The effect of soil quality on 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

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Introduction

The limited use of fertilizer in sub-Sahara Africa (SSA) amidst low agricultural productivity and poverty has sustained debate on what policies are needed to realize fertilizer's potential benefits in Africa given that average fertilizer use is reported to be 9 kg per hectare (ha) in SSA, compared to 73 in Latin America and 100–135 in Asia (IFDC 2006).

Many studies of fertilizer market development in SSA have focused on economic and market factors (infrastructure, institutions and incentives) that impede or foster increased fertilizer demand (Kherallah et al. 2000; Poulton, Kydd and Doward 2006). The persistent low fertilizer use in SSA suggests that more is involved in fertilizer demand than just market level factors. In particular, do economic factors– such as cash liquidity – cease to be relevant once soil quality degrades sufficiently? Yet, few studies by social scientists have dwelt on how soil biophysical conditions affect farmer fertilizer demand.

A body of literature on smallholder market participation has emphasized the role of transaction costs in smallholder behavior (de Janvry, Fafchamps and Sadoulet 1991; Vakis, Sadoulet and de Janvry 2003; Bellemare and Barrett 2006). The core point of this literature is that household-specific transaction costs give rise to idiosyncratically missing markets among households in ways that may have consequences for peasant household response to price incentives. Barrett (2008) shows that in addition to transaction costs, contract enforcement mechanisms, and information availability, households' *productive assets*[2] have an important bearing on their ability and incentives to participate in agricultural markets. Private asset endowments not only enable self-insurance and liquidity which help encourage market participation or technology adoption, they can also provide crucial complementary inputs to production, increasing the returns of other inputs, such as fertilizer. Improving poor households' productive assets may be central to stimulating market participation and escape from semi-subsistence poverty traps. This point may be critical to

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[2] Italics ours

understanding fertilizer market participation and application rates since natural capital in the form of native soil nutrients is typically non-tradable 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, we would expect fertilizer purchasing and application behavior to vary markedly with farmers' soil quality.

The core contribution of this paper is to determine how complementarities between fertilizer and soil carbon content (SCC) that have been reported in the literature on SSA agriculture (Zingore et al. 2007) affect smallholder fertilizer demand. We investigate the possibility of discontinuities in fertilizer demand patterns, and in the factors determining fertilizer application rates, conditional on soil quality status. We thus 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. By endogenously splitting our sample into two soil quality regimes (low-SCC and high-SCC) to allow for the possibility that different soil condition regimes may have distinct fertilizer demand behavior, we 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.

Conceptual and empirical 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 other goods bought from the market, q^m. The household earns income *I* from production, sale of agricultural crops, from off-farm earnings and unearned income. Crop output q^o is generated using a production technology, $q^o = q^o\left(V \middle| A,S,G,Z\right)$ that transforms purchased fertilizer inputs, *V*, and 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 q^o, part of which is consumed in the household as q^a. The household utility function is represented by:

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

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

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

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

where p^a, p^m and p^v are the market prices for agricultural goods, manufactured goods and variable inputs, respectively. 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:

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

Note that 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.* Thus each household has its own conditional factor demand for fertilizer. In this paper we pay particular attention to how soil quality, *S*, affects fertilizer demand due to the complementarily between soil organic matter (SOM) reflected in SCC and nutrients introduced through inorganic fertilizer application. As we discuss later, these SCC-determined regimes, may have distinct policy implications for the two groups of farmers.

Empirical model

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. 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. We therefore hypothesize that controlling for household- and farm-specific factors-farmers' fertilizer application behavior will be structurally different between the two regimes defined by a SCC threshold. We can estimate that threshold and then, conditional on the estimated threshold, test whether fertilizer demand patterns vary on either side of it.

We apply a switching regression framework, splitting the data into two segments using grid search techniques as in Hotchkiss (1991) and Hansen (2000). Let v_{1i} and v_{2i}, $i = 1,...,N$, 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 variables $\left(p^a, p^v, p^m, Z, S, G, A, I\right)$ 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. In the manner of a von Liebig understanding of limiting factors in crop production (Paris 1992), 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 be defined by the following:

$$v_{1i} = X_{1i}\beta_1 + u_{1i} \tag{5}$$

$$v_{2i} = X_{2i}\beta_1 + u_{2i} \tag{6}$$

Note, 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 sub-sample belonging to regime 2. What is actually observed is a single variable v_i defined by:

$$v_{\mathrm{i}} = \begin{cases} v_{1i} \text{ iff } S_i > \lambda^* \\ v_{2i} \text{ iff } S_i \leq \lambda^* \end{cases} \tag{7}$$

