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## Abstract

We use panel data from a sample of smallholder farmers in Kenya to test how the effects of nonfarm earnings on demand for fertilizer vary across different crops, namely: a major food staple (maize), an emerging cash crop (vegetables), and a traditional export crop (tea). We find that, holding other factors constant, nonfarm earnings from either business or salaried work detract from fertilizer application rates on maize and vegetables. While nonfarm salaried earnings appear to have no effect, business income positively affects fertilizer use and application rates on tea. Results suggest competition for household resources between farm and nonfarm sectors among growers of Kenya's main staple and emerging cash crops, but possible complementarity among tea growers, who farm a traditional perennial export crop with longer planning horizons.



***Keywords**:* nonfarm income, fertilizer, maize, cash crops

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**Acronyms**

| | |
|---|---|
| CFA | Control Function Approach |
| CRE | Correlated Random Effects |
| DFID | Department for International Development |
| FAO | Food and Agriculture Organization |
| FE2SLS | Fixed Effects, two-stage least squares |
| ha | Hectare |
| KES | Kenya Shillings |
| kgs | Kilograms |
| Km | Kilometer |
| MSU | Michigan State University |
| N kgs per ha | Nitrogen nutrient kilograms per hectare |
| USAID | United States Agency for International Development |

## 1. Introduction

As a consequence of economic and environmental change across rural African communities, nonfarm work contributes a growing share of the household income—especially among smallholder farm families who struggle to survive on diminishing farm sizes with declining land quality. More than a decade ago, Bryceson (2000) reported case study findings of nonfarm earnings that ranged from 55% to 80% of household income. Considering farm surveys conducted in 23 countries during the 1990s and 2000s, Reardon, Stamoulis, and Pingali (2007) reported that nonfarm income represented an average of 34% of rural household income.

Multiple factors have contributed to this dynamic situation, many of which are context-specific. Barrett, Reardon, and Webb (2001) differentiated them as ‘pull’ and ‘push’ factors. Bezu, Barrett, and Holden (2012) examined the relationship between nonfarm employment and the social mobility of rural households in Ethiopia, concluding that income growth is positively associated with the nonfarm share of income. In the Oromia region of Ethiopia, Van den Berg and Kumbi (2006) found that land-poor households are pushed into nonfarm activities, reducing income inequality. According to Mathenge and Tschirley (forthcoming 2015), smallholder farmers engage in off-farm work as a long-term strategy to deal with anticipated weather risks. 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 Western Kenya, Djurfeldt (2012) finds that while lack of nonfarm earnings aggravates the seasonal variability of income among poorer households, wealthier households utilize these earnings to meet both farm and nonfarm expenditures.

Recently, comparing longitudinal data among eight African countries, Djurfeldt and Djurfeldt (2014) concluded that “distress-driven” diversification out of agriculture into nonfarm activities appears to have slowed, with households moving in and out of farm and nonfarm work in response to economic incentives. Optimistically, they portray a complementarity among grain productivity, crop diversification on farms, and nonfarm opportunities. By contrast, in a detailed study of land resource use and rural livelihoods in Western Kenya, Mutoko, Hein, and Shisanya (2014) found that, despite major differences across farm types, land productivity is generally low, intensification lacking, and household reliance on off-farm income rising.

In this paper, we focus on the decision to intensify crop production through applying inorganic fertilizer. Past research has often demonstrated a negative relationship between off-farm work and investment in agricultural production (Ahituv and Kimhi 2002; Chikwama 2004; Morera and Gladwin 2006; Davis et al. 2009; Davis, Carletto, and Winters 2010); by contrast, Lamb (2003) found off-farm work and input use on crops to be complementary. Soil fertility is a binding constraint to crop productivity in most regions of Sub-Saharan Africa, and there is a general consensus that raising productivity will require at least some inorganic fertilizer in addition to other soil amendments (Bationo 2004). In their study of Western Kenya, Marenya and Barrett (2007) have shown that nonfarm income positively affected the adoption of integrated soil fertility management practices (including mineral fertilizer, stover lines, and manure). Among inputs that enhance soil fertility, cash constraints are thought to be particularly severe for fertilizer, but these depend on credit availability. Recently, Mathenge, Smale, and Tschirley (2014) estimated input demand for fertilizer and hybrid seed in maize production in Kenya. They found that greater earnings from nonfarm sources detracted from use of these inputs, especially in areas with greater productivity potential.

In addition, recognizing that credit sources depend very much on the value chain, we hypothesize a priori that the effects of nonfarm earnings on fertilizer use depend on crop type and nature of nonfarm work. Nonfarm income may provide the means to purchase fertilizer with cash, overcoming the problem of absent credit markets. For example, no formal credit services are provided directly for maize production in Kenya. At the same time, the engagement of household members in nonfarm activities, including informal business and migration to towns for salaried work can divert labor resources from agricultural activities and peak period tasks. In comparison to maize, which is a staple food crop, traditional cash crops such as tea and some export-oriented vegetables have vertically-integrated supply chains in which credit services are bundled with inputs and marketing arrangements (Minot and Ngigi 2010; Maura and Muku 2007).

