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Soil quality and fertilizer use rates among smallholder farmers in western Kenya

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Abstract

Studies of fertilizer use in sub-Saharan Africa have been dominated by analyses of economic and market factors having to do with infrastructure, institutions, and incentives that prevent or foster increased fertilizer demand, largely ignoring how soil fertility status conditions farmer demand for fertilizer. We apply a switching regression model to data from 260 farm households in western Kenya in order to allow for the possibility of discontinuities in fertilizer demand based on a soil carbon content (SCC) threshold. We find that the usual factors reflecting liquidity and quasi-fixed inputs are important on high-SCC plots but not on those with poorer soils. External inputs become less effective on soils with low SCC, hence the discernible shift in behaviors across soil quality regimes. For many farmers, improved fertilizer market conditions alone may be insufficient to stimulate increased fertilizer use without complementary improvements in the biophysical conditions that affect conditional factor demand.

JEL classification: Q12, Q18, Q24

Keywords: Fertilizer demand; Fertilizer policy; Soil carbon; Soil organic matter; Switching regression

1. Introduction

The growing contrast between the productivity-enhancing role played by fertilizer in other regions and the very limited use of fertilizer in sub-Saharan Africa (SSA) has reenergized debate on the types of policies needed to realize fertilizer's potential benefits in Africa. SSA farmers use only 9 kg of fertilizer per hectare (ha), compared to 73 in Latin America and 100–135 in Asia, where as much as 50% of the Green Revolution yield growth is attributed to fertilizer use (IFDC, 2006). The literature highlights the development policy imperative of increasing fertilizer use in SSA (Crawford and Jayne, 2006; Gregory and Bumb, 2006; Kelly, 2006; Kherallah et al., 2002; Morris et al., 2007; Poulton et al., 2006). These studies show that while agricultural sector reforms in the last two decades have increased private sector participation in input and output markets, SSA's agricultural sectors have registered only marginal increases in fertilizer use overall. While in some cases these marginal increases represent improvements in use rates over the pre-reform period, in most places, farm, and plot-level demand for fertilizer remain inadequate to deal with declines in soil fertility and food supply. The result is that agricultural productivity growth in SSA over the past several decades has lagged far behind that in other world regions and remains well below that required to meet food security and poverty reduction goals (Poulton et al., 2006).

What drives low fertilizer application rates among SSA farmers? Studies of fertilizer market development in SSA have been dominated by analyses of economic and market factors having to do with infrastructure, institutions, and incentives that impede or foster increased fertilizer demand (Gabre-Madhin, 2005; Gregory and Bumb, 2006; Jayne et al., 2003; Kherallah et al., 2002; Omamo et al., 2001; Poulton et al., 2006). These factors are undeniably important. However, the apparent sluggish response by farmers to improved market conditions in the wake of widespread liberalization over the past 20 years suggests that more is involved in fertilizer demand than just market level factors. Waithaka et al. (2007) allude to the role that nonmarket factors such as climatic and soil conditions play in determining farmers' input use rates. But there has been little explicit study by social scientists of how soil biophysical conditions affect farmer fertilizer demand, in particular whether economic factors commonly thought to impede or foster fertilizer purchase—such as cash liquidity—cease to be relevant once soil quality degrades sufficiently.

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Using plot-level data on soil quality and plot age (i.e., how long plots have been continuously cultivated since initial conversion from native forest), we investigate the possibility of discontinuities in fertilizer demand patterns, and in the factors determining fertilizer application rates conditional on soil quality status. We find notable differences between farmers operating higher quality plots and those managing lower quality plots, with the latter generally cultivated for longer time periods than the former. Our findings suggest that biophysical variables, captured here by soil carbon content, play an important role in determining rates of fertilizer use in addition to the usual household socioeconomic and transaction cost variables used in the literature (de Janvry et al., 1991; Jayne et al., 2003; Omamo et al., 2001). Considering the high-profile policy efforts now underway in SSA to promote market-led agricultural development through increased fertilizer use (IFDC, 2006), these issues have important policy implications that we explain in the article's concluding section.

2. Background

The problem of fertilizer adoption is both important in itself and because it embodies all the problems of technology adoption that we encounter in developing countries. The analysis of fertilizer demand has largely employed familiar models of adoption analysis. For example, several studies have emphasized farmers' lack of access to credit and insurance as a limiting factor to fertilizer uptake (Croppenstedt et al., 2003; Duflo et al., 2005; Duong and Izumida, 2002; Gregory and Bumb, 2006; Jayne et al., 2003; Kherallah et al., 2002; Omamo et al., 2001; Poulton et al., 2006). This has led to the call for microfinance and microfinance services for the poor liquidity constrained rural households (Morduch, 2000; Robinson, 2001; von Pischke et al., 1983). There is also widespread recognition that rural markets do not work well in rural SSA. Mineral fertilizers are imported, expensive to ship overland given the often-poor state of roads and physical security, and thus tend to be very expensive (Diagne and Zeller, 2001; Jayne et al., 2003; Omamo et al., 2001).

An emerging body of literature on smallholder market participation has similarly emphasized the role of transaction costs in smallholder behavior (Bellemare and Barrett, 2006; de Janvry et al., 1991; Goetz, 1992; Key et al., 2000; Renkow et al., 2004; Staal et al., 1997; Vakis et al., 2003). The core point of this literature is that household-specific transaction costs give rise to idiosyncratically missing markets among agrarian households that may have important consequences for peasant household response to price incentives. A subthread of the fertilizer adoption literature has similarly focused on transactions costs. For example, a Tobit analysis of factors determining fertilizer use rates in eastern Kenya shows that while there was an increase in the number of farmers using fertilizer due to increased village input retailing, use rates remain low due to high transaction costs that reduce fertilizer's profitability for farmers (Freeman and Omiti, 2003). Another adoption study, by Adesina (1996), similarly found distance from a farmer's field to the market an important factor that discourages fertilizer use.

