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Destination or Distraction? Querying the Linkage between Off-farm Income and Farm Investments in Kenya

by

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EXECUTIVE SUMMARY

Off-farm earnings account for a substantial and growing share of household income among smallholder farmers in most of Sub-Saharan Africa, but evidence concerning the effects of these earnings on investment in food production remains sparse. Conceptually, some factors may *push* farm families to send members in search of cash to relieve expenditure constraints or serve to meet consumption needs under duress; other factors *pull* members of rural households toward the promise of steady, dependable income. Previously published research suggests that the search for off-farm income has a negative impact on farm investments.

In this study, we explore the relationships among three types of off-farm earnings (labor on other farms, known as farm *kibarua*; income from self-employed businesses; and income from salaries or wages, including remittances) and investment in fertilizer use in maize production. We test the robustness of linkages by applying a range of econometric models, utilizing panel data collected between 2000 and 2010 in four waves from a sample of Kenyan smallholders. In particular, we hypothesis that as rural economies change with economic development, family labor used in producing maize, the primary staple food, could be drawn toward other sources of income because these are more remunerative—diminishing its use in activities such as fertilizer application or weeding. Also, if income is high enough in other activities, it may make more sense to buy than to produce maize.

Two features of the underlying relationship complicate the choice of econometric models. First, not all farm households in the dataset earn income from off-farm sources, and many farm households apply no fertilizer. Thus, both earnings and investment variables have a large proportion of zeros. Second, there is reason to expect that farm families make their decisions regarding labor allocation to farm and off-farm activities simultaneously. This suggests the potential for endogeneity in the off-farm earnings and fertilizer use variables. Various approaches have been recommended to address these problems, each with advantages and disadvantages.

We explore and compare several of these methods, to gauge the robustness of findings. Recent concerns about identification strategies and other shortcomings of non-linear models lead us to estimate two-stage Fixed Effects Instrumental Variables (FEIV) as a base case. We also estimate a seemingly unrelated, recursive probit model in which the binary decisions to work off-farm and to apply fertilizer are simultaneously estimated. To reflect the continuous nature of the variables of interest when values are observed above zero, we then estimate a Tobit-Tobit specification in which off-farm income is first predicted and then used to explain fertilizer application rates (an instrumented, Control Function Approach or CFA). A Cragg model is also tested to reflect the notion that separate underlying processes may shape the decisions to use fertilizer and the amount used. Finally, we apply Generalized Propensity Score Matching (GPSM) to capture possible non-linearities or threshold effects in the relationship between earned income levels and fertilizer applied. In all three of the non-linear regression models, we employ the Mundlak-Chamberlain technique (also known as Correlated Random Effects, or CRE model) to control for time-invariant unobserved effects that may be related to household decision-making. The outcome of interest—fertilizer application rate—is measured in terms of N nutrient kgs per ha, which has the double advantages of being a more precise measure of nitrogenous fertilizer application and a universal measure that takes into account the many different combinations (fertilizer formulae) through which nitrogen is applied by farmers surveyed.

The overall picture that emerges portrays the effects of non-farm income sources (business and salary earnings) on fertilizer use in maize as consistently and strongly negative. This suggests competition between farm family investments in maize production and nonfarm sectors. At the same time, the relationship between fertilizer use in maize production and earnings from labor on other farms (farm *kibarua*) is statistically weak though positive, perhaps reflecting their minor importance in household income, their relative infrequency, and the role they play in easing cash constraints for some households.

Comparisons also show sensitivity of some estimated parameters to modeling assumptions. Application of the GPSM model adds to our understanding by demonstrating that the magnitude of the marginal effects of non-farm income on fertilizer use rates varies as income changes.

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ACRONYMS

2SLS	two-stage least squares
APEs	average partial effects
CBS	Central Bureau of Statistics
CF	Control Function
CFA	control function approach
CRE	correlated random effects
FAO	Food and Agricultural Organization of the United Nations
FEIV	Fixed Effects, Instrumental Variables
FEIV2SLS	Fixed Effects, Instrumental Variables, Two-Stage Least Squares
GPSM	Generalized Propensity Score Matching
Ha	hectare
IV	instrumental variables
KES	Kenya Shilling
Kgs	kilograms
Km	kilometer
KNBS	Kenya National Bureau of Statistics
N	nitrogen
OLS	Ordinary Least Squares

1. INTRODUCTION

Often scrambling to survive (Bryceson 2002) in a volatile world, smallholder farmers in Sub-Saharan Africa rely on multiple sources of income earned beyond their farm gate. Bryceson's (2000) estimates of the off-farm income share, derived from case studies, ranged from 55% to 80%. Citing surveys undertaken in 23 countries during the 1990s and 2000s, Reardon, Stamoulis, and Pingali (2007) estimated that nonfarm income represented an average of 34% of rural household income. Matsumoto, Kijima, and Yamano (2006) reported that off-farm income represented less than 30% of total household income in Uganda and Ethiopia, and 45% in Kenya. In all three countries, cash income from working on neighboring farms was slight in magnitude (ibid.).

The experience of the Green Revolution in Asia demonstrated that agricultural development can stimulate the growth of the nonfarm rural economy through rising rural wages and farm family incomes. From this perspective, farmer adoption of productivity-enhancing technologies, and especially those that are relatively labor-intensive, encourages the development of local labor markets (Renkow 1993). Multiplier effects are transmitted via factor and product markets and favor households that are net consumers and labor suppliers. Empirical evidence of such transformations in Sub-Saharan Africa, however, remains limited (Otsuka and Yamano 2006; Otsuka and Larson 2013). Some policy makers view the rural nonfarm economy as a pathway out of poverty, but such growth does not occur automatically (Haggblade, Hazell, and Reardon 2010).

Barrett, Reardon, and Webb (2001) conceptualized the linkages between farm and non-farm sectors in terms of *push* and *pull* factors. For example, in the Oromia region of Ethiopia, van den Berg and Kumbi (2006) found that households are pushed into nonfarm activities through inadequate access to land resources. In Mozambique, Cunguara, Langyintuo, and Darnhofer (2011) concluded that nonfarm work is a coping strategy for farm households when faced with drought, concurring that poorer households were more likely to engage in less remunerative activities. In a recent overview of detailed studies in eight countries of Sub-Saharan Africa, Djurfeldt and Djurfeldt (2014) concluded that diversification of income sources outside of agriculture appears to be driven less by distress and increasingly by shifts in producer incentives and non-farm opportunities. According to Mathenge and Tschirley (2010), Kenyan smallholder farmers engage in off-farm work as a long-term strategy to deal with anticipated weather risks.

For some households, off-farm work of family members could serve as a temporary source of cash in times of distress. For others, employment outside the farm could be a more desirable alternative to farming, and farming serves as a cushion in case wages fall short or family members are laid off. For others still, off-farm work could serve as a key complement to farm work; the income generated may allow credit-constrained households to purchase inputs in a timely manner. This last instance is our interest here. Until recently, few studies have formally tested the linkage between off-farm employment decisions of smallholder farmers and their choice of farming techniques using farm household data (Davis et al. 2009). Ahituv and Kimhi (2002) found a negative relationship between off-farm work and investment in agricultural production.

Here, we test the linkages between off-farm earnings and investments in fertilizer on maize in Kenya. Credit is not provided directly for smallholder production of maize, the dominant food staple in Kenya. In the major maize-growing regions of Kenya, a majority of smallholders grows hybrids and has been familiar with them since shortly after the nation's independence. Soil fertility is a binding constraint to crop productivity in most regions of

Sub-Saharan Africa, and there is a consensus that raising productivity will require at least some mineral fertilizer in addition to other soil amendments (Bationo 2004). In their study of western Kenya, Marenya and Barrett (2007) found that non-farm income positively affected the adoption of integrated soil fertility management practices, including mineral fertilizer, stover lines, and manure. Mathenge, Smale, and Tschirley (2014) found that income from off-farm sources, and specifically nonfarm sources, competes with use of mineral fertilizer in maize production, particularly in more productive areas where use rates are higher.

Kenya's smallholder maize growers are a diverse population with respect to human capital, physical assets, land resources, and the rural economic activities in which they engage. We hypothesize a priori that the effects of off-farm income on fertilizer investment depend on the *type* of work generating that income. Ostensibly, earnings from outside the farm may compensate for missing and imperfect credit markets by providing ready cash for fertilizer purchases as well as other household needs. However, losing adult household members to salaried employment in nearby towns, or allocation of scarce labor time to informal businesses could detract from maize production. Fertilizer application requires labor at crucial points in the growing cycle, and the response of maize yield to fertilizer is strongly affected by the timing of application. In particular, piece work on other farms, called farm *kibarua* in Kenya, may compete directly for labor in peak period tasks.

