certification program. As a result, there are some differences in the questionnaires. Because of missing values and attrition, our sample is unbalanced and contains 4,126 observations on 2,104 households.[21]

The survey data were supplemented with district level data on output prices from Ethiopia's Central Statistical Authority and fertilizer prices from the Ministry of Agriculture and Rural Development, Agricultural Marketing Directorate. Data on rainfall for the survey years came from the Ethiopian Meteorological Agency.[22] The climate variable was constructed from average values (1960-90) of historical spatial data prepared by the Climate Research Unit (Mitchell et al. 2002). For each year of the panel, we

[19] For a related discussion, see Feder and Umali (1993).
[20] This section draws on Gurara and Larson (2013).
[21] By design, the survey is meant to capture the diverse geography of Ethiopia, and may not be nationally representative of Ethiopian farmers.
[22] Survey sites were matched with data from the closest weather station.

construct a measure of weather by taking the ratio of average rainfall for the growing season to the thirty-year average for the same period and place.

Consistent with the national figures, the 2006 wave data show that the Amhara and Oromia regions have higher proportions of fertilizer users (61 percent and 58 percent, respectively) followed by SNNP and Tigray regions (57 percent and 55 percent, respectively). However, in terms of consumption per hectare of fertilized land, SNNP and Tigray regions exhibit higher fertilizer application rates with averages of 153 kg and 144 kg, per hectare, followed by Amhara and Oromia regions with averages of 129 kg and 111 kg per hectare. The lower intensity of fertilizer use in Oromia may be related to the region's soil type.[23]

Table 3 shows that around 68 percent and 63 percent of the households in the sample used one or more types of fertilizer (DAP, Urea or a mix of the two) in 2004 and 2006. The average fertilizer consumption increased from 42 to 55.7 kilograms per hectare in between the two rounds when both user and non-user households are considered. Considering only households that used fertilizer, a similar trend is observed, as consumption increased from 61 to 88 kilograms per hectare. At the plot level, average consumption per hectare increased from 116 to 167 kilograms. Still, surveyed farmers used chemical fertilizer on only 45 percent of their cropped area in 2006.

Application rates were below recommended rates, even for farmers that adopted fertilizer-using technologies. The timing of applications differed from recommended practices as well. For instance, while the Ethiopian Agricultural Research Institute recommends the application of urea over two cycles, the 2004 wave of the panel data shows that farmers who apply fertilizer do so all at once and none of the surveyed households applied urea in two cycles These outcomes are consistent with the notion that the choice of applied technology is constrained by market and household circumstances, although it is difficult to pin down the exact mechanism. It may be the case that the research findings were not adequately communicated to extension staff, that extension staff was unable to communicate the findings to farmers, or that farmers were unable to recognize the full benefits of best practices. It might also be the case that the practices advocated by extensions services are not best suited for all farms due to heterogeneity in climate and soils, a distinction that farmers may know better than researchers or extension staff.

The outcomes may also be linked to limited investments due to constraints on credit and wealth. Credit plays an important role in acquiring chemical fertilizers. In the 2004 survey wave, 61.5 percent of households received fertilizer on credit, while cash purchases accounted for only 37.7 percent (Table 4). Moreover, the pattern of credit in financing fertilizer purchases is not uniform across different regions. While credit finances more than 80 percent of purchases in Oromia, shares of credit-purchases drop to 35.7 percent and 40 percent in SNNP and Amhara regions, respectively. In Tigray, credit finances around 63 percent of fertilizer purchases. In terms of access to credit (from all type of sources such as friends, banks, microfinance and

[23] For instance, the Ethiopian Ministry of Agriculture study recommends a lower dose of fertilizer per hectare (at 150 kg per ha. vs. the usual 200 per ha.) for vertisols soil type with improved Durhum wheat seed type.

cooperatives), more households in Amhara and Oromia have access to credit than households in Tigray and SNNP. The average obtainable credit ceiling is also higher in Oromia and Amhara.

Limited wealth and limited credit may have cumulative effects as well, as farmers fail to make fixed investments in land improvements and essential farm implements. The efficacy of fertilizer also depends on land preparation. The Ethiopian Agricultural Research Institute best practice guides suggest three to five cycle of pre-harvest land preparation to get the optimal results from fertilizer applications. However, among surveyed farmers, 57 percent of households report that they lack land-preparation tools.

Reluctance on the part of market agents to extend credit is understandable, as 62 percent of households ran into difficulty repaying an input loan on one or more occasions. The survey revealed three major reasons for default: low yields due to rain failure; low output prices; and the timing of repayments, in particular being forced to repay immediately after harvest when output prices are depressed.

The survey also points to inadequacies in the performance of agents marketing fertilizers. Timely and adequate supply of fertilizer is one of the major problems reported by households surveyed in the 2004 round. More than 70 percent of the households reported that fertilizer is often supplied late and around 40 percent of the households reported that supplies were inadequate. The survey results also point to high fertilizer prices and inflexible credit repayment schedules as problems that constrain fertilizer use.

There are also historical reasons why Ethiopian fertilizer markets may be incomplete. The structure of fertilizer markets in Ethiopia has constantly changed since the mid-1990s when, following the fall of the Derg regime, the state monopoly on the distribution of fertilizer was lifted. By 1996, 67 private wholesalers and about 2,300 retailers handled roughly two-thirds of the fertilizer market (World Bank, 2006). By the study period, this had dramatically changed. By 2004, a combination of companies with potential political affiliations and a public enterprise, the Agricultural Input Supply Corporation, dominated the wholesale market, with cooperatives handling an increased share of the wholesale market. By 2006 fertilizer was distributed to farmers through a combination of extension agents, local governments and cooperatives, and some private retailers.[24] Despite the resulting complexity of the fertilizer market, Heisey and Norton (2007) found that, on average, the margins between farmgate and import prices for fertilizers in Ethiopia compare well to similarly calculated margins in South Africa and other African economies – although the margins are still high in comparison to Asia or Latin America. At the same time, Mezgebo (2005) notes large regional differences in fertilizer margins, suggesting heterogeneity in how local markets function.