Our analysis builds on the work of Mathenge, Smale, and Tschirley (2014) by comparing input demands for fertilizer among crop categories. We compare the role of nonfarm work among three categories of crops: a major food staple (maize), an emerging cash crop (vegetables), and a traditional export crop (tea). We also disaggregate nonfarm income in order to examine differences between the role of informal business as compared to salaried and wage employment.

We are able to exploit data collected from a panel of 1200 smallholder farm households distributed across the major agricultural zones of Kenya in four waves that span a decade (2000 through 2010). To accommodate the censored structure of the fertilizer application in the case of maize, while controlling for potential endogeneity, we apply an instrumented Control Function Approach (CFA).We employ the Correlated Random Effects (CRE) model to handle unobservable heterogeneity. We use Fixed Effects, two-stage least squares (FE2SLS) in the cases of vegetables and tea, which are continuous variables, and as a robustness check in the case of maize. We define fertilizer application in terms of nitrogen nutrient kilograms per hectare (N kgs per ha). N nutrient kgs is calculated by the percentage content represented by N in the type of fertilizer used. Farmers observe the physical kgs of mineral fertilizer they apply, but most Kenyan farmers today also know the nutrient content of the type they use.

Next, we summarize the conceptual basis that serves to guide our econometric approach. We then describe the methods, including the data source, econometric model, and operational variables. Results are presented in the fourth section and conclusions drawn in the final section.

## 2. Conceptual Approach

Our conceptual approach is framed in the general perspective of the household farm (Singh, Squire, and Strauss 1986), and influenced by the model proposed by Mathenge, Smale, and Tschirley (2014), which addresses labor allocation to farm and nonfarm activities in Kenya. The agricultural household chooses the amounts consumed of goods produced on and off-farm and decides how to allocate family labor among farm and non-farm activities, and leisure, in order to maximize utility. At the beginning or during the cropping season, cash earnings can be spent on input purchases for crops, used to hire farm labor, or invested in nonfarm businesses. The household may also attempt to obtain credit. In addition to an expenditure constraint, an on-farm technology constrains choices. This technology, as well as market conditions, differs according to whether maize, tea, or vegetables are produced.

Due to market imperfections of various types, the household faces endogenous prices for inputs and outputs that vary according to transactions costs that reflect human capital and wealth, as well as market infrastructure and observed prices. Input demands, including demand for fertilizer, are derived from optimal choices of labor and goods. In the special case where markets may be functionally perfectly and the household organizes production commercially, prices alone, technology, and agro ecological conditions, would shape optimal farm decisions. That is, household-specific characteristics would not affect farm choices. Even then, however, these would likely affect off-farm labor supply and farm choices, via the labor constraint.

Earnings from off-farm activities serve as a means of resolving expenditure constraints, but household members may also choose to invest income earned in previous seasons in self-employed businesses. Further, off-farm activities may impose constraints on use of inputs on the farm. For example, working off-farm may compete with use of labor fertilizer application.

Maximizing utility subject to expenditure, market, and technology constraints, we can solve the resulting first-order conditions with respect to all the choice variables and derive a fertilizer demand function. The fertilizer demand function can be expressed in reduced-form as: (1) $Z_c^* = Z_c(w, \boldsymbol{P}, Y, C, \boldsymbol{H}, \boldsymbol{M})|\boldsymbol{A}$. $Z_c$ denotes fertilizer use by crop. Market prices for labor, inputs and outputs are expressed as $(w, P)$. The vector H includes the characteristics of the farm household that pertain to transactions costs, such as human and physical capital.

The vector ***M*** refers to other characteristics of market infrastructure. The vector *A*, on which fertilizer demand  is conditioned, represents agroecological parameters, such as rainfall or soils. The variable C expresses access to credit sources, which potentially relaxes expenditure constraints. Income *Y* includes off-farm earnings and any savings from a previous period.

Here, to test the hypothesis that the role of nonfarm earnings in fertilizer investment differs by the source of earnings, we differentiate between two categories of nonfarm earnings: salaried labor/pensions or remittances, and other self-employed business activities. To test the hypothesis that the role of nonfarm earnings in fertilizer investment differs by the attributes of the crop, we compare three categories of crops: a food staple (maize), an emerging cash crop (vegetables), and a traditional cash crop (tea). Additional details of our specification are provided next.