This paper has two purposes. The first is to test the relationships among various sources of off-farm earnings and fertilizer use among smallholder farmers. The second is to query the empirical approaches that can be used to model these relationships in applied work, testing the robustness of findings. We differentiate by type of off-farm activity, distinguishing between labor on other farms (farm *kibarua*), self-employed or informal businesses, and salaried employment (including remittances from household members employed away from home). We are able to exploit data collected from a panel of 1,243 smallholder farm households distributed across the major agricultural zones of Kenya in four waves that span a decade (2000 through 2010).

We invoke several econometric approaches to estimate the relationship between off-farm income and fertilizer application rates. These include a seemingly unrelated, recursive probit model in which the binary decisions to work off-farm and to apply fertilizer are simultaneously estimated; a Tobit-Tobit specification in which off-farm income is first predicted and then used to explain fertilizer application rates using an instrumental variables Control Function Approach (CFA) (Smith and Blundell 1986); a Cragg model, which relaxes the constraint that parameters are the same in the binary and continuous segments of the fertilizer decision; and a Generalized Propensity Score Matching (GPSM) model to capture potential non-linear or threshold effects in the relationship between income earned and fertilizer applied. In all non-linear specifications, we employ the Mundlak-Chamberlain technique (also known as Correlated Random Effects, or CRE model) to control for time-invariant unobserved effects that may be related to household decision-making. The outcome of interest—fertilizer application rate—is measured in terms of nitrogen (N) nutrient kilograms (kgs) per hectare (ha), which has the double advantages of being a more precise measure of nitrogenous fertilizer application and a universal measure that takes into account the many different forms in which nitrogen is applied within the sample. For purposes of a base comparison, we also estimate the model with a two-stage Fixed Effects (FEIV) approach that assumes linearity of the dependent variable as well as the potentially endogenous variable.

Next, we summarize our conceptual approach. Section 3 discusses the specification issues and related econometric models. Results are presented in the fourth section. Conclusions and implications for Kenya's development policy are drawn in the final section.

2. CONCEPTUAL APPROACH

We view smallholder maize growers in Kenya as agricultural households whose members choose how to invest their labor supply across various on-farm and off-farm activities while also deciding how much cash to invest in purchasing mineral fertilizer to apply in producing their most important staple food crop, maize.

In thinking about how to test the effect of off-farm income on fertilizer application to maize, it is useful to articulate a hypothetical experiment. We might randomly assign off-farm jobs with differing wages and hours to individuals, assuming that each individual can perform his/her assigned jobs irrespective of education, age, gender, and experience. Because job assignments are random, some households will not have any individuals with off-farm work. In this context, the effect on fertilizer application of any off-farm work can be estimated as a simple difference in mean amounts utilized per hectare, comparing those assigned and not assigned off-farm work.

Clearly, whether and how much to work off-farm are not decided randomly, and nor are whether or how much fertilizer to apply to maize. We can imagine a household choosing, each season, which members to dispatch to work off-farm and which to keep on the farm based on the capital endowments cited above. We can think of household members collectively forming a portfolio, with each of the members' occupations chosen each season so that the household best meets its needs for steady consumption and investment. Moreover, we consider that many of the household characteristics and endowments that influence the portfolio of economic activities also influence how much fertilizer is applied to maize.

Another way that our observational data is likely to deviate from data generated with a randomized experiment is that households may make the two decisions simultaneously. For some households, depending on cash constraints and the value of maize output to the household (which is household-specific and endogenous in the model of the agricultural household), the desire to apply fertilizer may push members to work off-farm. Off-farm work may also compete for labor used in maize production, especially if it involves working on other farms during peak periods of labor demand. Because labor and fertilizer are complements in maize production, drawing labor away from production (e.g., weeding, timing of fertilizer application) reduces yield response to fertilizer. This effect would be more pronounced among labor-constrained households.

In general, working off-farm generates benefits such as earning cash and acquiring non-agricultural experience, but has opportunity costs in terms of on-farm tasks, home production, education, or leisure. For tractability in comparing models empirically, we can reduce the household portfolio problem to that of a representative agent who allocates, each season, a part of his or her time to off-farm work and the remainder to leisure, home tasks, and farm work.

The agent decides to work off-farm only to the extent to which the expected benefit outweighs the opportunity cost in terms of on-farm productivity. Similarly, the same agent chooses to apply mineral fertilizer to his maize to the extent that the expected net benefit outweighs the costs of doing so. For the reasons mentioned above, these two decisions may be made simultaneously. However, we make the simplifying assumption that the amount of off-farm income earned influences the fertilizer application rate, but not vice versa. The timing of the fertilizer application decision relative to the income-reporting period, combined with the general absence of farm credit, partially justifies this decision.

Our three main econometric approaches ask subtly different questions about this general relationship between off-farm income and fertilizer use. As we will describe in greater detail below, the seemingly-unrelated bivariate probit (*biprobit*) model considers the interrelationship between the *binary* work and fertilizer use decisions; the Tobit-Tobit model (nested in the Cragg model) with the CF approach treats the income amounts and fertilizer application rates as (continuous) censored variables; and the GPSM assumes that the marginal effect of additional off-farm earnings may differ depending on the level of off-farm income. The biprobit and Tobit-Tobit (Cragg) models allow for potential selection on unobservable characteristics, albeit in distinct ways. On the other hand, the propensity score method can only control for selection on observed characteristics. Finally, all three models include the household means of time-variant variables (CRE). Adding these to the regression models helps to control for unobserved, household heterogeneity and its correlation with observed factors in non-linear models (Mundlak (1978) and Chamberlain (1984)). We also offer an FE model, reflecting they notion that this approach should be applied even when the data are binary or concentrated at zero (Angrist and Pischke 2009).

3. METHODS

3.1. Data

Our data source is an unbalanced panel collected in four waves of household surveys (2000, 2004, 2007, and 2010) by the Tegemeo Institute of Agricultural Policy and Development, Egerton University, Kenya, and Michigan State University, USA. The sampling frame was prepared in 1997 in consultation with the Central Bureau of Statistics (CBS), currently the Kenya National Bureau of Statistics (KNBS). Large farms and pastoral areas were not considered in the sampling domain. Considering the exclusion of households in Turkana and Garissa that were surveyed only in 1997 (these were not representative of agricultural households), the overall attrition was rate has been 13%. The analysis in this study is based on an unbalanced panel of maize growers, numbering 1,200 in 2000, 1,196 in 2004, 1,203 in 2007, and 1,208 in 2010. As can be seen by these numbers, there is no appreciable attrition among smallholder maize growers.

3.2. Specification Issues and Estimation

Three aspects are worth noting when considering econometric specifications of the general model described above: i) the jointness of the decisions to work off-farm (and the income generated from this work); ii) the panel structure of the observations; and iii) the non-trivial presence of zero observations in both variables of interest (off-farm earnings amounts and amounts of fertilizer applied to maize). Pooling all survey years, only 13.4% of sample households reported income from farm *kibarua*; over half (52.4%) earned income from self-employment in local business or informal activities, and nearly two-thirds (60.2%) received salaried or remittance income. Exactly one-third (33%) used no mineral fertilizer on maize.

We can envision the endogeneity of off-earnings in fertilizer usage that might result from the simultaneity of decisions about off-farm work and input investments. Fertilizer use in any season could depend on the earnings from off-farm work and the timing of receipts. Labor on other farms during the cropping season could compete with weeding and fertilizer application on own farms, but might also provide scarce cash to relieve financial constraints. Investment of labor time in informal business activities in the local rural economy could be complementary to investment on farms but also compete for labor and capital. Wages remitted from salaried employment might be more dependable and thus contribute positively to fertilizer use on maize, though it may also imply that key adults in the household are absent, diminishing capacity to engage in labor-intensive activities—especially in a food staple such as maize, since deficits could then be met through purchase. Endogeneity might also occur because of unobserved characteristics, leading to correlation of independent variables with error terms and bias if estimators are generated by ordinary least squares.

Potential endogeneity of decision-making can be addressed econometrically through several means. Fixed Effects, Instrumental Variables, Two-Stage Least Squares (FEIV2SLS) is appropriate for linear regression models applied to panel data. The FE approach handles time-invariant, intrinsic farm or household characteristics that are unobserved but correlated with errors. Dummy variables for each survey year control for time-varying, unobserved effects. Model diagnostics include i) the evaluation of the joint F-test for excluded instruments in the first stage regression; ii) Hansen's J test for overidentifying restrictions; and iii) the Wu-Hausman test of endogeneity. Failure to reject the null hypothesis in the Hansen-J test indicates that the 'extra' instrumental variables are exogenous in the structural equation, supporting the validity of the instruments.