But in a recent review of research on smallholder market participation in SSA, Barrett (2008) shows that in addition to transaction costs, which are largely determined by public goods such as roads, physical security, contract enforcement mechanisms, and information availability, households' productive assets have an important bearing on the ability and incentives of smallholders to participate in agricultural markets. Private asset endowments not only enable self-insurance and liquidity that circumvents some of the financing constraints that commonly limit market participation or technology uptake, they can also provide crucial complementary inputs to production, increasing the returns of other inputs, such as fertilizer. As a result, interventions aimed at improving poor households' access to productive assets may be central to stimulating smallholder market participation and escape from semi-subsistence poverty traps. This point may be critical to understanding fertilizer market participation and application rates since natural capital in the form of soil nutrients is typically nontradable but complementary to purchased fertilizer inputs in determining crop production. If a farm household's *ex ante* endowment of soil capital affects the productivity of fertilizer it might purchase, then we would expect fertilizer application (and purchasing) behavior to vary markedly with farmers' soil quality.

This point has been largely ignored in the literature to date. Farm size is the most common, and often the only, measure of land assets in most studies of fertilizer application. But this kind of formulation implausibly assumes homogeneity in the quality of land among households. Adesina (1996) found that a favorable biophysical environment is as important as proximity to markets in determining fertilizer use by smallholder rice cultivators in Cote d'Ivoire. Similarly, Mwangi (1997) showed that unfavorable soil quality depresses farmers' fertilizer demand. One important difference between Mwangi (1997) or Adesina (1996) and this article is that we use precise measures of soil quality data at plot level, as opposed to coarse subjective categorizations. Additionally, we hypothesize soil quality affects fertilizer demand patterns not only directly but, more fundamentally, by conditioning how factors such as household income or credit access affect fertilizer demand.

The core contribution of this article is to determine how complementarities between fertilizer and soil carbon content (SCC) that have recently been reported in the literature on SSA agriculture (Marenya and Barrett, forthcoming; Zingore et al., 2007) affect smallholder fertilizer demand. We introduce a novel approach to the study of smallholder fertilizer adoption and application rates by developing a simple behavioral model that explains why one might see threshold effects in farmer fertilizer application behavior and then using plot-level soils, fertilizer use and plot age data in an endogenous switching regressions model we examine fertilizer use conditional on soil quality. We thereby not only reinforce the intuitive point that soil quality matters to fertilizer uptake, we also explicitly show

how plot-level biophysical measures of soil quality influence the salience of more conventional transaction costs and liquidity constraints variables in determining fertilizer application rates among smallholders. We do this by endogenously splitting our sample into two soil quality regimes to allow for the possibility that different soil condition regimes may lead to distinct fertilizer demand behaviors.

The choice of SCC as a measure of soil quality is appropriate because soil carbon is increasingly recognized as the single best summary statistic for soil fertility status associated with soil organic matter (SOM) stocks (Manlay et al., 2007). SCC is itself a function of a complex suite of factors, including soil conservation, cropping patterns, and the application of organic fertilizers and biomass recycling. Soil carbon itself is biochemically slow-moving, so that changes in SOM do not occur quickly in response to a single season's activities but are, rather, the cumulative result of patterns over an extended period, commonly measurable in years or even decades. Thus, plot SOM can be reasonably taken as exogenous to farmer fertilizer application decisions in a given period. Additionally, SOM pools act as nutrient reservoirs and regulate the availability of soluble nutrients to plants, both directly and because organic matter provides carbon needed by soil microbial communities for metabolic processes that in turn release nutrients for crop uptake (Bationo and Mokwunye, 1991). When farmers fail to replenish soil carbon, either due to scarcity of organic resources (e.g., animal manure, reincorporated crop residues) or failure to rest soils after a period of continuous cultivation that draws down nutrient and SOM stocks through harvest and leaching, loss of soil carbon may create conditions that make the use of inorganic fertilizers less productive because nutrients introduced by fertilizer application are then less available to plants. Of course, if farmers apply less fertilizer and thereby generate less biomass that can be reincorporated into the soil this can generate a reinforcing feedback loop that undermines the restoration of soil health.

Where SCC is low, fertilizer use may prove unprofitable for a broad range of application levels due to low expected returns via marginal crop yield gains (Marenya and Barrett, forthcoming). In this case, fertilizer market reforms or relaxing household-specific liquidity or transaction cost constraints may not markedly improve incentives to increase fertilizer use because the SCC-conditional yield response is too low to make fertilizer use profitable, even if transactions costs are lower or credit becomes available. For such farmers, fertilizer use might only increase if market and price incentives are accompanied by programs that also increase SCC, thereby boosting the expected marginal productivity of fertilizer.

On the other hand, farmers whose plots have reasonably high levels of SCC already enjoy high-expected marginal product of fertilizer use. In this soil quality regime, improvements in marketing infrastructure that make fertilizer more available and less costly to purchase, or improvements in output prices or farmer liquidity, should lead directly to increased fertilizer use as soil fertility is not limiting and farmers therefore respond more readily to marginal price incentives. We need to be cautious, however, not to project the behaviors of this more familiar—and in some environments perhaps a larger—cohort onto those other farmers who struggle to cultivate SOM-deficient soils.

3. Conceptual model

We conceptualize smallholder farmer demand for fertilizer using a simple, stylized model of household behavior. Assume a representative household maximizes utility defined over consumption of a vector of agricultural commodities, q^a, and a vector of other goods bought from the market, q^m. The household earns income from production and possibly sale of agricultural crops and from off-farm earnings, I (which includes unearned income). Crop output q^o is generated using a production technology, $q^o = q^o\ (V|A,\ S,\ G,\ Z)$ that transforms purchased variable fertilizer inputs, V, given quasi-fixed inputs (land area, labor, livestock, machinery) represented by A, soil quality, S, public goods and services such as roads, grades and extension services, G, and household characteristics that act as productivity shifters such as education, farming experience, age, etc. (Z), into crop output, part of which is consumed in the household as q^a. The household utility function is represented by

$$U = U(q^a, q^m) \tag{1}$$

subject to two constraints: the household's cash budget constraint and the production technology

$$p^v q^v + p^m q^m + p^a q^a = p^a q^o(V\,|A, S, G, Z) + I, \tag{2}$$

$$q^o = q^o(V\,|A, S, G, Z), \tag{3}$$

where p^a, p^m, and p^v are, respectively, the market prices for agricultural goods, manufactured goods bought from the market, and variable inputs. Assuming an interior solution to the household's optimization problem, we can in theory solve for the variable input demand as a function of all exogenous or quasi-fixed variables

$$q^v = q^v(p^a, p^v, p^m, Z, S, G, A, I). \tag{4}$$

A final element is the household-specific variation in shadow prices due to household-specific variation in transactions costs. While market prices are common to everyone, the transactions costs of bringing fertilizer or manufactured goods back to one's farm or evacuating harvested crop from farm to market will vary across households. Furthermore, while public goods will be common to all, *A, I, S,* and *Z* will vary across households as well, making the marginal returns to inputs vary depending on household-specific capabilities as expressed in *A, S,* and *Z*, as well as household-specific shadow prices.