The changing structure of fertilizer markets came as a consequence of a government decision to promote "packets" of high-yielding seeds, fertilizers and extension services. Following a set of successful pilots, the approach was rapidly expanded under Ethiopia's Participatory Demonstration and Extension

[24] A 2006 report by the Ethiopian Economic Association/ Ethiopia Policy Research Institute (EEA/EEPRI) estimated that the public sector handled about 70 percent of the retail market. See Gebremedhin, Hoekstra and Tegegne (2006) on the evolving role of extension agents in Ethiopia.

Training System (PADETS). For the most part, the packets were sold on credit after a 10 to 35 percent down payment (DSA, 2006). Credit was extended through the Commercial Bank of Ethiopia through cooperatives, local authorities and micro-lending institutions, which also handle record keeping and the collection of interest and principal.

Questions included in the 2004 survey about PADETS and other extension programs show the reach of the government programs and provide anecdotal evidence that constraints, rather than limited profitability, prevent farmers from adopting more productive technologies. Households participating in the 2004 wave were asked if they participated in an extension program and how productivity gains from the package are compared with traditional practices. More than 64 percent of the sampled households participated in a program and 95 percent of the households found the new technology more profitable than the traditional one. More than 50 percent of the households responded that production increased by 50 percent while 20 percent of households reported production increase of more than 50 percent. Only a small proportion of households (7 percent) felt that the extension package was riskier than the traditional practices and only 11 percent of the households opted out of the extension package program.

Although fertilizers, pesticides, seeds and land-management practices are all important components of high-yielding technologies, the price of fertilizer plays a dominant economic role in the cost of competing technologies. Data from the 2006 wave of the survey shows that, among farmers that used fertilizer, the cost of chemical fertilizers averaged around 18 percent of the total value of outputs while the share of all remaining purchased inputs (including improved and traditional seeds, hired labor, transportation, rented oxen and tractor) averaged around 9 percent.

As Table 4 indicates, chemical fertilizer was not the only nutrient employed by farmers in the survey. Surveyed farmers often applied animal manures too, especially in 2006. The table also reveals differences in how the two types fertilizers are marketed. For most farms, chemical fertilizers reached the farm through formal markets – that is, they were generally purchased with cash or on credit. In contrast, almost 80 percent of organic fertilizer reached the farm through informal channels; most organic fertilizer was recovered from animals owned by households, or was given freely by neighbors. Some land owners provided manure to their tenants, accounting for another 13.5 percent.

Empirical Results

Estimation results from the panel selection models, with and without group means, are given in Table 5. In general, the model fits well and differences between the two versions of the model are minor. The signs on the determinants are consistent with expectations, as are tests of significance for most of the individual parameters. The correlations between the error-components of the two model equations, reported in the final rows of the table, are statistically significant, which is consistent with our selection specification.

Selection equation

As discussed, the determinants of the selection equation are designed to account for market performance and the capacity of households to adjust for market shortcomings on their own. Turning to the first group, the first three variables indicate the delivery of services: whether chemical fertilizer is available nearby, whether credit has been extended and whether extension services have been provided. The signs associated with all three variables are significant and positive, in line with expectations.

The next two variables relate to climatic and market risks that may discourage agents from entering markets and present hurdles to households when markets are incomplete. The climate variable, which measures average rainfall, has a positive and significant coefficient, indicating that rainfall and fertilizers are complementary inputs. This is reasonable for the study area, since the demand for fertilizer in the aggregate is expected to be lower in arid areas and higher in areas where growing-season rainfall totals are higher.

Weather variability is likely to result in output variability, and in areas with weak output markets or inadequate storage services, this translates into more volatile output prices and more variable fertilizer demand. This creates hurdles for fertilizer providers, who will find it more difficult to manage inventories and judge profits. In addition, households subjected to greater weather variability face greater risks, weakening their capacity to build wealth or repay credit and further eroding the willingness of agents to extend credit. For all of these reasons, price volatility is expected to have a negative impact on fertilizer adoption and our results are consistent with this expectation.[25] However, the parameter is not statistically distinguishable from zero in the augmented version of the model that includes group means. We speculate that this has to do with the relationships among climate, price volatility and household wealth, which reenter the selection equation via group mean effects.

Results associated with the second set of explanatory variables indicate that larger households headed by younger individuals with greater stocks of human, financial and social capital are more likely to adopt fertilizer using techniques. The first three determinants in the selection equation – household size, age and level of literacy of the household head – relate to the household's ability and capacity to implement farming techniques that use chemical fertilizers. As discussed, larger families may be in a better position to manage income risks by diversifying sources of income. Larger families may also be better positioned to work around labor market imperfections, permitting family members to engage in land preparation and other labor-intensive activities associated with fertilizer use. The negative relationship between age and adoption may also be related to labor market imperfections since advancing age may limit the ability of farmers to fulfill essential and physically demanding tasks in the face of a weak labor market. Age might also be related to information hurdles or risk aversion, since older farmers may be reluctant to find out about new methods or

[25] Dercon and Christiansen (2011) construct a measure designed to capture the risk of bad-weather losses and find that it stifles the adoption of fertilizer use.

experiment with them.[26] Alternatively, better educated farmers may have a greater capacity for processing information and for innovation.[27] In addition, wealthier families are in a better position to self-insure and self-finance and otherwise cope with incomplete markets.

Results from the selection equation also indicate that being in a position of local authority increases the probability of adopting fertilizer-using techniques. This positive and statistically significant relationship may be a direct one since fertilizer and credit supplies are channeled through a variety of local public and cooperative agencies. It may be that politically active households are better informed about state-sponsored programs and are therefore more likely to participate in them. Moreover, discretion is given to local agencies, opening the programs to local influence (DSA 2006).[28] As a consequence, local leaders may receive preferred access to the programs or better terms.[29] It is also possible that politically active farmers possess unobservable entrepreneurial characteristics that make them more likely to adopt new technologies and also adopt leadership roles. Our result may capture any or all of these channels. Whatever the case, the effects are additional to those captured directly by the access to credit and extension variables already discussed. Moreover the positive effect associated with council membership is robust to our treatment for potential correlated group effects.