We estimate FEIV2SLS as a preliminary step only—to serve as a *linear benchmark*. The effects of time-invariant variables that are hypothesized to be pertinent for fertilizer use, such as soil quality, cannot be estimated with an FE model. When both the dependent variable and the potentially endogenous variable are non-linear, Wooldridge (2010) argues that two-stage estimation (as in 2SLS) is inappropriate because it implies that in this case, in the second stage, a nonlinear function of an endogenous variable is replaced with the same nonlinear function of fitted values from the first-stage estimation. Angrist and Pischke (2009) contend that Ordinary Least Squares (OLS) has conceptual robustness that more efficient structural models (such the Tobit) often lack; since nonlinear models (probit, logit, Tobit) are built around a nonlinear transformation linear latent index, these make distributional assumptions which can lead to identification via functional form. According to the authors, the same principle applies to two-stage estimation with instrumental variables (IV). IV approaches capture local average treatment effects regardless of whether the dependent variable is binary, censored, or continuous.

Treating household decisions about whether to allocate labor off-farm and whether to apply fertilizer on maize as binary, joint decisions, we then estimate three sets of two seemingly unrelated, recursive, biprobit models—one for each type of off-farm earnings. The dependent variables in the regression system can be considered as latent variables for which only the dichotomous outcomes can be observed (Maddala 1983). In addition to a shared vector of exogenous variables in each pair of equations, the fertilizer use equation includes the binary variable indicating non-zero off-farm earnings. In so doing, we make the simplifying assumption that the decision to work off-farm has already been made at the time of the fertilizer application decision. Denoting the (binary) off-farm work and fertilizer use decisions for household *i* in year *t* as W_{it} and F_{it}, respectively,

$$W_{it} = \begin{cases} 1 & if\ X_{it}'\gamma + v_{it} > 0 \\ 0 & otherwise \end{cases}$$

$$F_{it} = \begin{cases} 1 & if\ \alpha W_{it} + Z_{it}'\beta + u_{it} > 0 \\ 0 & otherwise \end{cases}$$

$$cov[v_{it}, u_{it}] = \rho$$

In allowing a non-zero correlation between the two error terms, we take into account potential selection (into fertilizer use) based on unobserved variables.

Diagnostic statistics include both the Wald test of correlation among the errors, i.e., the estimated ρ, and the t-test on the regressor measuring off-farm earnings (to test a systematic relationship). Although Maddala (1983) highlighted a potential problem of identification, Wilde (2000) concluded that in contrast to linear simultaneous equations with only continuous endogenous variables, in recursive multiple equation probit models with endogenous dummy regressors, no exclusion restrictions for the exogenous variables are needed if there is sufficient variation in the data. That condition is ensured by the assumption that each equation contains at least one varying exogenous regressor, an assumption which is rather weak in economic applications.

The biprobit specification above considers the joint nature of only the binary decisions to work off-farm and apply fertilizer. That is, it tells us the general effect of the presence of off-farm income on households' likelihood of applying any mineral fertilizer. Ultimately, however, we are interested in how an additional Kenya Shilling (KES) of off-farm earnings changes the intensity of fertilizer application. Therefore, we now consider amounts of off-farm earnings and fertilizer applied per hectare of maize as continuous (albeit censored) variables.

To test and control for potential endogeneity with censored variables, we apply the Control Function (CF) /instrumental variables approach originally proposed by Smith and Blundell (1986) with the Correlated Random Effects (CRE) method of Mundlak (1978) and Chamberlain (1984). As in a two-stage least squares (2SLS) model, the CFA requires use of instrumental variables to test for endogeneity. The first stage involves a Tobit regression of the suspected endogenous (continuous) off-farm income variable *w* on the instruments and all the explanatory variables in the structural model. In the second stage, however, the (continuous and censored) fertilizer application rate *f* is estimated as a function of off-farm income variable with the residual from the first stage added as an explanatory variable. Here we control for selection into fertilizer use based on unobservable characteristics by including the residual from the work decision in the fertilizer decision (i.e., the CF approach)[1].

$$w_{it} = \begin{cases} {w_{it}}^* & if\ {w_{it}}^* = {X_{it}}'\gamma + v_{it} > 0 \\ 0 & otherwise \end{cases}$$

$$f_{it} = \begin{cases} {f_{it}}^* & if\quad {f_{it}}^* = \alpha w_{it} + {Z_{it}}'\beta + \delta \hat{v}_{it} + u_{it} > 0 \\ 0 & otherwise \end{cases}$$

In the CF approach, the test of endogeneity is the statistical significance of the coefficient of the residual $\hat{v}$ in the structural regression. Failure to reject the null hypothesis of exogeneity implies that the decision to work off-farm can be treated as if it were exogenous to fertilizer use. We estimate three such Tobit-Tobit CF-CRE models, one for each source of off-farm earnings.

The above Tobit-Tobit CF-CRE specification inherently assumes that the second-stage (binary) decision to use any fertilizer is determined by the same process that predicts the amount of fertilizer applied. We test this assumption by specifying an alternative model—a double hurdle Cragg model (1971)—which allows the regression parameters to differ between the decision to fertilize maize (Tier 1) and the dosage applied (Tier 2). To test whether the Tobit or Cragg model better fits the underlying data-generating process, we use a log-likelihood ratio test of the restricted (Tobit) vs. the unrestricted (Cragg) regressions. We also compare the qualitative results of the two approaches by estimating a set of unconditional average partial effects for each. Note that the unconditional average partial effects from the Cragg model are essentially the second-tier (conditional) partial effects weighted by the (conditional) first-tier average partial effects; therefore, the effects of the two tiers can be captured in a single set of average partial effects. Finally, standard errors on the unconditional average partial effects for both specifications are bootstrapped to take into account the two-stage estimation procedure, given that we reject the null hypothesis of endogeneity (by rejecting the null hypothesis that the coefficients on the first-stage residuals equal zero).

[1] Although the same letters are used to denote the coefficients and errors across equations, note that these have different values and interpretations across the empirical specifications.

Treatment models offer another, distinct, approach to accounting for the self-selection of households into the decision to apply mineral fertilizer on maize. Here the treatment is the *level* of off-farm income. Generalized Propensity Score Matching (GPSM) allows us to model the effects of treatment (off-farm earnings) on fertilizer demand continuously in terms of dosages, allowing non-normal distributions of earnings variables (Hirano and Imbens 2004; Guardabascio and Ventura 2013). We estimate a conditional density function of income level given the household variables X, $R=r(w|X)$. Households can then be stratified on the propensity score R and, conditional on R, the marginal effect of off-farm income calculated. If the income amount, conditional on R, is independent of household characteristics X, then the estimated marginal relationship between income level and fertilizer application rate may be considered unbiased (Rosenbaum and Rubin 1983). This assumption of conditional independence can be tested using the Rosenbaum sensitivity test.

We apply this approach, controlling for the panel nature of the underlying data with CRE (as above), and bootstrapping confidence intervals. Nonetheless, it is important to recognize that only households applying fertilizer can be included in this GPSM model, and that the estimation procedure was never designed for data with high levels of censoring. Thus, the model is not well-suited to the structure of our underlying data, particularly to the regressions that investigate the role of farm *kibarua*. Another limitation of this approach in our context is that it is not conducive to testing the effects of other determinants of fertilizer use across the full range of application rates.

3.3. Variables

In our empirical setting, farm families organize their labor among farm and non-farm activities in order to maximize utility over income, consumption goods and leisure, but face shadow prices due to market imperfections that are household-specific and vary according to characteristics of family members, and physical characteristics of farms and markets. In our conceptualization, the vector X includes household, farm, and village characteristics that will theoretically influence the off-farm work decisions. Likewise, the vector Z contains covariates thought to determine fertilizer use.

Variables and their definitions are shown in Table 1. In terms of human capital or quality of labor supply, we use the count of adults (above 15 years of age) who are educated, differentiating between men and women. Female headed-households represent a minority in our data set, and are to some extent the consequence of life-cycle changes in the sample over the time period of the survey (Smale 2011). We know that a defining feature of female headship is that it implies one adult fewer in terms of labor supply and household farm management. The count of adults considers this aspect.

Land area owned is relatively fixed over time (as compared to land cultivated), and we divide this variable by household size in order to standardize its value and facilitate the interpretation of the marginal effect. We include the total value of assets (farm equipment, buildings, consumer durables) as indicators of longer-term income or investments of past income streams. As such, we would argue that they are recursive rather than endogenous in the annual decision to apply fertilizer to maize. To control for credit access, we use the frequency of credit recipients in the village during the relevant survey season. Dairy production and tea are treated as long-term farm investments that appear in both the labor allocation and fertilizer use decisions. Generally speaking, both of these involve relatively well-integrated value chains with planned production decisions that reflect expected prices.