Thus each household has its own conditional factor demand for fertilizer. Whether a household buys fertilizer depends on whether the market price per unit of fertilizer p^v, adjusted for the

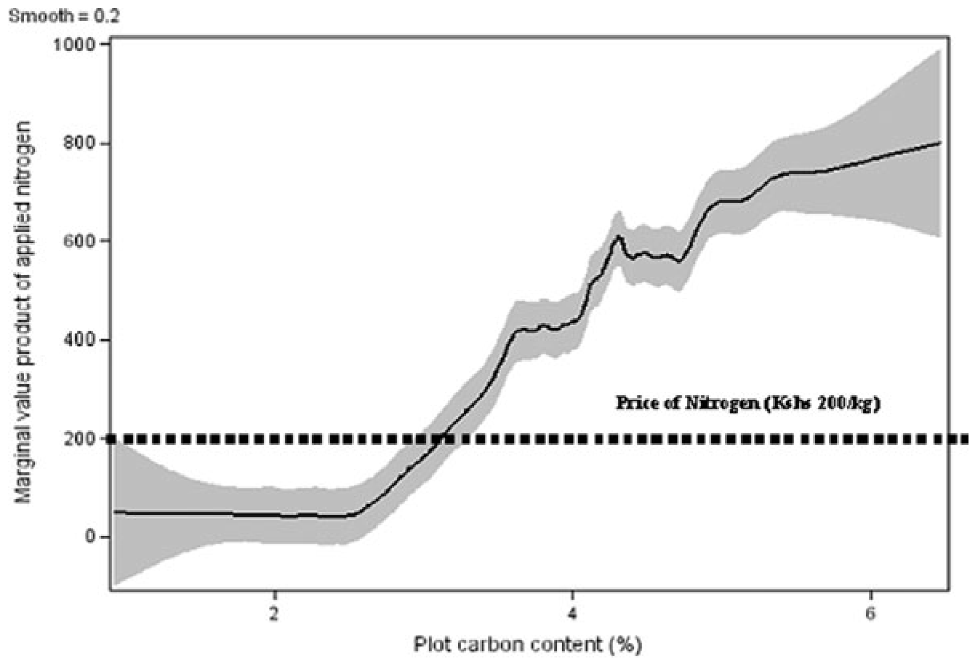

Fig. 1. Estimated marginal value product of nitrogen fertilizer (Kshs/kg N) conditional on plot soil carbon content (line shows the nonparametric regression, while the shaded areas reflect the 95% confidence band around the conditional mean). From Marenya and Barrett (forthcoming).

household-specific transactions costs of buying the fertilizer, is at least equal to the marginal value product (MVP) of fertilizer, evaluated at p^a, i.e., $p^o(\partial q^o/\partial v)$ less the household-specific transactions costs of selling crop.

The household's net market position for fertilizer can be represented by an indicator variable denoted $M = 1$ if the household enters the market to buy fertilizer amount $q^v > 0$ and $M = 0$ if it elects not to buy the input. The household pays the price p^v plus transaction costs τ^v per unit of fertilizer bought. These transaction costs depend on public goods and services (e.g., radio broadcast of prices that affect search costs, extension service information on crop marketing strategies, road accessibility to market), household, and farm-specific characteristics, Z (e.g., educational attainment, gender, age) and other household assets, A (e.g., transport equipment) and liquidity from farm and nonfarm earnings, I, all of which might affect transaction costs. Therefore the household's fertilizer market participation decision can be represented as follows:

$$\left.\begin{array}{lll} M = 1 & \text{if} & p^o(\partial q^o/\partial v) \geq p^v + \tau^v(Z, A, G, I) \\ M = 0 & \text{if} & p^o(\partial q^o/\partial v) < p^v + \tau^v(Z, A, G, I) \end{array}\right\}. \tag{5}$$

In this article, we focus in particular on how soil quality, S, affects fertilizer demand due to the complementarity between SOM reflected in SCC and nutrients introduced through inorganic fertilizer application. This complementarity is clearly reflected in the sigmoid-shaped estimated relationship between SCC and the expected MVP of nitrogen fertilizer, as reported in Marenya and Barrett (forthcoming) and reproduced in Fig. 1. The vertical axis shows the marginal value product per kg of nitrogen applied on maize plots in the same sample of farms studied in this article. At an average nitrogen price of Kshs 200 per kg, it appears that many farmers whose plots have SCC below about 3% may find the use of fertilizer suboptimal because low SCC causes the MVP of nitrogen fertilizer to fall below its price. In the low-SCC regime (below roughly 3% SCC), farmers should not respond to marginal changes in the price of maize. Above that threshold, the expected MVP of fertilizer increases rapidly, so that marginal changes in the price of either maize (which shifts the MVP curve upward) or fertilizer can lead to a significant increase in fertilizer uptake at the extensive, as well as intensive, margins. At higher levels of SCC, liquidity constraints in particular may limit farmers' fertilizer purchases.

These two regimes, defined by the threshold at which fertilizer application starts to become profitable, have distinct policy implications for farmers in the two soil quality regimes. For those whose SCC falls below the profitability threshold, market reforms that marginally improve prices or initiatives to relax farmer liquidity constraints may not markedly improve incentives to increase fertilizer use because the SCC-determined yield response is too low for fertilizer to be profitable without massive subsidies, which may not be the best use of scarce resources to aid poor smallholders. For such farmers, fertilizer use may only increase if such standard economic incentives are accompanied by programs that help them improve the fertility of their soils by replenishing depleted SOM. On the other hand, farmers whose plots have reasonably high levels of SCC and therefore high-expected marginal product of fertilizer can benefit immediately from improvements in seasonal credit availability or in marketing infrastructure that make fertilizer more available and less costly and that boost crop prices. Such interventions should lead to increased fertilizer use at the intensive margin, among farmers already using fertilizer.