Demand for chemical fertilizer

The middle panel of Table 5 shows the estimated parameters of the fertilizer demand equation, adjusted for selection. The first result is that Ethiopian farmers in the sample were sensitive to the price of fertilizer relative to output prices. This is consistent with market-based outcomes. It is also consistent with the notion that, by raising fertilizer costs and reducing farm-gate prices for surplus production, high transport costs dampen the use of fertilizers by African farmers. The sensitivity of demand to relative prices suggests that fertilizer subsidies can stimulate farmer demand, to the extent that the subsidies effectively lower local prices. However, in contrast to investments that reduce transport costs, the direct effects will be temporary and work to reduce input prices only rather than both components of the input-output price ratio. Still, lasting effects could accumulate through the build-up of household wealth, an outcome that longer longitudinal studies might address.

[26] Croppenstedt and Demeke (2003) and Dercon and Christiansen (2011) also found that larger households were more likely to use fertilizer.

[27] Because education is tied to a farmer's capacity to innovate or understand new methods and manage other kinds of risk, the notions of education and risk aversion can be confounding. Pitt and Sumodiningrat (1991) argue that illiterate farmers are more risk averse and, consequently, less willing to take on the additional risks associated with fertilizer use. Yesuf and Köhlin (2009) also find that their measure of risk aversion limits fertilizer demand in a bivariate censured regression model.

[28] To obtain fertilizer credit under most programs, farmers are required to pay a certain percentage of the fertilizer cost as down payment, but the size of the down payment is not uniform. For example, in the Oromiyo region, the down payment is generally 25-30 percent, but can run as high as 60 percent and some farmers receive loans without a down payment.

[29] Banful (2011) argues that fertilizer vouchers in Ghana were targeted to garner political support.

As discussed, farmers in the study area also apply organic fertilizers. Applications of organic fertilizers provide nutrients directly and build up the organic content of soils, which increases the efficacy of chemical fertilizers.[30] As a result, organic fertilizer use could factor as either a complement or substitute in an input demand equation for fertilizer. To avoid estimation problems, we use livestock density to proxy the quantities of manure available for application rather than application rates, since organic and inorganic fertilizers are likely jointly determined. As discussed earlier, most organic fertilizer originates locally and reaches the farm through non-market channels, so manure availability and manure use are closely associated. Moreover, in addition to addressing a statistical problem, the approach likely accounts for past practices and missing measurements concerning the organic content of soils. Returning to the question of whether chemical fertilizers are substitutes or complements, our findings suggest that organic fertilizers and chemical fertilizers are complements.[31]

The results also suggest a statistically significant and negative association between the intensity of fertilizer and farm size. This is contrary to the positive correlation between land size and fertilizer use in Feder, Just and Zilberman (1985), but consistent with the results reported in Croppenstedt and Demeke (2003) in Ethiopia and Nkonya et al. (1997) in Tanzania. In the Tanzanian study, the authors suggest that farmers with larger land holdings sometimes hedge risks by using a mix of fertilizer application strategies that work to lower average rates. Potentially, the relationship could also be related to incomplete labor markets, which limit a household's ability to take on the complementary tasks of land preparation and application. In either case, these arguments are tied to included-variables (wealth and household labor), yet the scale result remains robust when group means are added to the model, leaving the root cause of this often-found relationship unclear.

Parameter estimates associated with age and the literacy of the household head, which were significant in the adoption of fertilizer-use, were not statistically significant determinants of the intensity of fertilizer use. The finding associated with age is consistent with other studies and indicates the impediments associated with age, once overcome, do not affect the intensity of fertilizer use. [32] Similarly, household size appears to factor into the choice of technology, but not its implementation.[33] In contrast, literacy does have a positive impact on fertilizer use.

As discussed, wealth can mitigate weaknesses in credit and insurance markets. The results suggest this effect is a continuous one, allowing households to risk increasing levels of sunk costs associated with larger applications of fertilizers. While climate plays a role in adoption, our results on the effects of

[30] Results from Kenya, reported in Marenya and Barrett (2009), suggest that adding organic matter to the soils would raise the expected profits from applying chemical fertilizers.
[31] Matsumoto and Yamano (2013) report a similar finding using data from Uganda. See Marenya and Barrett (2009) for an intuitive discussion of the physical and economic aspects of fertilizer efficiency and the organic content of soils.
[32] Nkonya et al (1997), Croppenstedt and Demeke (2003), and Alem et al. (2010) report similar findings.
[33] Household size is significant in several studies that treat adoption and demand jointly in a censured regression. Dercon and Christiaensen (2011) report results similar to ours.

contemporaneous weather outcomes are muted. In general, fertilizer applications are made before weather outcomes are known, although farmers can make adjustments when fertilizer is applied in a series of doses and also reduce fertilizer applications when rains are late. As discussed, the practice of applying fertilizer in stages is reportedly uncommon in Ethiopia and our results indicating that farmers make other adjustments are mixed. The estimates for both models suggest that fertilizer use is reduced when rains are lower than normal, but the findings are statistically robust only when group means are included. And finally, the time effect estimates suggest that fertilizer demand increased between the first and second waves, even after adjusting for changes in other determinants. This provides indirect evidence of a positive trend in the adoption of fertilizer-using technologies that is consistent with technology adoption theory (Feder and Umali 1993).

Conclusion

In this paper, we develop a conceptual framework in which the decision environment faced by agents providing inputs and services influences the farming methods (technologies) available to farmers and the relative profitability of those technologies. This and exogenous features of households and the land they farm combine to create the decision environments that lead to observed choices about applied technologies and derived fertilizer demand. Through this mechanism, the conceptual model suggests that heterogeneity in household decision environments explains the pervasive heterogeneity of household choices about using fertilizer observed in African survey data.