Table 1. Variables and Definitions

Variable	Definition
Dependent variables	
Fertilizer use	1=apply fertilizer to maize, 0 otherwise
Fertilizer application rate	Nitrogen nutrient kgs applied to maize per hectare
Potentially endogenous variables	
Farm labor (*kibarua*) earnings	Income from farm labor on other farms, in nominal KES ‘000
Business/informal earnings	Income from self-employed business or informal activities, in nominal KES ‘000
Salary earnings	Income from salaries or remittances, in nominal KES ‘000
Exogenous variables	
Women’s education	No. of women with any formal education in household
Men’s education	No. of men with any formal education in household
Total land per capita	Land owned by household/household size
Total assets	Total nominal value (KES) of all household and farm assets, including farm and transport equipment, livestock, buildings, consumer durables (ln)
Farm wage rate	average wage paid to farm labor in village (ln)
Fertilizer price	average farm-gate price of fertilizer applied to crop, weighted by share of type in total kgs (ln)
Credit	No. of village households receiving credit in survey season
Distance fertilizer	Distance (kilometer (km)) from farm-gate to nearest fertilizer source
Area in tea	Ha invested in tea production by household
Dairy production	Household also engages in dairy production
Rainfall	Main season rainfall in survey season (mm) at nearest meteorological site
Soil depth	Soil depth (FAO classification)
Soil quality	1=village has soils with high humus content according to FAO classification (see text); 0 otherwise
Population density	Village population density (persons/km2)
Instrumental variables	
Nonfarm share	Total nonfarm earnings (business and salary)/total income, by location
Distance telephone	Median distance (km)to public telephone among villagers
Distance electricity	Median distance (km) to source of electricity among villagers

Source: Authors.

Market characteristics are measured by the farm wage rate and fertilizer price, calculated as the village averages (as the market price faced exogenously by individual farmers) and logged. Per farmer, the fertilizer price is weighted by share of type in total kgs applied before taking village averages. Maize output prices include large number of missing observations, and imputing these at the village level introduces strong correlations among prices. Thus, we rely on the directly affected input prices, in effect treating the maize price as likely to vary in proportion to fertilizer prices at the village scale. Distance to source of fertilizer reflects transactions costs. Population density, also measured at the village scale and drawn from secondary data sources, is hypothesized to be related to incentives for intensification (Boserup 1965) as well as the push-pull pressures to work off own farms.

Farm physical features are captured in rainfall, soil quality and the depths of soils. The inclusion of the long term (village) rainfall variable helps to control for heterogeneity across zones and regions. Recognizing the significance of soil quality, we have also included a village-specific dummy variable for high humus content or highly productive soils developed by the Food and Agricultural Organization (FAO) from data collected in 1980, obtained from the Kenya Soil Survey and the Ministry of Agriculture. According to sources cited by Sheahan (2011), high-humus soils have nutrient-rich material resulting from the decomposition of organic matter and are found in areas which were originally under forest or grasslands; soil depth could be an indicator of potential root depth, meaning deeper soils could yield higher growth levels, and is included.

As would be expected, vectors *X* and *Z* share most variables but, importantly, *X* contains three variables that do not appear in *Z*. The first, nonfarm earnings as a share of total income by location, is calculated as the total amount of nonfarm earnings divided by total household income among all households surveyed at that location. In Kenya, the location is an administrative area containing multiple villages. Thus, this variable is an indicator of the structure of income-generating activities in the broader decision-making context of the farm household. The second is the distance of households to public telephones—specifically, the median distance (km) from the households in the sample villages to the nearest public telephone. Mobile phones were not extensively used in rural Kenya until fairly recently, and were not recorded in all survey years. This variable, and the similarly constructed third variable—distance to the nearest source of electricity—represent the presence of physical infrastructure related to nonfarm employment opportunities, but not necessarily to the choice variables of individual households.

Finally, the means of time-varying, household-level explanatory variables are included as additional regressors in the model. This correlated random effects method helps to control for unobserved heterogeneity and its correlation with observed factors in non-linear models (Mundlak (1978) and Chamberlain (1984)).

4. RESULTS

4.1. Descriptive Statistics

Mean earnings from on-farm and off-farm sources, and the mean share that each represents in total household income, are shown in Table 2 (pooled across survey years). On-farm income from sales of crops and livestock products generated roughly two-thirds of the household income of smallholder maize growers over the time period of the panel survey (2000-2010). Of the remaining third provided by off-farm earnings, salaries and remittances from absent members contributed the major share (17.5%, averaging 45,097 KES), followed by engagement in a range of local (either formal or informal) business activities (14.2%, averaging 33,844 KES). Averaging only 2,285 KES in nominal terms, work by farm family members on other farms generates only 2.7% of household income.

Table 2. Distribution of Total Household Income by Income Source and Crop, All Years

	Nonfarm					
	Business/ informal (1)	Salary (2)	Farm labor (3)	All Off-Farm (1+2+3)	All On-Farm (4)	Total (1+2+3+4)
Mean share	0.142	0.175	0.027	0.344	0.656	1.00
S.D.	0.217	0.242	0.097	0.280	0.281	
Mean amount (KSH nominal)	33,844	45,097	2,285	81,226	129,790	211,016
S.D.	110,972	106,338	8,780	156,730	176,289	269,574

Source: Authors.

Figure 1. Mean Annual Off-farm Income by Source, by Total Household Income Quintile

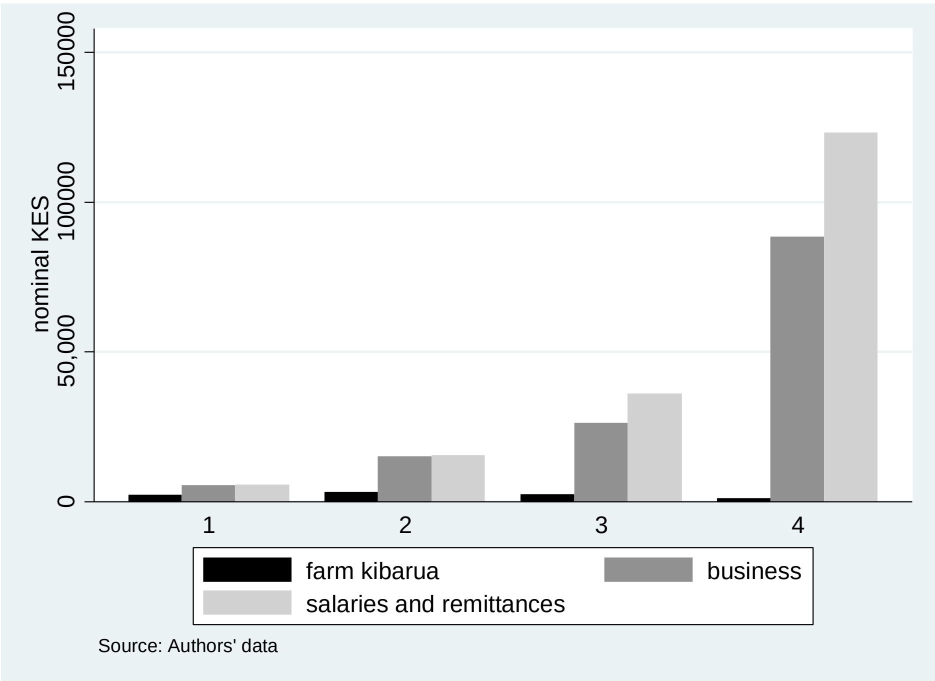


Figure 1 shows that labor on other farms (*farm kibarua*) constitutes an unimportant category of off-farm income, regardless of total income quartile. By contrast, salaries/remittances and business expand sharply from a very small level (nearly comparable in magnitude to *kibarua* earnings) among the poorest households to at least 100,000 among the richest. Salaries and remittances differentiate as the largest single category of earnings as income rises. This finding attests to the importance of steady, non-farm income sources in the daily life of smallholder farmers in Kenya, and illustrates the strength of linkages between farm and non-farm sectors as the nation entered the current decade.

Table 3 shows the binary relationships among the decisions to allocate labor off-farm and apply fertilizer to maize on smallholder farms over this same time period. Interestingly, while differences in the likelihood of using fertilizer to do not appear large in magnitude between the group that earns from one source vs. the group that does not, the Pearson chi-squared test suggests that differences are statistically significant for the farm *kibarua* and business categories, as well as off-farm earnings in general, but not between those with and without salary earnings. One explanation might be that salary/remittance earnings are predictable, and thus labor allocation to these sources does not affect the decision to use fertilizer on maize. It is noteworthy that in all other cases, households with off-farm earnings are less likely to apply fertilizer to maize—indicating that these compete for resources rather than reinforce each other.