4. Empirical model

The conceptual model above suggests that the factors that influence fertilizer uptake vary depending on whether one lies above or below the SCC level at which fertilizer uptake becomes profitable in expectation. If this is true, then estimation of fertilizer demand on a sample that pools plots across the SCC threshold would lead to biased estimates, reflecting an artificial composite of farms with low SCC whose fertilizer use rates are largely nonresponsive to liquidity constraints and prices and those with higher SCC who are responsive. We therefore hypothesize that controlling for household- and farm-specific factors, farmers' fertilizer application behavior will be structurally different between two regimes defined by a SCC threshold. Of course, we do not know exactly where that threshold lies, although prior results suggest it is in the neighborhood of 3% SCC (Fig. 1). But we can estimate that threshold and then, conditional on the estimated threshold, test whether fertilizer demand patterns vary on either side of it. To achieve this we apply a switching regression framework, splitting the data into two segments following the method developed by Hansen (2000) to identify an optimal threshold.

Differences in fertilizer use rates on either side of an apparent SCC threshold may arise under either of two different situations. First, if there is no behavioral difference across SCC levels, but SCC levels are associated with different farmer characteristics, then we may still find differences in fertilizer application rates between the low-SCC and high-SCC groups. But these differences in fertilizer application rates would not arise due to SCC differences. Alternatively, fertilizer use rate differences may result from otherwise-identical farmers responding differently based on their SCC status. In this case, SCC regime matters fundamentally to fertilizer demand patterns. After establishing that there are differences in fertilizer application rates across the two groups of farmers, we set out to see which of these explanations fits the data best.

We use recent sample splitting methods based on grid search techniques, as discussed in Hotchkiss (1991) and Hansen (2000). Let v_{1i} and v_{2i}, $i = 1, \ldots, N$, denote the dependent variable fertilizer use rates (kg/ha) to be explained in each of the two regimes. Let X_{1i} and X_{2i} be $1 \times k_1$ and $1 \times k_2$ vectors of all the explanatory variables (p^a, p^v, p^m, Z, S, G, A, I) that explain fertilizer use rates in each regime. Let β_1 and β_2 be $k_1 \times 1$ and $k_2 \times 1$ parameter vectors, respectively. Based on the von Liebig understanding of limiting soil factors in crop production, we think of SCC as the variable that determines the threshold that separates the two regimes. Finally, u_{1i} and u_{2i} are error terms. The switching regression can then be defined by the following set of equations

$$v_{1i} = X_{1i}\beta_1 + u_{1i} \tag{6}$$

$$v_{2i} = X_{2i}\beta_2 + u_{2i}. \tag{7}$$

Note, however, that X_{1i} and X_{2i} are observed only partially, since X_{1i} is only observed for that part of the sample belonging to regime 1 and X_{2i} is only observed for the subsample belonging to regime 2. What is actually observed is a single variable v_i defined by

$$v_i = \begin{cases} v_{1i} \text{ iff } S_i \geq \lambda^* \\ v_{2i} \text{ iff } S_i < \lambda^* \end{cases}, \tag{8}$$

where λ is the characteristic of the observations used to classify them in the two regimes and λ^* is the cutoff value that determines the initial classification. We hypothesize that S is a relevant variable for λ. So if S_i exceeds the cutoff value S^*, observation i falls into regime 1, and into regime 2 otherwise. The switch point, S^*, is unknown and thus needs to be estimated as well. We can now define the indicator variable R to classify observations into either regime as

$$R_i = \begin{cases} 1 \text{ iff } \lambda_i \geq \lambda^* \\ 0 \text{ iff } \lambda_i < \lambda^* \end{cases}. \tag{9}$$

This allows us to summarize (5)–(7) as

$$v_i = R_i X_{1i}\beta_1 + (1 - R_i) X_{2i}\beta_2 + g_i. \tag{10}$$

Here, $g_i = R_i u_{1i} + (1 - R_i) u_{2i}$ is the error term. Following Hansen (2000), we select the parameter vector $\{\beta_1, \beta_2, \lambda^*\}$ that minimizes the sum of squared errors,

$$\mathrm{E}_n(\beta_1, \beta_2, \lambda^*) = \sum_{i=1}^{n} g_i^2. \tag{11}$$

By estimating Eq. (10) over a range of values of λ^*—i.e., estimating β_1 and β_2 conditional on λ^*—and then doing a grid search to choose the optimal λ^*, we determine the optimal sample splitting point.

A further complication is introduced by the inherent censoring of observed fertilizer application within a given regime. One could assume that the factors that lead farmers to self-select out of fertilizer use are the same as those that determine application rates conditional on use and use a conventional Tobit estimator, as several previous papers have. However, since variables such as fixed transactions costs (e.g., travel time between the farm and fertilizer purchase or crop sales points) should affect the dichotomous choice of whether or not to participate in the market, but not the continuous choice of fertilizer application rate conditional on purchase, we opt instead for a Heckman selection model specification for Eqs. 5–7 above. We then test statistically to verify that this choice is appropriate in these data.

5. Study area and data description

The data were collected from sites in seven different villages in Vihiga and South Nandi Districts in western Kenya, with one site per village. The region is classified by the Kenya Agricultural Research Institute (KARI) as a moist transitional agroecozone characterized by medium to low soil fertility levels. The cropping system is dominated by maize, often with bean intercrops, grown on small plots averaging 0.5 to 1.0 ha. (Place et al., 2002). The rural populations in this region are among the poorest in the country, with 49.9 and 58.1% of the population in Nandi and Vihiga Districts, respectively, living below the national rural poverty line of Kshs 1239/month (US$0.57/day) per person (Kenya, 2000a, 2000b).