We then develop a consistent statistical model in which the implicit adoption function is influenced by market performance and the capacity of households to overcome market shortcomings. We argue that heterogeneity in the set of available technologies has ramifications for statistical models since the observed set of fertilizer-using technologies are not drawn from identical sets of locally available technologies, potentially leading to biased estimates. We address this problem by using a panel-selection model.

Results from the estimated model are consistent with the notion that adverse market conditions limit the availability and therefore the adoption of fertilizer-using technologies. Nevertheless, the results suggest that markets are present in rural Ethiopia and that, despite variations in market performance, farmers in the aggregate respond to relative prices. This provides a potential pathway for subsidies to stimulate demand. Still, lowering fertilizer prices may not change the decision environment for agents and farmers in fundamental ways, with the consequence that market performance and farmer choice revert to old equilibriums if subsidies are not maintained. Other research has shown that high transport and transaction costs in rural Ethiopia are structural constraints that penalize farmers by raising input prices and lowering output prices at the farmgate, setting economic perimeters on the adoption of fertilizer-using technologies. The conceptual model and findings from the empirical model suggest that policies that lower transaction costs, by supporting infrastructure improvements and by improving the business environment in which commercial agents operate, can generate deeper effects than do subsidies by expanding the technologies available to farmers for any given price outcome. New and adaptive research into plant varieties that use nutrients more efficiently or systems that generate organic nutrients can help as well by allowing farmers to depend less on input markets.

The results also suggest that households with greater wealth, human capital and authority can exploit those assets to overcome hurdles that stand in the way of using fertilizers. This shows that households are resourceful in finding ways to compensate for market weaknesses. However, it also implies a self-enforcing link between low agricultural productivity and poverty, since low-asset households are less able to cope with market imperfections on their own. This in turn has consequences for incomes, food security and the sustainability of soils as the resource poor can remain trapped in an eroding livelihood strategy. It is therefore important to experiment with technological and economic solutions that target places where markets are incomplete.

Bibliography

Abuja Declaration (2006): Abuja Declaration on Fertilizer for the African Green Revolution, issued at the Africa Fertilizer Summit: African Union Special Summit of the Heads of State and Government. Abuja, Nigeria, 13 June 2006.

Adenikinju, A.F., and O. Olugboyega (1999): “Characteristics and Behavior of African Factor Markets and Market Institutions and their Consequences for Economic Growth,” CID Working Paper 31. Center for International Development at Harvard University. Harvard: Mass.

Akiyama, T., J. Baffes, D.F. Larson, P. Varangis (2001): Commodity Market Reforms: Lessons of Two Decades. Washington: World Bank.

Alem, Y., M. Bezabih, M. Kassie, and P. Zikhali (2010): "Does Fertilizer Use Respond to Rainfall Variability? Panel Data Evidence from Ethiopia," Agricultural Economics 41(2): 165-175.

Alene, A.D., V.M. Manyong, G. Omanya, H.D. Mignouna, M. Bokanga, and G. Odhiambo (2008): “Smallholder Market Participation under Transactions Costs: Maize Supply and Fertilizer Demand in Kenya”, Food Policy 33 (4): 318-328.

Antle, J.M. (1983): “Sequential Decision Making In Production Models,” American Journal of Agricultural Economics 65(2): 282–290.

Atwood, D. (1990): “Land Registration in Africa: The Impact on Agricultural Production,” World Development 18(5): 659-671.

Bacha, D., G. Aboma, A. Gemeda, and H. D. Groote (2001): "The Determinants of Fertilizer and Manure Use in Maize Production in Western Oromiya, Ethiopia," Seventh Eastern and Southern Africa Regional Maize Conference Proceedings.

Banful, A.B. (2011): "Old Problems in the New Solutions? Politically Motivated Allocation of Program Benefits and the ‘New’ Fertilizer Subsidies." World Development 39(7): 1166-1176.

Barrett C.B. (1996): “On Price Risk and the Inverse Farm Size-Productivity Relationship,” Journal of Development Economics 51(2): 193-215.

Bekele, T. and W. Höfner (1993): “Effects of Different Phosphate Fertilizers on Yield of Barley and Rape Seed on Reddish Brown Soils of the Ethiopian Highlands,” Fertilizer Research 34(3):243-350.

Binswanger, H. and P. Pingali (1988): “Technical Priorities for Farming in Sub-Saharan Africa,” Research Observer 3(1): 81-98.

Binswanger, H.P., and J. McIntire (1987): “Behavioral and Material Determinants of Production Relations in Land-Abundant Tropical Agriculture,” Economic Development and Cultural Change 36(1): 73-99.

Bromley, D.W., and Chavas, J.-P. (1989): “On Risk, Transactions, and Economic Development in the Semiarid Tropic,” Economic Development and Cultural Change 37(4): 719-36.

Bumb, B.L., M.E. Johnson, and P.A. Fuentes (2012): “Improving regional fertilizer markets in West Africa.” IFPRI Policy Brief 20. Washington: International Food Policy Research Institute.

Buresh R.J., P.A. Sanchez, and F. Calhoun (1997): Replenishing Soil Fertility in Africa. Madison: Soil Science Society of America and American Society of Agronomy.

Byerlee, Derek., David Spielman, Dawit Alemu, and Madhur Gautam (2007): "Policies to Promote Cereal Intensification in Ethiopia: A Review of Evidences," IFPRI Discussion Paper 00707. Washington: International Food Policy Research Center.

Chamberlin, J. and T.S. Jayne (2013): “Unpacking the Meaning of ‘Market Access’: Evidence from Rural Kenya,” World Development 41(1): 245-264.

Cooter, R. and J.T. Landa (1984): “Personal versus Impersonal Trade: The Size of Trading Groups and Contract Law,” International Review of Law and Economics 4(1): 3-103.