Table 3. Fertilizer Use on Maize, by Source of Off-farm Earnings

Source of off-farm earnings		Applied fertilizer on maize			Pearson Chi-sq
		No	Yes	Total	p-value
Work on other farms					
	no	1,344	2,821	4,165	
		32.27	67.73	100	
	yes	250	392	642	0.001
		38.94	61.06	100	
Business					
	no	667	1,621	2,288	
		29.15	70.85	100	
	yes	927	1,592	2,519	0.002
		36.8	63.2	100	
Salary or remittances					
	no	641	1,273	1,914	
		33.49	66.51	100	
	yes	953	1,940	2,893	0.693
		32.94	67.06	100	
Any off-farm earnings					
	no	147	1,447	1,594	
		9.22	90.78	100	
	yes	450	2,763	3,213	0.000
		14.01	85.99	100	

Source: Authors.
Note: *no* numbers differ by source because farmers earning income from more than one source.

Table 4. Fertilizer Application Rates on Maize, by Source of Off-farm Earnings

Source of off-farm earnings		Average N nutrients kg/ha		
		Mean	Std. Err.	Pr(|T| > |t|)
Work on other farms				
	no	13.25	0.219	
	yes	10.87	0.557	0.000
Business				
	no	13.74	0.303	
	yes	12.20	0.275	0.000
Salary or remittances				
	no	13.57	0.33	
	yes	12.52	0.259	0.012
Any off-farm earnings				
	no	15.74	0.590	
	yes	12.54	0.217	0.000

Source: Authors.

The statistics in Table 4 underscore this result in the case of the continuous variable measure the rate of N nutrient kgs applied per ha of maize. In this case, however, application rates are shown to be lower across all categories of off-farm earnings, including salaries/remittances.

4.2. Regression Results

In this section we present and discuss the results of seemingly unrelated, recursive bivariate probit models (Table 5); first- and second-stage Tobit CF-CRE models (Tables 6-7); Cragg models (8-9); and GPSM models (Figures 2-3). The base FEIV model results are reported in the Appendix.

Diagnostic statistics suggest that pairwise decisions to allocate labor to off-farm work and apply fertilizer to maize are correlated in terms of both observed and unobserved factors (Table 5, recursive bivariate probit models). That is, the Wald test evaluating each off-farm earning source and fertilizer use decisions leads us to reject the null hypothesis of independence in each pair of regressions. The sign on the regression coefficient is positive in the case of farm *kibarua*, but negative for receipt of business or salary/remittance income. This latter finding is consistent with descriptive statistics, but the former is surprising given the descriptive statistics reported above. Coefficients on other explanatory variables are of some interest. For example, education of either women or men positively influences the decision to use fertilizer on maize, while men's education positively influences prospects for earning from either business or salaries and remittances. Neither positively relates to working on other farms. The same directional relationships appear with respect to total assets (wealth), supporting the notion that households allocating labor to work on other farms are among the poorer.

However, both those who work on other farmers and those who earn salary income have less land to exploit per capita. As expected, fertilizer prices are negatively associated with the decision to apply fertilizer to maize. Credit receipts at the village scale are complementary to business and salary earnings, but negatively related to application of fertilizer in the *kibarua* equations. This may reflect the crops more often addressed through credit programs, which are cash crops with formulaic fertilizer requirements that are designed to reflect profitability objectives, much more than a food staple like maize, especially among poorer households.

Table 5. Seemingly Unrelated Bivariate Probit Model Testing the between Receipt of Off-farm Earnings and Use of Fertilizer on Maize, by Category of Earnings

	Work on other farms	Apply fertilizer to maize	Business	Apply fertilizer to maize	Salary or remittances	Apply fertilizer to maize
Women's education	-0.0457	0.115***	0.0385	0.109***	0.0416*	0.110***
	(0.0330)	(0.0271)	(0.0238)	(0.0251)	(0.0239)	(0.0245)
Men's education	0.0277	0.0228	0.0769***	0.0667***	0.0895***	0.0825***
	(0.0276)	(0.0224)	(0.0202)	(0.0202)	(0.0203)	(0.0200)
Total land per capita	-0.0745*	0.000444	-0.0292	-0.0202	-0.0318*	-0.0277
	(0.0422)	(0.0229)	(0.0187)	(0.0186)	(0.0193)	(0.0198)
Total assets (ln)	-0.115***	0.0343	0.0659**	0.0421	0.0673*	0.0439
	(0.0413)	(0.0367)	(0.0328)	(0.0327)	(0.0346)	(0.0341)
Farm wage rate (ln)	0.125	0.00559	-0.0227	0.0285	-0.205***	-0.0752
	(0.0825)	(0.0711)	(0.0646)	(0.0640)	(0.0681)	(0.0662)
Fertilizer price (ln)	-0.0282	-0.463***	-0.137	-0.422***	-0.127	-0.384***
	(0.146)	(0.112)	(0.105)	(0.104)	(0.109)	(0.102)
Credit	0.0495	-0.146*	0.252***	-0.0202	0.197**	-0.0308
	(0.105)	(0.0872)	(0.0807)	(0.0809)	(0.0822)	(0.0793)
Distance to fertilizer	-0.0107	-0.00793	0.00830*	-0.00441	0.0112**	-0.00401
	(0.00671)	(0.00566)	(0.00445)	(0.00490)	(0.00459)	(0.00492)
Area in tea (ha)	-0.686**	0.481	0.0755	0.200	-0.366	-0.0953
	(0.336)	(0.321)	(0.194)	(0.236)	(0.235)	(0.249)
Dairy production	-0.0366	0.306***	-0.0690	0.162***	-0.0375	0.149***
	(0.0580)	(0.0481)	(0.0466)	(0.0454)	(0.0471)	(0.0447)
Rainfall	-0.000864***	0.000831***	0.000487***	0.000575***	-0.000152	0.000132
	(0.000136)	(0.000105)	(0.000102)	(9.54e-05)	(0.000106)	(9.75e-05)
Soil depth	-0.0106	0.0753***	-0.0204*	0.0366***	-0.00218	0.0418***
	(0.0141)	(0.0122)	(0.0113)	(0.0109)	(0.0112)	(0.0108)
Soil quality	0.0681	0.177***	-0.181***	0.0400	0.136**	0.205***
	(0.0707)	(0.0592)	(0.0555)	(0.0541)	(0.0560)	(0.0542)
Population density	-0.000355**	0.00117***	-0.000206*	0.000882***	0.000552***	0.00129***
	(0.000156)	(0.000165)	(0.000115)	(0.000144)	(0.000116)	(0.000140)
Nonfarm share	-1.349***		1.519***		1.793***	
	(0.193)		(0.135)		(0.136)	
Distance to electricity	-0.00605		0.0167***		0.0101***	
	(0.00402)		(0.00257)		(0.00269)	
Distance to telephone	0.0321***		-0.0156***		-0.0232***	
	(0.00786)		(0.00594)		(0.00581)	
2004	-0.172**	0.0912	-0.134**	-0.0142	0.0142	0.0900
	(0.0810)	(0.0651)	(0.0591)	(0.0592)	(0.0599)	(0.0587)
2007	0.211**	0.156**	0.152**	0.286***	-0.0401	0.160**
	(0.0870)	(0.0754)	(0.0693)	(0.0697)	(0.0700)	(0.0679)
2010	-0.0745	0.527***	0.0777	0.389***	0.206*	0.448***
	(0.148)	(0.116)	(0.108)	(0.107)	(0.112)	(0.106)
Farm labor		1.369***				
		(0.0979)				
Business/Informal				-1.480***		
				(0.0349)		
Salary						-1.433***
						(0.0365)
Constant	5.144***	-2.879***	-0.773	0.0273	-1.673***	-0.586
	(0.718)	(0.587)	(0.527)	(0.527)	(0.558)	(0.535)
Observations	4,807	4,807	4,807	4,807	4,807	4,807
Log pseudolikelihood	-3877		-5433			-5259
Wald test of rho=0:	chi2(1) =49.1		chi2(1) =325			chi2(1) =224
	Pr>chi2=0.000		Pr>chi2=0.000			Pr>chi2 0.000

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In that case, priority would be placed on cash crops.