Participants for this study were selected from an original sample of 60 farms used in a soil science experiment by Kinyangi et al. (2005). These had been selected in a stratified random sample on the basis of how long cultivation had been going on in each village since the agricultural plots were originally converted from forest. The aim was to sample farms that had been cultivated for less than five years to 100 or more years. The data thus represent a chronosequence of sites that were converted from forest to agriculture in roughly 1900, 1930, 1950, 1970, 1985, 1995, and 2000, on which Kinyangi et al. (2005) conducted experimental trials. To establish that use of these sites actually changed at the times specified, we investigated local records from district and agricultural offices and spoke with elderly community members. Specific locales within the study area had been cultivated for varying lengths of time providing more continuous variation in plot ages. Since these areas are socioculturally similar and physically proximate to one another, with similar institutional and physical infrastructure, intersite differences for other reasons are likely quite modest.

In addition to the original 60 households, we randomly sampled a further 200 households from the same sites, for a total of 260 households. Within each conversion age stratum (site), a census of all maize growing households was conducted with the help of local provincial officials. From those lists, each household was subjectively assigned by the field survey team and the local chief, subchief and village elders to a wealth tercile based on quality of dwelling, farm size, educational attainment, type of employment, and social standing in the village. Households were then selected randomly from these conversion age-wealth tercile strata to include 10–15 households from each wealth tercile in each selected village. Household- and plot-level data were then collected in June–July 2005 using a structured questionnaire to elicit recall responses on farm production and other pertinent data for the preceding long rainy season. All the maize and maize–bean plots cultivated by each of the 260 households were included in the survey. The data collected from the adult responsible for managing each plot included variables such as crop outputs, variable inputs (family labor and hired labor used, disaggregated for each major activity, fertilizer, manure, and other inputs used), the age of the plot (i.e., the specific year in which it was converted from forest) and details on the plot manager (gender, age, educational attainment). Data were also collected from each household on variables such as time taken to bring fertilizer to the farm and availability of formal and informal credit.

We also collected soil samples from each of these households' 445 maize and maize–bean plots at 10 cm depth (i.e., the ploughing layer) at five different positions within each plot. The samples within a plot were mixed to create a composite, plot-specific soil sample. We then had the World Agroforestry Centre (ICRAF) soil laboratory use wet chemistry and near-infrared spectroscopy (NIRS) methods to establish the SCC and nutrient content of these plot-specific soil samples, following protocols developed by Shepherd and Walsh (2002) and Cozzolino and Moron (2003).[1]

Table 1 presents definitions and descriptive statistics for all the variables used in the empirical analysis. Households averaged 1.7 plots sown in maize; we focus on those plots exclusively, some of which were intercropped with beans. The two right-hand columns separate the sample based on the estimated optimal SCC threshold (the estimation of which we explain below). As is plain in that table, there is considerable dispersion within each SCC regime, but also important—if not always statistically significant—differences between the two regimes. In particular, we note that fertilizer application rates are nearly twice, on average, on the high-SCC plots than on the low-SCC plots. But the former households also have higher incomes and better credit access, enjoy more frequent extension agent visits and somewhat larger farms than do those on poorer soils. So it is impossible to sort out the extent to which soil conditions affect fertilizer use patterns on the basis of descriptive statistics alone. Hence the need for multivariate regression analysis.

From Eq. (4), demand for variable input fertilizer is given by $q^v = q^v(p^a, p^v, p^m, Z, S, G, A, I)$. Since the data were collected within a compact geographical area, there was no observed variation in the prices for fertilizer or maize between households. That leaves only variables reflected in *Z, S, G, A,* and *I* to be used in the empirical model. In the vector *Z* we include age, years of education, and gender of household head. We also included variables that captured liquidity constraints such as access to institutional credit, if the fertilizer dealer allowed credit purchase, and household per capita income. Other variables included were those that affect transaction costs such as ownership of bicycles and ox-carts, time taken to reach dealer, and whether farmers had quality problems with fertilizer.

[1] See Marenya and Barrett (forthcoming) for more details on these data and the soil testing methods used. Please note that the average SCC of 3.36% in our sample may appear slightly higher than in other studies that do not stratify to ensure inclusion of samples from plots recently converted from forest. In the present sample, 23% of the plots had been cultivated for less than 10 years since conversion from forests.

Table 1
Variable means (standard deviations), by SCC regime

Variable	Definition	Whole sample	Sample below SCC 2.7%	Sample above SCC 2.7%
Fertilizer application rate	Kilograms of nitrogen from fertilizers applied during 2004. The three fertilizer types identified in the sample were diammonium phosphate (DAP), calcium ammonium nitrate (CAN) and urea, with 18% and 17% and 46% nitrogen, respectively. The total nitrogen applied per plot was computed from the sum of the *N* volume of each type of fertilizer applied.	5.67 (3.23)	3.38 (3.53)	7.95 (4.27)
Average plot carbon content	Laboratory determined percent soil carbon content.	3.36 (1.27)	2.07 (0.40)	4.44 (0.55)
Plot size (ha)	Individual plot size as measured by GPS units	0.36 (0.36)	0.37 (0, 17)	0.38 (0.24)
Total area under maize	In ha, total of all maize plots/household	0.57 (0.47)	0.51 (0.43)	0.63 (0.49)
Age of household head	In years	49.79 (11.64)	50.98 (13.88)	50.98 (13.52)
Formal education of household head	Years of formal schooling	4.20 (2.70)	4.27 (2.24)	4.00 (2.39)
Male household head	Dummy, = 0 if household decision maker is female = 1 if male	0.60	0.55	0.53
Per capita income[a]	Mean partial annual income per capita (in Kenya shillings)	15, 070.24 (5, 676)	13,107 (9,576)	14,161 (7,676)
Extension visit frequency	Dummy, = 1 if farmer had any extension contact during 2005, = 0 otherwise	0.40	0.39	0.41
Institutional credit access	Dummy, = 1 if farmer had received any credit in previous 2 years, 0 if otherwise	0.18	0.13	0.21
Credit obtained from dealer	Dummy, = 1 if dealer allowed credit purchase and = 0 if full payment is required at the time of purchase	0.20	0.15	0.20
Use of machinery	Dummy, = 1 if farmer use draught implements or tractor in land preparation, sowing, or weeding	0.59	0.58	0.60
Use of maize hybrid seed	Dummy, = 1 if farmer planted hybrid, = 0 otherwise	0.73	0.67	0.78
Total time taken to reach dealer	Time in hours for a round trip to the fertilizer dealer	1.31 (1.46)	1.29 (1.23)	1.32 (1.65)
Plot age	Number of years since plot was converted from forest	28.9 (22.6)	31.02 (23.16)	26.81 (7.72)
Whether farmers encountered quality problems with fertilizer	Yes = 1, 0 otherwise	0.23	0.24	0.23
Ownership of bicycle or ox-cart	Yes = 1, 0 otherwise	0.62	0.62	0.61
Number of plot-specific observations		445		
Percentage of plots with no nitrogen fertilizer application		21		
Percentage of plots applying nitrogen at ≥ 20 kg/ha (recommended rate)		3		
Plot size (ha)		0.31		