Crawford, E., V. Kelly, T.S. Jayne, and J. Howard (2003): “Input Use and Market Development in Sub-Saharan Africa,” Food Policy 28(4): 277-92.

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

CSA (2008): "Agricultural Sample Survey 2007/2008: Farm Management Practices Volume III," Addis Ababa: The Federal Democratic Republic of Ethiopia Central Statistical Agency.

Deininger, K., and S. Jina (2006). “Tenure Security and Land-related Investment: Evidence from Ethiopia.” European Economic Review 50(5): 1245-1277.

Demeke, M., V. Kelly, T. S. Jayne, A. Said, J. C. L. Vallee, and H. Chen (1998): "Agricultural Market Performance and Determinants of Fertilizer Use in Ethiopia," Addis Ababa: Grain Market Research Project Working Paper 10, Ministry of Economic Development and Cooperation.

Dercon, S. (2005): Insurance Against Poverty. Oxford and New York: Oxford University Press.

Dercon, S., (1996): “Risk, Crop Choice, and Savings: Evidence from Tanzania,” Economic Development and Cultural Change 44(3): 485-513.

Dercon, S., and L. Christiaensen (2011): “Consumption Risk, Technology Adoption and Poverty Traps: Evidence from Ethiopia.” Journal of Development Economics 96(2): 159-73

Dillon, J.L and J.R. Anderson (1971): “Allocative Efficiency, Traditional Agriculture, and Risk,” American Journal of Agricultural Economics 53(1): 26-32.

DSA (2006): "Study on Improving the Efficiency of Input Market: Volume 1," Addis Ababa: Development Studies Associates.

EEA/EEPRI (Ethiopian Economic Association/ Ethiopia Economic Policy Research Institute) (2006): Evaluation of the Ethiopian Agricultural Extension with Particular Emphasis on the Participatory Demonstration and Training Extension System (PADETES). Addis Ababa, Ethiopia.

Feder, G. (1980): “Farm Size, Risk Aversion and the Adoption of New Technology under Uncertainty,” Oxford Economic Papers 32(2): 263-283.

Feder, G. (1985): The Relation between Farm Size and Farm Productivity: The Role of Family Labor, Supervision and Credit Constraints. Journal of Development Economics 18(2-3): 297-313.

Feder, G., and D.L. Umali (1993): "The Adoption of Agricultural Innovations: a Review. Technological Forecasting and Social Change, 43: 215-239.

Feder, G., and T. Onchan (1987): "Land Ownership Security and Farm Investment in Thailand," American Journal of Agricultural Economics 69(2): 311-320.

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): 255-298.

Fufa, B., and R. Hassan (2006): "Determinants of Fertilizer Use on Maize in Eastern Ethiopia: A Weighted Endogenous Sampling Analysis of the Extent and Intensity of Adoption," Agreko 45(1): 38-49.

Gebremedhin, B., D. Hoekstra, and A. Tegegne (2006): "Commercialization of Ethiopian Agriculture: Extension Service from Input Supplier to Knowledge Broker and Facilitator," IPMS Working Paper 1. Nairobi: International Livestock Research Institute.

Goetz, S. (1992): "A Selectivity Model of Household Food Marketing Behavior in Sub-Saharan Africa," American Journal of Agricultural Economics 74(2): 444-452.

Greene, W. H. (2007): Limdep Version 9.0 Econometric Modeling Guide. New York: Econometric Software, Inc.

Gregory, D. I., and B.L. Bumb (2006): "Factors affecting the supply of fertilizer in Sub-Saharan Africa," Agriculture and Rural Development Discussion Paper 24. Washington: World Bank.

Gurara, D.Z., and D.F. Larson (2013): "The Demand for Fertilizer when Markets are Incomplete: Evidence from Ethiopia," in K. Otsuka and D.F. Larson (eds): An African Green Revolution: Finding Ways to Boost Productivity on Small Farms. Dordrecht: Springer.

Haggblade, S., P.B.R Hazell. and T. Reardon (2007): Transforming the Rural Nonfarm Economy, Baltimore: Johns Hopkins University Press.

Heaton, J., and D.J. Lucas (1996): "Evaluating the Effects of Incomplete Markets on Risk Sharing and Asset Pricing," Journal of Political Economy 104(3): 443-487.

Heckman, J.J. (1979): "Sample Selection Bias as a Specification Error," Econometrica 47(1): 153-161.

Heisey, P.W. and G. Norton (2007): "Fertilizers and Other Farm Chemicals" in R. Evenson and P. Pingali (eds.) Handbook of Agricultural Economics, Amsterdam: Elsevier.

Henao, J., and C. Baanante (2006): Agricultural Production and Soil Nutrient Mining in Africa: Implications for Resource Conservation and Policy Development. IFDC, Muscle Shoals, AL.

Hoff, K., and J.E. Stiglitz (1990): "Introduction: Imperfect Information and Rural Credit Markets – Puzzles and Policy Perspectives," World Bank Economic Review 4(3): 235-250.

Holden, S. and R. Lunduka (2012): "Do Fertilizer Subsidies Crowd Out Organic Manures? The Case of Malawi," Agricultural Economics 43(3): 303-14.

Honore, B. E., and E. Kyriazidou (2000): "Panel Data Discrete Choice Models with Lagged Dependent Variables," Econometrica, 68(4), 839-874

Howard, J., E. Crawford, V. Kelly, M. Demeke, and J.J. Jeje (2003): "Promoting High-Input Maize Technologies in Africa: the Sasakawa-Global 2000 Experience in Ethiopia and Mozambique," Food Policy 28(4): 335-248.

Jayne, T. S., J. Govereh, M. Wanzala, M. Demeke (2003): "Fertilizer Market Development: A Comparative Analysis of Ethiopia, Kenya, and Zambia," Food Policy 28(4): 293-316.

Jayne, T., T. Yamano, J. Nyoro (2004): "Interlinked Credit and Farm Intensification: Evidence from Kenya." Agricultural Economics 31(2-3): 209-18.