Rainfall is positively related to use of fertilizer, which makes sense given the need for adequate soil moisture, but is negatively related to work on other farms. This suggests that more such work may occur in drier areas, or that work on other farms is a response to expectations of distress when rainfall is low in the current season (rainfall is also highly correlated between years, as mentioned in the discussion of variables). Soil depth and quality (humus content) is positively related to use of fertilizer. Higher population densities contribute to greater propensity to earn from salaries and remittances in the non-farm sector, but are associated with less likelihood of earning from local businesses or farm *kibarua*—since these may imply too much local competition for labor, and a need to send family members outside the location to work. Consistent with the Boserupian hypothesis, higher population densities seem to instigate intensification in agriculture (via fertilizer use). Exclusion restrictions seem to be met by the use of the three instruments (nonfarm share of earnings at the location scale, median distances to nearest sources of electricity and public, land line telephones).

First-stage, reduced form regressions estimated by the Tobit CF-CRE approach are presented in Table 6. Using the censored variable rather than the binary variable in the earnings models, we see the strongly positive relationship of men's and women's education to both business and salary earnings and the contradicting signs on farm labor. Women's education is negatively related to this source of earnings, controlling for men's education, which shows a positive sign but is weak in significance. As in the binary models, but even more strongly, farm size per capita is negatively associated with amounts earned from both farm *kibarua* and salaries/remittances, but has no effect on business earnings. Land resource constraints are clearly push factors in labor allocation between farm and non-farm activities of different types. Farming systems are shown to matter in these regressions: more area in tea diminishes earnings on other farms, and dairy production curbs earnings from business or salaries. Both of these are major investments of labor, but tea is more predictable and has higher expected returns per unit of labor. Again, the generally significant coefficients on the instrumental variables attest to their suitability.

Table 7 displays the second-stage, structural regression models estimated with the Tobit (CF-CRE) approach. Coefficients represent unconditional, average partial effects (APEs) and standard errors are bootstrapped for 100 iterations. Overall, the *kibarua* equation is the weakest model, as might be expected given the large share of zeros and relatively small amounts for the positive values. The censored variable model confirms the positive relationship of education (men or women) to rates of N nutrients (kg/ha) applied to maize, particularly in the non-farm equations (business or salary earnings). Fertilizer application may not neutral to scale—more land per capita is associated with lower application rates among farm households whose members also earn salaries, although the magnitude is small. Asset values are also significant and positively associated with N use on fertilizer among households with earnings from business or salaries. Consistent with theory, N nutrient application rates are inversely, and strongly related to fertilizer prices—these coefficients are all significant at 1% and their effects are the highest in magnitude among continuous variables. On the other hand, as has been found repeatedly in other studies based on these data, distance to fertilizer source is not a highly significant determinant of nitrogen use because these distances have declined dramatically over the past decade or so (Ariga and Jayne 2009). Again, the effect of credit receipt at the village level appears to be negative—suggesting that, ceteris paribus, other activities may compete for fertilizer on maize. In the bootstrapped model, however, these effects are relatively weak statistically. Dairy production is complementary to fertilizer use in the case of households engaged in *kibarua*—suggesting, perhaps, that among dairy farmers, who may experience fewer seasonal peaks in labor demand, working on other farms and N application rates are complementary. Rainfall, soil depth, and quality continue to appear to encourage N application on maize. Soil humus, in particular, has effects of relatively large magnitude. The Boserupian hypothesis persists in the case of non-farm, salaried employment. Year effects are strong.

Table 6. First-stage, Reduced-form Tobit Model Predicting Off-farm Earnings

	Farm labor	Self-employed business	Salaried employment
Women's education	-345.2**	4,558***	6,425***
	(154.7)	(1,665)	(1,312)
Men's education	234.1*	3,573**	10,933***
	(127.0)	(1,542)	(1,345)
Total land per capita	-516.5***	-92.97	-1,784**
	(190.1)	(1,993)	(873.6)
Total assets (ln)	-496.3***	8,593***	9,164***
	(172.9)	(2,031)	(1,890)
Farm wage rate (ln)	708.0**	4,145	-8,478**
	(351.4)	(3,472)	(3,805)
Fertilizer price (ln)	-112.2	-10,229	-6,858
	(529.1)	(8,403)	(6,235)
Credit	501.4	9,747**	6,056
	(443.6)	(4,599)	(4,590)
Distance to fertilizer	-19.95	75.66	463.6*
	(28.20)	(200.7)	(239.0)
Area in tea (ha)	-3,034**	-3,367	-9,762
	(1,360)	(11,381)	(17,716)
Dairy production	12.70	-9,986***	-8,130***
	(242.6)	(2,793)	(2,750)
Rainfall	-2.416***	20.70***	-1.001
	(0.589)	(7.416)	(5.721)
Soil depth	65.57	-1,305**	-871.4
	(62.10)	(603.9)	(628.9)
Soil quality	478.2	-11,305***	3,158
	(311.7)	(3,405)	(3,069)
Population density	-1.829***	-4.550	12.09**
	(0.652)	(5.882)	(5.054)
Nonfarm share	-2,295**	50,576***	90,801***
	(910.9)	(10,589)	(10,013)
Distance to electricity	45.14**	64.45	-403.9**
	(18.43)	(165.4)	(171.0)
Distance to telephone	97.97**	143.5	-209.4
	(47.61)	(352.4)	(378.0)
2004	-623.0*	-1,157	7,836***
	(350.4)	(3,425)	(3,029)
2007	1,015***	7,744*	5,225
	(365.1)	(4,476)	(3,743)
2010	499.7	9,869	25,352***
	(563.8)	(9,295)	(6,251)
Observations	4,807	4,807	4,807
Log pseudolikelihood	-8553.7953	-35104.06	-39416
F(24, 4783)	11.19	5.38	12.40

Estimated with Mundlak-Chamberlin (Correlated Random Effects) method.
Average partial effects with standard errors estimated by Delta method.
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Second Stage, Structural Tobit Model Testing Relationship of Off-farm Income to Fertilizer Use on Maize

	Kibarua	Business	Salary
Women's education	1.226*	3.212***	2.250***
	(0.743)	(1.038)	(0.461)
Men's education	0.234	2.356**	2.757***
	(0.481)	(1.027)	(0.595)
Total land per capita	0.302	-0.277	-0.595**
	(0.916)	(0.931)	(0.232)
Total assets (ln)	0.608	4.446**	2.004***
	(0.749)	(1.778)	(0.505)
Farm wage (ln)	0.0395	2.888	-0.756
	(1.206)	(2.112)	(1.109)
Fertilizer price (ln)	-8.484***	-12.75***	-9.363***
	(1.507)	(4.408)	(1.579)
Credit (village)	-2.258*	0.707	-1.922*
	(1.234)	(3.081)	(1.051)
Distance to fertilizer	-0.0924	-0.104	-0.0394
	(0.0670)	(0.0978)	(0.0477)
Area in tea	4.045	-1.162	-1.256
	(5.255)	(7.184)	(2.727)
Dairy	3.225***	-2.616	0.893
	(0.665)	(2.593)	(0.811)
Rainfall	0.0127***	0.0152***	0.00636***
	(0.00349)	(0.00392)	(0.00218)
Soil depth	1.332***	0.265	0.871***
	(0.296)	(0.535)	(0.287)
Soil quality	5.451***	-0.808	5.552***
	(1.707)	(3.319)	(1.301)
Population density	0.00636	0.00403	0.00872***
	(0.00403)	(0.00369)	(0.00200)
2004	0.449	0.680	2.470**
	(1.617)	(1.905)	(0.973)
2007	2.241	7.607***	4.755***
	(1.396)	(2.619)	(0.992)
2010	8.979***	13.87***	14.43***
	(1.567)	(4.535)	(2.018)
Income source	0.000115	-0.000204***	-9.86e-05***
	(0.000207)	(6.44e-05)	(2.34e-05)
Residual (stage 1)	-0.000131	0.000206***	0.000100***
	(0.000203)	(6.45e-05)	(2.35e-05)
Observations	4,807	4,807	4,807

Note: Estimated with Mundlak-Chamberlain (CRE) method (means not reported). Bootstrapped standard errors in parentheses (100 iterations). Unconditional APEs. *** p<0.01, ** p<0.05, * p<0.1

In terms of the variable of interest, these coefficients are roughly consistent with those of the binary model. That is, farm labor is positively associated, but other labor sources are negatively associated, with application rates—although the farm labor coefficients are not statistically significant. It is noteworthy that until standard errors are bootstrapped, farm labor coefficients are statistically significant, while the significance of other coefficients is generally consistent with those of the bootstrapped regression but higher. Residuals are statistically significant in the business and salary earnings regression. On the basis of the

Tobit CF-CRE approach, we conclude that unobserved factors in the error structure of the variables are correlated between the two earnings and N use equations.