[a] Income estimates are only partial because not all household autonomous consumption of home-production and labor incomes were recorded in the survey, thus these figures understate total per capita income. This measure is computed from the two most important sources of income declared by the household, gross inflows of transfers and the value of maize and bean output in 2004, taking care to avoid prospective double counting in those (few) cases where maize/bean sales was one of the two most important sources of income.

Table 2
Regime-specific estimates of fertilizer use and application rates (SCC excluded)

Variables	Probit of fertilizer use (= 1 if yes, 0 if no)				Fertilizer application rate (kg/ha *N* per plot)			
	Subsample below 2.70%		Subsample at/ above 2.70%		Subsample below 2.70%		Subsample at/ above 2.70%	
	Coefficient	Standard error	Coefficient	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
Constant	1.73***	0.64	0.08	0.65	9.54***	3.01	7.12	26.33
Age of household head	−0.01	0.01	−0.01	0.13	−0.03	0.03	−0.08	0.15
Plot size	0.0002**	0.0001	0.0003***	0.0001	0.0001	0.0001	0.001	0.001
Education of household head	0.04	0.05	0.003	0.04	0.10	0.13	0.16	0.63
Male household head	0.11	0.22	0.30	0.22	0.54	0.65	3.69	4.28
Per capita income	0.77	0.50	0.66	1.25	0.24	0.21	0.00002	0.00005
Extension visit frequency	0.11	0.22	2.20	0.22	0.34	0.60	1.64	3.74
Institutional credit access	0.04	0.31	0.30	0.24	1.46	4.60	1.60*	0.92
Credit obtained from dealer	0.04**	0.02	0.009	0.26	2.76	1.59	2.76*	1.59
Total time taken to dealer	−0.26*	0.15	0.06	0.13				
Use of hybrid seed	0.25***	0.08	0.25***	0.08	3.78**	1.70	4.31	1.04
Use of machinery	0.36	0.25	0.07***	0.02	0.12	0.64	3.74	5.88
Plot age	−0.003	0.001	−0.005	0.005	−0.03**	0.01	−0.06	0.08
Problem with fertilizer quality	−0.16	0.26	−0.58	0.4	−0.54	0.73	−3.74	5.88
Bicycle/ox-cart ownership	0.21	0.24	0.99	0.22	0.43	0.69	2.02	3.51
Inverse Mills ratio					2.54**	1.28	3.93**	1.86
Correlation coefficient between probit and application rate equations (rho)					0.77	0.32	0.87	0.46
LR test ($\chi^2(1)$) of independence of equations/rho = 0 (*P*-value)					47.18(0.00)		64.65 (0.00)	
LR test ($\chi^2(18)$) of $\beta_{SCC\mathrm{high}} = \beta_{SCC\mathrm{low}}$ (*P*-value in parentheses)					87.34 (0.00)		na	
Observations (*N*)					202		243	

Note: Standard errors appear in parentheses. *,**,*** denote statistically significant at the 10%, 5%, and 1% level, respectively.

6. Regression results

Ultimately, we want to see if the determinants of fertilizer application rates are affected by ex ante soil quality not just directly but also by changing the relation between fertilizer use and standard economic incentives reflected in cash liquidity, via household income and credit access, and in ownership of quasi-fixed inputs such as machinery or farmer education. If there exists a soil quality threshold that creates an extensive margin for profitable fertilizer use, then the usual behavioral responses to changes in liquidity, prices, and quasi-fixed input availability may only apply above the threshold, at the intensive margin of fertilizer use.[2]

The key first step is thus to identify the soil fertility threshold, as explained above. We used the entire range of SCC observed in our sample plots (0.9–6.0%), using a grid search with intervals of 0.3. The minimum sum of squared errors occurred at a SCC level of 2.70%, reasonably close to the level that seems visually, per Fig. 1, to reflect the point at which fertilizer use becomes remunerative on these farms. We therefore divided the 445 plots into two samples, with 202 plots with SCC below 2.70 being low-SCC and the other 243 at or above 2.70 being classified in the high-SCC regime.

Tables 2 and 3 present the Heckman selection model results for the two regimes. First we estimate two different specifications, one which only uses SCC to split the sample, thereby assuming no fertilizer use response to changing SCC within a given regime (Table 2), and the other including SCC as a regressor, as well as using it to split the sample optimally (Table 3). The latter model is clearly preferable, noting that the LR test for the joint significance of all the SCC, SCC^2, and SCC^3 rejects the null at less than the 1% significance level for the low-SCC, high-SCC, and whole sample regressions. We therefore restrict the ensuing discussion to the results displayed in Table 3. We offer Table 2 purely to establish how important it is to control for SCC both as a regime-shifter and as an independent variable that matters in its own right. Other covariates are plainly correlated with SCC and thus the point estimates of non-SCC regressors are significantly affected by the omission of SCC from the regression, as casual comparison of Tables 2 and 3 clearly indicates.

[2] In principle, it would be desirable to control for household-specific unobserved heterogeneity by using household fixed effects in estimating plot-specific fertilizer application rates. However, this requires restricting estimation to a subsample having at least two plots. Since the mean number of maize plots per household was only 1.7, we lose too many observations to make that estimation strategy work with these data, unfortunately.