Jha, D. and B. Hojjati (1993) "Fertilizer Use on Smallholder Farms in Eastern Province, Zambia." Research Report 94. Washington: International Food Policy Research Institute.

Johnson, M., P. Hazell, and A. Gulati (2005): "The Role of Intermediate Factor Markets in Asia's Green Revolution: Lessons for Africa?" American Journal of Agricultural Economics 85(5): 1211-1216.

Key, N., E Sadoulet, and A. de Janvry (2000): "Transaction Costs and Agricultural Household Supply Response," American Journal of Agricultural Economics 82(2): 245-259.

Kimhi, A. (2006): "Plot Size and Maize Productivity in Zambia: Is There an Inverse Relationship?" Agricultural Economics 35(1): 1–9.

Krugman, P. (1991)" "Increasing Returns and Economic Geography," Journal of Political Economy 99(3): 485–499.

Kyriazidou, E. (1997): "Estimation of a Panel Data Sample Selection Model," Econometrica 65(6): 1335-1364

Lamb, R. (2003): "Fertilizer Use, Risk, and Off-farm Labor Markets in the Semi-Arid Tropics of India," American Journal of Agricultural Economics 85(2): 359-371.

Larson, D.F., and F. Plessmann (2009): "Do Farmers Choose to be Inefficient? Evidence from Bicol," Journal of Development Economics 90(1): 24-32.

Larson, D.F., and M. León (2006):"How Endowments, Accumulations, and Choice Determine the Geography of Agricultural Productivity in Ecuador," World Bank Economic Review 20(3): 449-71.

Larson, D.F., J.R. Anderson, and P. Varangis (2004): "Policies on Managing Risk in Agricultural Markets," World Bank Research Observer 19(2): 199-230.

Larson, D.F., K. Otsuka, T. Matsumoto, and T. Kilic (2013): "Should African Rural Development Strategies Depend On Smallholder Farms? An Exploration of the Inverse-Productivity Hypothesis," Agricultural Economics 45(1): 1-13.

Lele, U.J., R.E. Christiansen, and K. Kadiresan (1989): Fertilizer Policy in Africa: Lessons from Development Programs and Adjustment Lending, 1970-87. Washington: World Bank.

Lipton, M. (1976): "Agricultural Finance and Rural Credit in Poor Countries," World Development 4(7): 543-553.

Lipton, M. (2006): "Can Small Farmers Survive, Prosper, or be the Key Channel to Cut Mass Poverty?" The Electronic Journal of Agricultural and Development Economics 3(1): 58–85.

Lipton, M., and M. Lipton (1993): "Creating Rural Livelihoods: Some Lessons for South Africa from Experience Elsewhere," World Development 21(9): 1515-1548.

Lucas, D.J. (1993): "Asset Pricing with Incomplete Markets," Hitotsubashi Journal of Economics, 34 (Special Issue): 163-179.

Mankiw, N.G. (1986): "The Equity Premium and the Concentration of Aggregate Shocks," Journal of Financial Economics 17(1): 211-219.

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.

Marenya, P.P., and C.B. Barrett (2009):" Soil Quality and Fertilizer Use Rates among Smallholder Farmers in Western Kenya," Agricultural Economics 40(5): 561-72.

Massey, D.S., J. Arango, G. Hugo, A. Kouaouci, A. Pellegrino, and J. E. Taylor (1993): "Theories of International Migration: A Review and Appraisal," Population and Development Review 19(3): 431-466.

Matsumoto, T., and T. Yamano (2013):"Soil Fertility, Fertilizer, and the Maize Green Revolution in East Africa," in K. Otsuka and D.F. Larson (eds.), An African Green Revolution: Finding Ways to Boost Productivity on Small Farms, Dordrecht: Springer.

Mehra, R., and E.C. Prescott (1985): "The Equity Premium: A Puzzle," Journal of Monetary Economics 15(2): 145-161

Melitz, M. and G.I.P. Ottaviano (2008): "Market size, trade, and productivity," Review of Economic Studies 75(1): 295-216.

Mezgebo, T. (2005) "Structure, Conduct and Performance of Fertilizer Marketing Industry of Ethiopia", draft.

Mitchell, T.D, M. Hulme, and M. New (2002): "Climate Data for Political Areas," Area 34(1): 109-112.

Morduch, J. (1999): "Between the State and the Market: Can Informal Insurance Patch the Safety Net?" World Bank Research Observer 14(2): 187-207.

Morris, M., V.A. Kelly, R.J. Kopicki, and D. Byerlee (2007): Fertilizer Use in African Agriculture: Lessons Learned and Good Practice Guidelines. Washington: World Bank.

Morrison, B.M. (1980): "Rural Household Livelihood Strategies in a Sri Lankan Village," Journal of Development Studies 16(4): 443-462.

Moschini, G., and D. Hennessy (2001): "Uncertainty, Risk Aversion and Risk Management for Agricultural Producers" In B. Gardnerand G. Rausser (eds.) Handbook of Agricultural Economics, vol. 1A, Agricultural Production, Amsterdam: Elsevier Science.

Moseley, W.G., J. Carney, and L. Becker (2010): "Neoliberal Policy, Rural Livelihoods, and Urban Food Security. In West Africa: A Comparative Study of The Gambia, Côte d' Ivoire, and Mali," Proceedings of the National Academy of Sciences of the United States of America 107(13): 5774-5779.

Mu, R., and D. van de Walle (2011): "Rural Roads and Local Market Development in Vietnam," Journal of Development Studies 47(5): 709-734.

Mundlak, Y. (1988): "Endogenous Technology and the Measurement of Productivity," in Susan M. Capalbo and John M. Antle (eds) Agricultural Productivity: Measurement and Explanation. Washington: Resources for the Future.

Mundlak, Y. (1993): "On the Empirical Aspects of Economic Growth Theory," American Economic Review 83(2): 415-420.

Mundlak, Y. (1996)" Production Function Estimation: Reviving the Primal," Econometrica 64(2): 431-438.