To check the robustness of these results, we provide the FEIV2SLS model in the statistical appendix, Table A. Variables that are constant (soils attributes) have been dropped automatically. The farm labor model does not satisfy any of the diagnostic criteria for IV, casting doubt on the models, as also suggested by our results reported above. In the case of both the business and salary regressions, we are able to reject the null hypothesis for coefficients on the instrumental variables (F-test p-value 0.000), as well as the Kleibergen-Paap test for underidentification (p-value 0.000), and reject the hypothesis of exogeneity (p-values 0.05, 0.03) but fail to reject the Hansen J test (p-values 0.53, 0.86 respectively). Other regression results are visibly weaker, but similar, in the FEIV2SLS business and salary models, although women's education does not appear to be significant, the effect of rainfall shifts in sign, and distance to fertilizer source becomes a significant factor. Neither of these latter effects is expected.

Comparing the Cragg model to the Tobit model with a likelihood ratio test (treating the Tobit as the restricted regression and the Cragg, in the form of a probit and a truncated regression, as two parts of the unrestricted model), we find that the restrictions are statistically significant. This result is intuitive since the test measures only the statistical efficiency of a model with twice as many parameters (long vs. short regression). Table 8 shows the Cragg-CRE model that is most comparable to the Tobit CF-CRE model because the regression standard errors have been bootstrapped (100 iterations) and unconditional APEs estimated (which combine both tiers of the double hurdle). Regression coefficients are remarkably similar in magnitude and statistical significance, although slightly larger in the case of the Cragg CRE.

In order to benefit from additional information provided by the Cragg CRE model, we present the conditional APEs generated in the two-tiered model in Table 9. These are also bootstrapped for 100 iterations. The signs of major variables are consistent between the first and second tiers, suggesting that education of adult men and women, assets, fertilizer prices, rainfall and soils characteristics influence both the decision to use fertilizer and application rates for N.

As in the other models presented, we find that *kibarua* equations are weak and the sign of both the main effect and residual effect from stage 1 are statistically insignificant. As above, earnings from both salary and business employment are inversely related to the likelihood of N application and N rates when applied to maize. Generally speaking, not so much is gained by estimating the Cragg model over the Tobit model in terms of interpretative, policy-relevant information.

Results of GPSM are depicted in Figures 2-3 for business and salary income sources only (as suggested above, those for *kibarua* are weak). The dosage function shows the change in the magnitude of effects of off-farm earnings sources on N use rates as the amount earned increases. Thus, the GPSM illustrates the sensitivity of fertilizer use to income changes. Figures 2 and 3 demonstrate an important point that is not evident when we apply either the Tobit or Cragg models: the magnitude of the marginal effects of non-farm income on fertilizer use rates varies as income changes. Each graph suggests inflection points. Findings should nonetheless be examined with caution; we have not overcome technical challenges, such as failure to attain the *balancing property* across classes of users (Guardabascio and Ventura 2013).

Table 8. Second Stage, Structural Cragg Model Testing Relationship of Off-farm Income to Fertilizer Use on Maize

	Kibarua	Business	Salary
Women's education	1.032	2.921***	2.069***
	(0.653)	(0.974)	(0.432)
Men's education	0.278	2.316**	2.815***
	(0.382)	(0.966)	(0.558)
Total land per capita	0.235	-0.329	-0.654***
	(0.743)	(0.897)	(0.248)
Total assets (ln)	0.674	4.324***	2.088***
	(0.681)	(1.636)	(0.530)
Farm wage (ln)	-0.105	2.457	-1.025
	(1.095)	(2.054)	(1.109)
Fertilizer price (ln)	-9.073***	-13.20***	-9.993***
	(1.434)	(4.180)	(1.575)
Credit (village)	-1.710	1.390	-1.222
	(1.186)	(2.912)	(1.108)
Distance to fertilizer	-0.0684	-0.0862	-0.0198
	(0.0670)	(0.104)	(0.0636)
Area in tea	4.317	-1.005	-1.014
	(4.804)	(7.333)	(3.022)
Dairy	2.669***	-2.859	0.383
	(0.634)	(2.497)	(0.797)
Rainfall	0.0118***	0.0142***	0.00561**
	(0.00302)	(0.00377)	(0.00225)
Soil depth	1.467***	0.503	1.035***
	(0.271)	(0.501)	(0.268)
Soil quality	6.311***	0.422	6.489***
	(1.438)	(2.958)	(1.159)
Population density	0.00556	0.00305	0.00797***
	(0.00395)	(0.00368)	(0.00223)
2004	0.440	0.633	2.484***
	(1.429)	(1.826)	(0.926)
2007	2.386*	7.616***	4.960***
	(1.272)	(2.401)	(0.973)
2010	9.353***	14.31***	15.04***
	(1.488)	(4.205)	(1.941)
Income source	0.000112	-0.000196***	-9.94e-05***
	(0.000176)	(5.72e-05)	(2.05e-05)
Residual (stage 1)	-0.000128	0.000197***	0.000100***
Observations	4,807	4,807	4,807

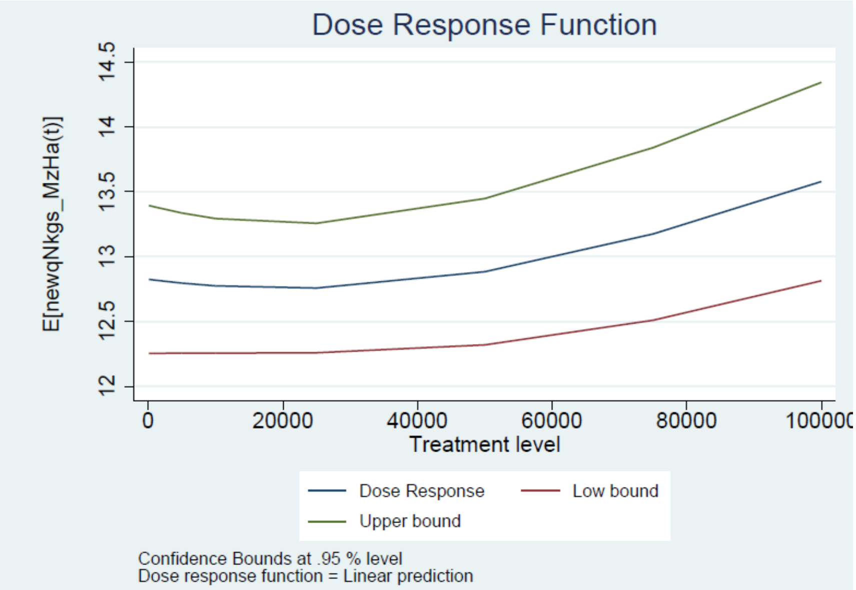
Note: Estimated with Mundlak-Chamberlain (CRE) method (means not reported). Bootstrapped standard errors in parentheses (100 iterations). Unconditional APEs. *** p<0.01, ** p<0.05, * p<0.1

Table 9. Second Stage, Structural Cragg Model Testing Relationship of Off-farm Income to Fertilizer Use on Maize (Both Tiers)