Table 3
Regime-specific estimates of fertilizer use and application rates (SCC included)

Variables	Probit of fertilizer use (=1 if yes, 0 if no)				Fertilizer application rate (kg/ha N per plot)			
	Subsample below 2.70%		Subsample at/ above 2.70%		Subsample below 2.70%		Subsample at/ above 2.70%	
	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
Constant	2.17	7.19	2.10	1.40	4.80	24.87	2.80	2.80
Age of household head	−0.01	0.02	−0.03*	0.02	−0.07***	0.02	−0.0004	0.001
Plot size	0.0002**	0.0001	0.0004***	0.0001	0.24	0.87	0.06**	0.03
Education of household head	0.05	0.05	0.09***	0.03	0.13	0.12	0.03**	0.01
Gender of household head	0.001**	0.0005	0.21***	0.05	0.45***	0.14	0.22	0.27
Partial income per capita	0.56	0.39	0.20	0.40	0.00001	0.00001	0.00004***	0.00001
Extension frequency	0.07**	0.03	0.25***	0.11	1.60*	0.99	0.78	1.56
Institutional credit access	0.03	0.31	0.32	0.25	0.34	0.80	0.64***	0.18
Credit obtained from dealer	0.01	0.33	0.07	0.26	0.46	0.54	1.29	1.79
Total time taken to dealer	−0.81***	0.31	−0.07	0.13	n.a.	n.a.	n.a.	n.a.
Use of Hybrid	0.16***	0.03	0.21**	0.09	0.23	0.62	0.11	1.99
Use of machinery	0.30	0.26	0.60***	0.25	0.19	0.59	0.64***	0.14
Plot age	−0.23	0.22	−0.04	0.05	−0.03**	0.01	−0.04	0.06
Problem with quality	−0.15	0.27	−0.67	0.55	−0.64	0.67	−0.30	2.07
Bicycle/ox-cart ownership	0.56	0.63	0.17	0.23	0.56	0.63	1.93	1.55
SCC	0.27	0.26	1.60*	0.94	1.25	4.07	0.64**	0.29
SCC^2	−3.82	6.61	−2.13	1.49	−1.96	21.68	−3.97**	1.71
SCC^3	0.64	1.17	1.62	1.09	0.54	3.74	0.31**	0.15
Inverse Mills ratio					2.25**	1.06	1.01**	0.49
Correlation coefficient between probit and application rate equations (rho)					0.87	0.56	0.69	0.22
LR $\chi^2(1)$ test of independence of equations/rho = 0 (P-value)					61.20 (0.00)	54.37 (0.00)		
LR test ($\chi^2(18)$) of $\beta_{SCC\text{high}} = \beta_{SCC\text{low}}$ (P-value in parentheses)					96.54 (0.00)	na		
LR $\chi^2(3)$ test of SCC = SCC^2 = SCC^3 = 0 (P-value)					57.34 (0.00)	51.91 (0.00)		
Observations (N)					202	243		

Note: Standard errors appear in parentheses. *,**,*** denote statistically significant at the 10%, 5%, and 1% level, respectively.

We begin by discussing the selection equation describing the choice whether or not to apply fertilizer. This equation is identified by the time taken to reach the agro-input dealer, a fixed cost that should not affect the fertilizer application rate conditional on using any fertilizer. Within the low-SCC regime, the likelihood of fertilizer use is negatively and statistically significantly related to travel time to reach the nearest fertilizer dealer. It is positively and statistically significantly associated with the frequency of extension visits, plot size, farmer's use of hybrid seed, and with the household head being male. By contrast, in the high-SCC regime, better educated, male farmers and those operating larger maize plots are more likely to use fertilizer. Older farmers are statistically significantly less likely to use fertilizer in this regime. Visits by extension agents have a significant positive effect on fertilizer use. The market access variable (time to dealer) has no significant effect on the discrete choice to use fertilizer on more fertile soils in the high-SCC regime. The use of machinery and hybrid seed were also positive predictors of the decision to use fertilizer in this regime.

There are some common patterns to fertilizer uptake across the two regimes, in particular based on farmer gender, extension access, and the use of hybrid seed. This may show that female farmers still face unequal access to resources as compared to their male counterparts (De Groote and Coulibaly, 1998). And extension agents may have a positive impact on farmers' managerial capabilities and productivity (Hussain et al., 1994), or they may merely create social pressure for farmers to use inputs and methods the agents advocate (Moser and Barrett, 2006), manifest in the use of both inorganic fertilizer and hybrid seed. But there are important differences across SCC regimes as well. In the high-SCC regime where fertilizer use should be profitable, plot SCC is statistically and significantly associated with the decision to use fertilizer. Older and less educated farmers are less likely to use inorganic fertilizers, reflecting a tendency toward traditional cultivation methods without modern inputs.

We overwhelmingly reject the null hypothesis of independence of the dichotomous fertilizer use and continuous fertilizer application rate equations in both high- and low-SCC regimes, as indicated by the likelihood ratio test of the null hypothesis that the estimated correlation coefficient between the errors in the two equations equals zero. The $\chi^2(1)$ test statistics are 61.2 and 54.37 for the low- and high-SCC regimes, respectively, both with a P-value of zero. Discrete fertilizer use decisions are clearly not statistically independent of the application rate decision. We therefore include the inverse Mills ratio (IMR) as a regressor in the second stage equation to control for the predicted probability of fertilizer use in order to correct for possible selection effects associated with unobserved factors that might simultaneously affect the discrete decision to use fertilizer at all and the continuous decision as to how much to apply. The coefficient estimate on the IMR regressor in the second stage regression is statistically significant in both regimes. Moreover the LR tests for the equality of parameters in the low- and high-SCC regime also reject the null hypothesis ($P = 0.00$), reinforcing the appropriateness of splitting the sample into these two regimes.

The second stage fertilizer application rate equations reveal striking behavioral response differences conditional on soil quality regime, as hypothesized earlier. Farmers' fertilizer application behaviors, conditional on expected use, appear to vary markedly with plot soil quality (high-SCC regime), and not just in direct response to soil quality, but also in their response to other variables conditional on soil quality.