Where λ is the characteristic of the observations used to classify observations into the two regimes and λ^* is the cutoff value that determines the initial classification. In our case, *S* is the 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 is estimated as well. We now define the indicator variable R to classify observations into either regime as

$$R_i = \begin{cases} 1 \text{ iff } \lambda_i > \lambda^* \\ 0 \text{ iff } \lambda_i \leq \lambda^* \end{cases} \tag{8}$$

Rewriting (5) - (7) we have:

$$v_i = R_i X_{1i}\beta_1 + (1-R_i)X_{2i}\beta_2 + g_i \tag{9}$$

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,

$$E_n\left(\beta_1, \beta_2, \lambda^*\right) = \sum_{i=1}^{n} g_i^2 \tag{10}$$

By estimating equation 9 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 jointly determine the optimal sample splitting threshold and the regime-specific behavioral parameters.

Study area and data description

Data for this study 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 characterized as a moist transitional agro-ecozone with a cropping system dominated by maize, often with bean intercrops, grown on small plots averaging 0.5 to 1.0 ha. (Place et al. 2002). Recent estimates show that 49.9 and 58.1 percent of the population in Nandi and Vihiga Districts, live below the national rural poverty line of Kshs 1239/month (US$0.57/day) per person (Kenya 2000).

We randomly sampled a total of 260 households for this study. 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 data such as 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). We also collected soil samples from each of the 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 were analysed at the World Agroforestry Centre (ICRAF) soil laboratory using wet chemistry and near-infrared spectroscopy (NIRS) methods to establish the SCC content of these plot-specific soil samples, following protocols developed by Shepherd and Walsh (2002).

Table 1 presents definitions and descriptive statistics for the variables used in the paper. Households averaged 1.7 plots sown in maize; we focus on those plots exclusively. We separate the sample based on the estimated optimal SCC threshold of 2.7%. There is considerable dispersion within and between the two SCC regimes. Fertilizer application rates are 55 percent higher, on average, on the high-SCC plots than on the low-SCC plots. 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. It is therefore not possible to sort out the effect of soil conditions on fertilizer use patterns on the basis of these descriptive statistics alone.

Regression results

We focus on the main nutrient of fertilizers used in the region, nitrogen (N). In order to estimate the marginal physical product of N fertilizer application, we apply a switching regression model to determine the response of yield to applied nitrogen under two different regimes reflecting whether SOM as represented by SCC or N impose a greater constraint on yields. Let y_{Ni} be the yield on plot *i* in the regime where N is limiting crop yield as denoted by subscript *N*, and let y_{Ci} represent the yield in the regime where SCC is limiting as denoted by subscript *C*. In the first regime, represented by f_N in eq. 11 below, we estimate yield response to N when N is limiting conditional on labor inputs as well as farmer and farm-specific characteristics denoted by *Z*. In the second regime, represented in eq. 11 by f_C, we estimate yield response when N is non-limiting, conditional on *Z*. Using a minimum operator, we mimic a von Liebig specification, following Paris (1992):

Table 1: Means (standard deviations) by SCC Regime of Variables used in Production Function and Fertilizer Use Regressions

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)
Maize-bean inter-crop	Dummy variable. Presence of maize-bean intercrop=1, pure stand maize=0	0.80 (0.40)	0.80(0.40)	0.82 (0.40)
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[3]	Mean partial annual income per capita (in Kenya shillings)	15070.24(5676)	13107(9576)	14161(7676)
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 stockists	Dummy, = 1 if stockist 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 stockiest	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		
Percent of plots with no nitrogen fertilizer application		21		
Percent of plot s applying nitrogen at ≥ 20 kg/ha (recommended rate)		3		
Plot size (ha)		0.31		

$$y_i = \min\left\{ f_N(N, \beta_N \left| Z, \beta_z, \varepsilon_N \right.), f_C(C, \beta_C \left| Z, \beta_z, \varepsilon_C \right.) \right\} \tag{11}$$

[3] 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.

where the β's represent parameter vectors and the ε's are regime-specific errors.

We used these first stage regression results[4] to compute the estimated marginal value product (MVP) of nitrogen fertilizer on each plot. The resulting estimates are consistent with previous findings in the literature. Expected output is increasing in both soil carbon and nitrogen fertilizer. The mean estimated MPP for nitrogen of 17.64 is within the range reported by other studies for East and Central Africa (Mbata 1997 and FAO 2001).