	Kibarua	Business	Salary	*Kibarua*	Business	Salary
Tier 1				*Tier 2*		
Women's education	0.0438**	0.0957***	0.0694***	0.337	1.710**	1.162***
	(0.0211)	(0.0280)	(0.0135)	(0.504)	(0.753)	(0.401)
Men's education	0.00221	0.0591**	0.0682***	0.339	1.776**	2.245***
	(0.0136)	(0.0267)	(0.0167)	(0.309)	(0.759)	(0.522)
Total land per capita	0.0138	-0.00375	-0.0119*	-0.0233	-0.368	-0.621***
	(0.0247)	(0.0241)	(0.00660)	(0.567)	(0.682)	(0.232)
Total assets (ln)	0.0142	0.111**	0.0468***	0.592	3.287***	1.762***
	(0.0207)	(0.0471)	(0.0146)	(0.656)	(1.257)	(0.587)
Farm wage (ln)	-0.00635	0.0740	-0.0235	0.0143	1.599	-0.852
	(0.0332)	(0.0560)	(0.0330)	(1.002)	(1.681)	(1.011)
Fertilizer price (ln)	-0.142***	-0.245**	-0.158***	-9.269***	-12.42***	-10.11***
	(0.0435)	(0.116)	(0.0444)	(1.397)	(3.160)	(1.527)
Credit (village)	-0.0459	0.0407	-0.0311	-1.251	0.935	-0.938
	(0.0366)	(0.0792)	(0.0298)	(1.144)	(2.276)	(1.111)
Distance to fertilizer	-0.00186	-0.00271	-0.000703	-0.0496	-0.0532	-0.0102
	(0.00176)	(0.00263)	(0.00127)	(0.0810)	(0.102)	(0.0835)
Area in tea	0.159	-0.0112	-0.00347	2.041	-1.131	-1.343
	(0.162)	(0.218)	(0.0986)	(3.640)	(5.134)	(2.319)
Dairy	0.0860***	-0.0707	0.0232	1.582**	-2.248	-0.0485
	(0.0201)	(0.0663)	(0.0240)	(0.681)	(2.009)	(0.825)
Rainfall	0.000265***	0.000293***	7.38e-05	0.00994***	0.0127***	0.00605***
	(8.75e-05)	(0.000103)	(6.21e-05)	(0.00262)	(0.00304)	(0.00211)
Soil depth	0.0242***	-0.00433	0.0121	1.466***	0.814**	1.154***
	(0.00908)	(0.0144)	(0.00861)	(0.249)	(0.398)	(0.244)
Soil quality	0.0554	-0.104	0.0610*	7.563***	3.202	7.613***
	(0.0487)	(0.0888)	(0.0363)	(1.148)	(2.152)	(1.003)
Population density	0.000439***	0.000356***	0.000487***	-0.00343	-0.00462*	-0.00110
	(0.000136)	(0.000113)	(8.86e-05)	(0.00313)	(0.00281)	(0.00171)
2004	0.0286	0.0299	0.0750***	-0.114	0.143	1.605*
	(0.0411)	(0.0484)	(0.0264)	(1.200)	(1.460)	(0.888)
2007	0.0357	0.174***	0.101***	2.477**	6.344***	4.435***
	(0.0424)	(0.0674)	(0.0286)	(1.192)	(1.860)	(0.973)
2010	0.145***	0.260**	0.279***	9.575***	13.61***	14.17***
	(0.0483)	(0.119)	(0.0548)	(1.470)	(3.133)	(1.804)
Income source	3.69e-06	-5.36e-06***	-2.50e-06***	6.43e-05	-0.000141***	-7.71e-05***
	(5.38e-06)	(1.72e-06)	(6.48e-07)	(0.000138)	(4.31e-05)	(1.73e-05)
Residual (stage 1)	-4.19e-06	5.37e-06***	2.61e-06***	-7.35e-05	0.000143***	7.56e-05***

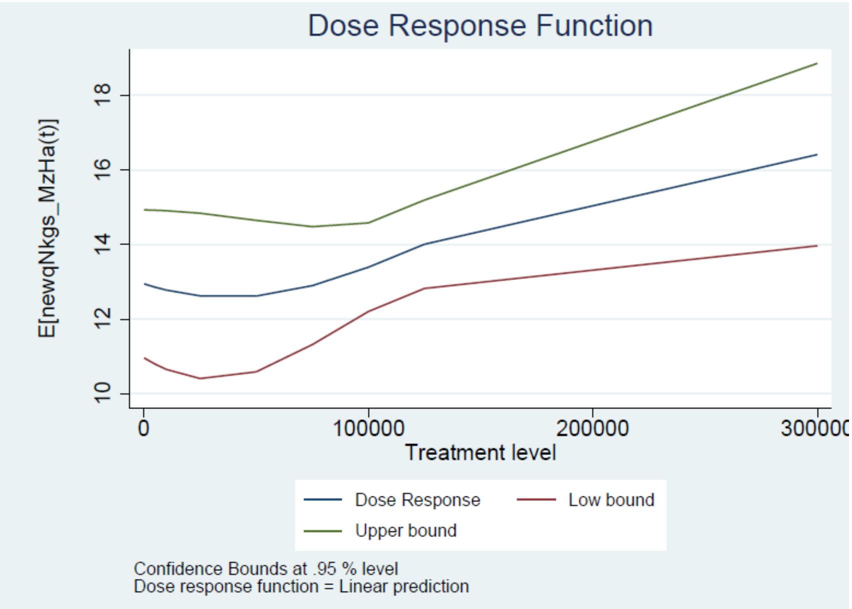
Note: 4,807 observations. Estimated with Mundlak-Chamberlain (CRE) method (means not reported). Bootstrapped standard errors in parentheses (100 iterations). Conditional APEs. *** p<0.01, ** p<0.05, * p<0.1

Figure 2. Dose Response Function, Effect of Salary Income on Fertilizer Use in Maize



Source: Authors.

Figure 3. Dose Response Function, Effect of Business Income on Fertilizer Use on Maize



Source: Authors.

5. CONCLUSIONS

Our first obvious conclusion is that decisions taken concerning allocation of labor on and off the farm by smallholders in Kenya, and decisions about the intensity of fertilizer use in maize, are endogenously related. We reject the exogeneity of off-farm earnings in most of our models.

It is also noteworthy that the overall pattern in terms of direction of effects, and even the relative magnitudes of some of the coefficients, is similar between business and salary models, but distinctly different, inconsistent, and also statistically weak for the farm labor models. Overall, we conclude that farm labor effects on fertilizer use in maize could be positive in sign but their magnitudes remain slight. Mathenge, Smale, and Tschirley (2014) found their effects to be of no significance in higher potential areas but of positive significance on use rates in lower potential zones. Future research might explore the interrelationships between farm *kibarua* and various types of farm investments, not limited to fertilizer use—and perhaps not limited to maize—while also considering the sequence of earnings and investment more carefully by investigating two major growing seasons in succession (the panel structure does not permit this). In addition, considering only those households in the poorest quartile (if the sample is larger) might furnish a more comprehensive picture of this potentially vulnerable group.

Our findings do repeatedly show, in contrast to the farm labor results, that non-farm earnings (either salary or business) bear a consistently negative, statistically robust relationship with N application rates on maize. Turning to the notion that off-farm work is in some cases a destination (pull) and in others a distraction (push), farm *kibarua* may serve as an emergency, fund-raising activity to ease cash constraints among some households. The negative marginal effect of income from allocating labor to comparatively higher-return activities (nonfarm) could signal a deliberate movement away from farm production.

The direction of the relationship between off-farm employment and on-farm investment in maize has important implications for public policy to support rural communities during the process of economic change. Not all of today's smallholder maize growers will be operational in the next generation of farmers; on the other hand, part-time farming may represent an equilibrium solution for at least some smallholder farmers. Ironically, the future of smallholder farming may lie in the measures taken to stimulate the rural nonfarm economy and provide jobs for those exiting farming—a favorable rural investment climate, provision of public goods, institutional development (Wiggins, Kirsten, and Llambi 2010).

This paper provides empirical evidence of the potential competition in resource commitments by smallholder farm families to farm and nonfarm sectors as Kenya's rural areas develop. The results generally support the view that nonfarm work may detract from, rather than complement production of maize, curbing the capacity of smallholders to invest and raise productivity of this important staple food on their own farms. Another way to view this result is to surmise that as nonfarm earnings contribute more and more to the welfare of some rural households, investing in maize will makes less and less sense because it will be cheaper to buy it from commercialized, full-time growers who sell their surplus.

APPENDIX

Appendix Table A. Second Stage, Fixed-effects, Instrumental Two-stage Least Squares Models

	Farm Labor	Business	Salary
Women's education	0.511	0.454	0.336
	(0.409)	(0.313)	(0.284)
Men's education	0.470	0.639**	0.991***
	(0.299)	(0.273)	(0.307)
Total land per capita	-0.129	-0.182	-0.278*
	(0.174)	(0.185)	(0.142)
Total assets (ln)	0.489	0.797**	0.844**
	(0.311)	(0.337)	(0.337)
Farm wage rate (ln)	0.522	1.049	0.595
	(0.756)	(0.738)	(0.687)
Fertilizer price (ln)	-6.831***	-6.365***	-6.366***
	(1.248)	(1.116)	(1.130)
Credit	0.762	2.188**	1.460
	(1.503)	(1.020)	(0.979)
Distance to fertilizer	-0.0638**	-0.0646**	-0.0473**
	(0.0324)	(0.0251)	(0.0228)
Area in tea (ha)	0.948	-0.0544	0.230
	(1.674)	(1.689)	(1.704)
Dairy production	0.715	0.0354	-0.125
	(0.859)	(0.526)	(0.526)
Rainfall	-0.00164	-0.00253*	-0.00297**
	(0.00161)	(0.00144)	(0.00147)
Population density	0.0108	0.0142**	0.00843
	(0.00789)	(0.00668)	(0.00709)
2004	1.128	1.119*	1.729**
	(0.701)	(0.653)	(0.734)
2007	1.217	1.251	2.023**
	(0.825)	(0.787)	(0.859)
2010	3.919***	3.917***	5.467***
	(1.325)	(1.273)	(1.452)
Farm labor	0.000587		
	(0.000600)		
Business		-3.26e-05*	
		(1.72e-05)	
Salary			-3.35e-05**
			(1.62e-05)
Observations	4,803	4,803	4,803

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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