On high-SCC plots, fertilizer application rate decisions follow patterns familiar from other adoption studies. Fertilizer application rates are increasing in plot size, the educational attainment of the household head, per capita household income, institutional credit access, and possession of quasi-fixed inputs such as agricultural machinery. Households with greater assets and greater borrowing or self-financing capacity (through cash income, usually from off-farm sources) use more fertilizer. Further, in the high-SCC regime, fertilizer use rates also are strongly and positively associated with SCC, and at an increasing rate, as reflected in the positive estimates of the coefficients on the higher-order polynomials of SCC. Farmer behavior seems to follow standard textbook models of behavior reasonably well at the intensive margin, within this soil fertility regime. Familiar policy prescriptions thus seem quite relevant: increase extension coverage and the availability of seasonal credit, improve marketing systems so as to increase crop prices and bring down fertilizer prices, enhance access to quasi-fixed inputs, etc.

The determinants of fertilizer application rates on low-SCC plots appear quite different, however. Fertilizer application rates are sharply lower on older plots and among older farmers and higher for among male farmers and those farmers who had better extension contact, but little else matters significantly. The result with respect to plot age is especially interesting since older plots grow less fertile due to continuous cultivation. The significant coefficient estimate on plot age may signal that farmers gradually abandon fertilizing older plots with low SCC. They have become, in practical effect, irreversibly degraded. By contrast, plot age has no effect on fertilizer application rates within the high-SCC regime, indicating that so long as soil organic matter can be conserved on the plot, farmers will continue to fertilize it regardless of plot since conversion uncultivated from forest.

In order to highlight the difference that this sample splitting estimation strategy makes, we also reestimated the Heckman selection model for fertilizer application, this time pooling the full sample. As reported in Table 4, the results (predictably) blend those from the two SCC-conditional regimes in Table 3. Younger and better educated farmers appear more likely to use fertilizer. The larger the plot size, the more likely fertilizer was applied. Similarly extension contact, use of hybrid, and plot SCC were shown to be positively associated with decision to apply fertilizer. Regarding factors associated with the rate of fertilizer application, we again find that better educated farmers and plots with higher SCC are associated with higher fertilizer application rates. Although statistically significant, there appears to be mild response to SCC and institutional credit access—masking the robust response that in fact prevails on high-SCC plots. Additionally there is a significantly negative effect due to plot age—which does not exist on high-SCC plots—and a significant positive effect of household liquidity on fertilizer use rates. These conventional, pooled regressions thus yield the familiar results of relatively modest farmer behavioral sensitivity to estimated returns and strong relations to underlying asset stocks and cash liquidity. Hence the familiar policy prescriptions for increasing fertilizer uptake among African smallholders. The problem is that if behaviors differ markedly depending on the quality of plots farmers own, as it seems to be the case in this sample, then the appropriate policy responses should differ by soil quality regime as well.

7. Conclusions

Our estimation results suggest that western Kenyan farmers' fertilizer application behaviors differ markedly across plots of different soil quality. Higher fertilizer application rates on soils with greater SCC do not appear to be due merely to a correlation between SCC and farmer characteristics. Rather, the relationship between those characteristics and fertilizer use patterns varies sharply depending on where a plot's SCC stands relative to an apparent fertility threshold at which point fertilizer use becomes remunerative. This new and important finding could only be uncovered using the novel switching (selection) regression approach we take.

Our results suggest that increased fertilizer uptake due to increased marginal returns through market-level interventions (e.g., subsidies to farmers or traders, improved infrastructure, etc.) is highly likely to occur at the intensive margin, among the wealthier farmers who cultivate high-SCC soils, while farmers cultivating low-SCC soils have statistically insignificant responsiveness to marginal improvements in the returns to fertilizer

Table 4
Whole sample estimates of factors affecting fertilizer use rates

Variable ($n = 445$ plots with plots fertilizer applied on 351 plots)	Probit of selection equation for fertilizer		Application rate equation	
	Coefficient	Standard error	Coefficient	Standard error
Constant	2.54	1.39	13.31**	6.44
Age of household head	−0.002*	0.001	−0.05	0.05
Plot size	1.01***	0.24	2.2	1.94
Education of household head	3.9*	2.18	0.04*	0.03
Gender of household head	1.27	0.97	1.27	0.97
Partial income per capita	0.000002	0.000002	0.0002**	0.00009
Extension frequency	0.08***	0.02	0.22	088
Institutional credit access	0.20	0.19	0.07*	0.04
Credit obtained from dealer	0.01	0.19	1.03	1.09
Total time taken to reach dealer	0.53	0.97	na	na
Use of hybrid	0.15***	0.02	0.55	0.97
Use of machinery	0.50	0.47	0.07	1.02
Plot age	−0.001	0.003	−0.11**	0.05
Problem with quality	−0.24	0.17	−0.25	1.03
Bicycle/ox-cart ownership	1.04	1.48	0.99	0.90
SCC	0.63**	0.26	0.006***	0.0015
SCC^2	−0.47	0.36	−0.48	2.20
SCC^3	0.04	0.03	0.51*	0.20
Inverse Mills ratio			2.29**	1.06
Correlation coefficient between probit and application rate equations (rho)			0.89	0.29
LRχ^2(1) test of independence of equations/ rho = 0 (P-value)	59.46 (0.00)			
LRχ^2(3) test of SCC = SCC^2 = SCC^3 = 0	50.08 (0.00)			

Note: Standard errors appear in parentheses. *,**,*** denote statistically significant at the 10%, 5%, and 1% level, respectively.

use, limiting the likely expansion of fertilizer use onto more degraded plots. Since high population density in western Kenya effectively precludes increasing average farm size for low-SCC farmers, and plot age and farmer gender are immutable, the main policy levers for increasing fertilizer application rates on degraded, low-SCC plots in the region appear to be through increased extension visits—which may not be beneficial if farmers are mainly conforming to agents' wishes rather than learning and increasing their productivity—and by recapitalizing soil organic matter on degraded farms. Standard economic instruments associated with increased farmer liquidity and market function seem unlikely to have much effect on more degraded plots. Since the more degraded plots also tend to be the ones cultivated by the poorest farmers in the region (Marenya and Barrett, forthcoming), this has significant implications for the design of pro-poor fertilizer strategies.

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