Figure 1 below shows a juxtaposition of returns plotted against SCC and fertilizer use rates plotted against plot level marginal product of fertilizer. The solid curve is a plot of fitted values of MVP. The dashed curve is a plot of estimated plot-level nitrogen

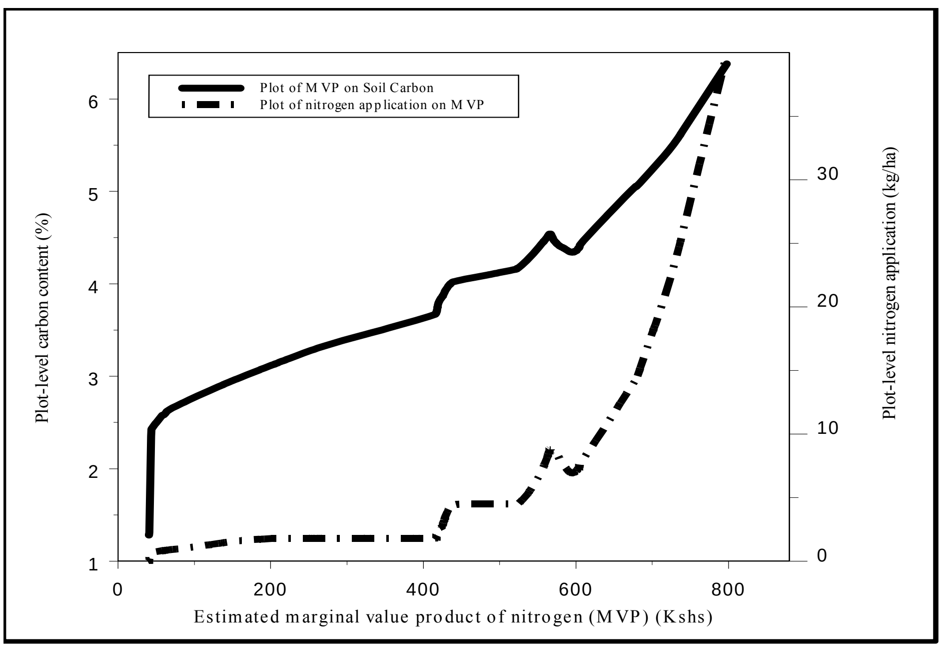

Figure 1: SCC, returns to fertilizer and nitrogen application rates

[4] Due to space limitations, the regression results for this section are not presented. These are available from the authors upon request.

application on fitted MVP. We observe that the estimated MVP of fertilizer application (reflected in the upper, solid curve, measured against the lefthand Y-axis) are low at low SCC levels, picking up after about 2.5% carbon, i.e., near the estimated threshold. Fertilizer application rates (reflected in the lower, dashed curve, plotted against the righthand Y-axis) are also low at low levels of estimated returns (MVP), picking up sharply at MVP Kshs 400. This shows that fertilizer application rates (uptake) rise steeply at MVP well above fertilizer costs (about Kshs 200), indicating that there are other, unobserved (transactions, borrowing, etc.) costs to fertilizer use, which are quite possibly the result of asset and liquidity endowments.

From table 2, we see that the determinants of fertilizer application rates on low-SCC plots appear quite different, however. 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 was 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, Byerlee and Heisey 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 towards 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 are 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.

Table 2: Probit Marginal Effects for the Probability of Fertilizer Use and Application Rates

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 χ^2 (1) test of independence of equations/rho=0 (p-value)					61.20 (0.00)		54.37 (0.00)	
LR test (χ^2 (18)) of $\beta_{SCC\ \mathrm{high}} = \beta_{SCC\ \mathrm{low}}$ (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. *, **, *** Statistically significant at the 10%, 5% and 1% levels, respectively.

Conclusions

Our results suggest that 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. There were statistically significant differences in fertilizer use rates in the high-SCC and low-SCC regimes. This appears to result from the fact that farmers with otherwise-identical plots exhibiting different fertilizer application behavior based on an SCC threshold. This raises important policy implications. For the group whose SCC falls below the some threshold, market reforms that marginally improve prices or initiatives to relax farmer liquidity constraints may not markedly improve incentives to increase fertilizer use. For such farmers fertilizer use will only increase if such standard economic incentives are accompanied by SOM recapitalization. Conversely, farmers whose plots have reasonably high levels of SCC (and therefore high expected MVP) of fertilizer can benefit from policy improvements that lead to credit availability, reduced marketing costs, and better output prices.

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