Mundlak, Y., R. Butzer and D.F. Larson (2012): "Heterogeneous technology and panel data: The case of the agricultural production function. Journal of Development Economics" 99(1): 139-149.

Myers, R. (1988): "The Value of Ideal Contingency Markets in Agriculture," American Journal of Agricultural Economics 70(2): 255–67.

Nkonya, E., T. Schroeder, and D. Norman (1997): "Factors Affecting Adoption of Improved Maize Seed and Fertilizer in Northern Tanzania," Journal of Agricultural Economics, 48(1): 1-12.

Norman, D.W. (1974): "Rationalising Mixed Cropping under Indigenous Conditions: The Example of Northern Nigeria," Journal of Development Studies 11(1): 3-21.

North, D.C. (1987): "Institutions, Transaction Costs and Economic Growth," Economic Inquiry 25(3): 419-428.

Otsuka, K. and D.F. Larson (2013): An African Green Revolution: Finding Ways to Boost Productivity on Small Farms, Dordrecht: Springer.

Paxson, C.H., and H. Alderman (1992): “Do the Poor Insure? A synthesis of the Literature on Risk and Consumption in Developing Countries,” World Bank Policy Research Working Paper 1008. Washington: World Bank.

Pitt, M. M., and G. Sumodiningrat (1991): "Risk, Schooling and the Choice of Seed Technology in Developing Countries: A Meta-Profit Function Approach, " International Economic Review 32(2): 457-473.

Pollak, R.A. (1985): “Transaction Cost Approach to Families and Households,” Journal of Economic Literature 23(2): 581-608.

Poulton, C., J. Kydd, and A. Dorward (2006): “Overcoming Market Constraints on Pro-poor Agricultural Growth in Sub-Saharan Africa,” Development Policy Review 24(3): 243-77.

Ricker-Gilbert J., T. Jayne, and G. Shively (2013): “Addressing the ‘Wicked Problem’ of Input Subsidy Programs in Africa,” Applied Economic Perspectives and Policy 35(2): 322–34.

Rosenzweig, M. R., and H.P. Binswanger (1993): “Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments,” Economic Journal 103 (416): 56-78.

Rosenzweig, M.R. (1988): “Risk, Implicit Contracts and the Family in Rural Areas of Low-income Countries,” Economic Journal 98(393): 1148-70.

Sachs, J., J. Mcarthur, G. Schmidt-Traub, M. Kruk, C. Bahadur, M. Faye and G. Mccord (2004): “Ending Africa's Poverty Trap,” Brookings Papers on Economic Activity 1, 117-216.

Saha, A., and J. Stroud (1994): "A Household Model of On-Farm Storage under Price Risk." American Journal of Agricultural Economics 76(3): 522-534.

Shively, G.E. and Ricker-Gilbert, J. (2013): "Measuring the Impacts of Agricultural Input Subsidies in Sub-Saharan Africa: Evidence from Malawi's Farm Input Subsidy Program," Global Policy Research Institute (GPRI) Policy Briefs 1(1): Article 4.

Simtowe, Franklin, Manfred Zeller, and Alious Diagne (2009): “The Impact of Credit Constraints on the Adoption of Hybrid Maize in Malawi.” Revue D’etudes En Agriculutre et Environment/ Review of Agricultural and Environmental Studies 91(1): 5-22.

Skees, J., P. Varangis, D.F. Larson, and P. Siegel (2005): “Can Financial Markets be Trapped to Help Poor People Cope with Weather Risks?” In S. Dercon (ed): Insurance Against Poverty, Oxford and New York: Oxford University Press.

Spielman, D.J., D. Byerlee, D. Alemu, and D. Kelemework (2010): “Policies to Promote Cereal Intensification in Ethiopia: The Search for Appropriate Public and Private Roles,” Food Policy 35(3): 185-94.

Stephens, E.C., and C.B. Barrett (2011): “Incomplete Credit Markets and Commodity Marketing Behaviour,” Journal of Agricultural Economics 62(1): 1-24.

Swaminathan H., R.S. Du Bois, J.L. Findeis (2009):”Impact of Access to Credit on Labor Allocation Patterns in Malawi,” World Development 38(4): 555-566.

Teklu, T. and A. Lemi (2005): “Factors Affecting Entry and Intensity in Informal Rental Land Markets in Southern Ethiopian Highlands,” Agricultural Economics 30(2): 117-128.

Udry, Christopher (1994): “Risk and Insurance in a Rural Credit Market: An Empirical Investigation in Northern Nigeria,” Review of Economic Studies 61(3): 495-526.

Van Dusen M, and J.E. Taylor (2005): “Missing Markets and Crop Diversity: Evidence from Mexico. Environment and Development Economics,” 10(4): 513-531.

Verbeek, M. (1990): "On the Estimation of a Fixed Effects Model with Selectivity Bias," Economics Letters, 34(3): 267-270.

Verbeek, M., and T. Nijman (1992): "Testing for Selectivity Bias in Panel Data Models," International Economic Review, 33(3): 681-703.

Wanmali, S. (1992): Rural Infrastructure, the Settlement System, and Development of the Regional Economy of Southern India. IFPRI Research Report 91, Washington: International Food Policy Research Institute.

Winter-Nelson, A., and A. Temu (2005): “Impacts of Prices and Transactions Costs on Input Usage in a Liberalizing Economy: Evidence from Tanzanian Coffee Growers.” Agricultural Economics 33(3): 243-53.

Woolcock, M. and D. Narayan (2000): “Social Capital: Implications for Development Theory, Research, and Policy,” World Bank Research Observer 15(2): 225-249.

World Bank (2006): National Fertilizer Sector Project: Implementation Completion Report. Africa Region. Washington: World Bank.

World Bank (2008): World Development Indicators. Washington: World Bank.

Wubeneh, N. G., and J. H. Sanders (2006): "Farm-Level Adoption of Sorghum Technologies in Tigray, Ethiopia," Agricultural Systems 91(102): 122-134.

Xu, Z., Z. Guan, T. S Jayne, and R. Black (2009): “Factors Influencing the Profitability of Fertilizer Use on Maize in Zambia,” Agricultural Economics 40(4): 437-46.

Yesuf, Mahmud and Gunnar Köhlin (2009): “Market Imperfections and Farm Technology Adoption Decisions – A Case Study from the Highlands of Ethiopia,” Working Papers in Economics 403, Gothenburg: University of Gothenburg.

Zabel, J. E. (1992): "Estimating Fixed and Random Effects Models with Selectivity," Economics Letters 40(3): 269-272.

Tables

Table 1: Definitions of Variables Used in the Estimation

Variables	Definition
Household size	Household size in numbers
Age	Age of the household head
Female head of household	Sex of the household head (Dummy, 1=Female)
Education	Education of household head (Dummy, 1= Grade 9 and above)
Credit	Access to credit from any source (Dummy, 1= participation)
Extension	Participation in the government's extension package (Dummy,1= participation)
Fertilizer distribution center	Availability of fertilizer distribution center at village level (Dummy, 1=yes)
Climate	Average June, July, August rainfall during the period of 1960-90 (in mm)
Price risk	Squared deviation of price from its 2002-04 and 2004-06 mean (at district level)
Wealth	Ownership of a house with corrugated iron roof (Dummy, 1=yes)
Village Council membership	Household's head membership status in the village council (Dummy, 1=yes)
Relative price	Ratio of fertilizer to cereal price at district level
Area	Land Area in hectare
Weather	Deviation of June, July, August rainfall from 1960-1990 June, July, August average
Livestock density	Local Livestock per hectare in tropical livestock units

Table 2: Descriptive Statistics

	First Wave=2004		Second Wave=2006		Panel	
Variables	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Household size	6.5	2.4	6.8	2.4	6.6	2.4
Age	44.7	13.5	47.5	13.3	46.1	13.5
Female head of household*	0.13	0.33	0.12	0.32	0.12	0.33
Education*	0.03	0.18	0.02	0.16	0.03	0.17
Credit*	0.71	0.45	0.75	0.43	0.73	0.44
Extension*	0.65	0.48	0.36	0.48	0.50	0.50
Fertilizer distribution center*	0.34	0.47	0.40	0.49	0.37	0.48
Climate	611	257	530	229	570	246
Price risk	0.32	0.63	0.30	0.61	0.31	0.62
Wealth*	0.47	0.50	0.59	0.49	0.53	0.50
Village Council membership*	0.16	0.36	0.16	0.37	0.16	0.37
Relative price	1.78	0.31	2.31	0.41	2.06	0.45
Area	2.58	5.92	2.10	8.37	2.33	7.30
Weather	13.6	170.6	-65.7	149.2	-27.1	164.8
Livestock density	6.8	8.2	8.9	26.1	7.9	19.6

Source: Authors' calculations based on EEA-World Bank survey, Central Statistical Authority, Ministry of Agriculture and Rural Development, Agricultural Marketing Directorate, and the Ethiopian Meteorological Agency. Note: * denotes binary variable.

Table 3: Sample statistics on output and fertilizer use, average values

	2004	2006
Value of Output in Birr per ha	1,405.90	1,807.70
Chemical Fertilizer in Kg	42.00	55.70
Manure in Kg	229.00	549.30
Chemical Fertilizer in Kg per fertilized hectare	116.00	167.00
Percentage of households using:		
Chemical Fertilizer	68.50	63.30
Manure	28.10	58.00
Improved Seeds	35.60	30.10

Source: Authors' calculations based on EEA-World Bank survey.

Table 4: Method of fertilizer acquisition in 2004, (% of total)

	Organic Fertilizer	Chemical Fertilizer
Cash	10.3	37.7
Credit	10.2	61.5
Left over stock	..	0.1
Provided by land owner to tenants	13.5	0.1
Provided for free	9.7	0.6
Own animal dung	56.4	..

Source: Authors' calculations based on EEA-World Bank survey.

Table 5: Selection model estimation results with independent or correlated group effects

	Group-means excluded		Group means included	
Selection equation parameters (adoption)	**Coefficients**	**Standard Error**	**Coefficients**	**Standard Error**
Market performance				
Fertilizer distribution center	0.270[a]	0.064	0.309[a]	0.062
Credit	0.363[a]	0.067	0.432[a]	0.066
Extension	0.852[a]	0.063	0.801[a]	0.062
Climate	0.001[a]	0.000	0.002[a]	0.000
Price risk	-0.121[a]	0.044	-0.015	0.044
Household capacity				
Household size	0.111[a]	0.012	0.101[a]	0.012
Age of household head	-0.005[b]	0.002	-0.010[a]	0.002
Education of household head	1.494[a]	0.253	1.274[a]	0.232
Wealth	0.128[b]	0.063	0.150[b]	0.062
Village Council membership	0.476[a]	0.090	0.551[a]	0.087
Selection-corrected regression parameters (per hectare demand)				
Relative price	-13.778[c]	7.61	-17.034[b]	7.822
Livestock density	0.532[a]	0.035	0.580[a]	0.034
Area	-0.839[a]	0.168	-0.913[a]	0.158
Household size	0.041	1.094	0.584	1.119
Age of household head	0.084	0.206	-0.044	0.211
Education of household head	26.953[b]	11.192	27.231[b]	11.714
Wealth	11.415[b]	5.510	9.896[c]	5.525
Weather	-0.025	0.016	-0.042[b]	0.017
Time effect	41.728[a]	6.838	41.848[a]	6.821
Error structure				
Disturbance standard deviation, σ	0.008	0.538	0.009	0.565
Correlation between regression and probit, ϱ:	-0.155[a]	0.042	-0.151[a]	0.044

Note: The superscripts a, b, and c indicate significance at the 1, 5, and 10 percent level, respectively. The models were estimated using LIMDEP version 9.0.