## 3. Methods

### 3.1. Data

The data is drawn from the Tegemeo Agricultural Policy Research and Analysis panel dataset covering four waves of household surveys (2000, 2004, 2007, and 2010) from rural Kenya. The sampling frame was prepared in 1997 in consultation with the Central Bureau of Statistics, currently the Kenya National Bureau of Statistics. Details of the sampling frame and approach are provided in Argwings-Kodhek et al. (1999).

### 3.2. Econometric Models and Specification Issues

Ideally, estimating input demand functions in a joint decision-making framework seems appealing and consistent with theory. Estimating these with our panel data will, however, lead to significant loss of observations because applying fertilizer to the crops jointly also implies that all three are grown simultaneously. All households in our sample grow maize, and many grow vegetables, but only a minority grows tea. Thus, given that the three crops are grown separately and fertilizer applied at different times, we estimate the three models of interest separately.

Two characteristics of our data constrain our choice of econometric models: i) potential endogeneity of nonfarm earnings, and ii) the censored structure of some of the outcome variables. That is, while input use could depend on nonfarm earnings, the need to work in nonfarm activities could be triggered by financial need for farm inputs. In addition, involvement in nonfarm farm work could compete for labor and capital with farming activities especially where input markets are missing.

The structure of the dependent variables differs by crop. In vegetable and tea production, all growers use fertilizer and regression models are linear. To account for and test for the potential endogeneity of nonfarm earnings in these models, we used FE2SLS. 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 over identifying 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. Under the null hypothesis that the specified endogenous regressors can be treated as exogenous, the Wu-Hausman test-statistic is distributed as chi-squared with degrees of freedom equal to the number of regressors tested.

In maize production, because about one-third of farmers do not apply fertilizer, the regression model is nonlinear. When both the dependent variable and the potentially endogenous variable are nonlinear, 2SLS is inappropriate because it implies that, in the second stage, a nonlinear function of an endogenous variable is replaced with the same non-linear function of fitted values from the first-stage estimation (Wooldridge 2010).

To test and control for potential endogeneity in the maize model, we apply the CFA. The control function approach is described by Wooldridge (2010) and in early work by Smith and Blundell (1986). As in a two-stage least squares (2SLS) model, the CFA requires use of instrumental variables to test for endogeneity. The first stage involves regressing the potentially endogenous variable on the instruments and all the explanatory variables in the structural model. In the second stage, however, the structural model is estimated with the observed endogenous variable and the residual from the first stage added as explanatory variables. In the CFA, the test of endogeneity is the statistical significance of the coefficient of the residual 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 decisions about fertilizer use.

Given the difficulties in controlling for unobserved heterogeneity in nonlinear models, we use the CRE technique. As proposed by Mundlak (1978) and Chamberlin (1984), the CRE technique helps to control for unobserved heterogeneity and its correlation with observed factors in nonlinear models. Application of the model requires that the means of time-varying explanatory variables are included as additional regressors in the model. In the maize models, we estimate a Tobit model with Correlated Random Effects Model (Tobit CRE). Application of the CRE approach requires that the means of time-varying explanatory variables be included in the regression.

Angrist and Pischke (2009: 197) contend that since nonlinear models (probit, logit, Tobit) are built around a nonlinear transformation of a linear latent index, these approaches make distributional assumptions which can lead to identification via functional form. According to the authors, ordinary least squares generate more robust results. Thus, Angrist and Pischke (2009) also recommend testing hypotheses by applying more conventional two-stage estimation with instrumental variables, which capture local average treatment effects regardless of whether the dependent variable is binary, censored, or continuous. Recognizing this perspective, we also test FE2SLS as a robustness check for the maize model and for initial diagnostic tests.

### 3.3. Variables

Input demand functions based on the reduced-form equation (1) were estimated to identify the determinants of farmer demand for fertilizer by crop and to assess how engagement in off-farm work affects these decisions. The dependent variable in all regressions is N nutrient kgs per ha, which is a more precise estimate of the amount of nitrogen applied per crop and standardizes among different types of fertilizer applied.

**Table 1. Variable Definitions**

| Variable | Definition |
|---|---|
| *Dependent variables* | |
| Fertilizer application rate | Nitrogen nutrient kgs applied to crop per hectare |
| *Potentially endogenous variables* | |
| 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 |
| *Other Explanatory 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 in village, 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 |
| Dairy production | Household also engages in dairy production |
| Rainfall | Main rainfall season 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 to electricity | Median distance (km) to source of electricity among villagers |

Source: Authors

Separate regression models were estimated by crop category. Vegetables include those primarily grown for cash (green beans, tomatoes, snap and snow peas, peppers, spinach, okra, eggplant, carrots, onions, cucumber, and cauliflower). Variable 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 of the survey. We know that a defining feature of female headship is that implies one adult fewer in terms of labor supply and household farm management. The count of male and female adults who are educated 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 and thus, recursive in the annual decision to apply fertilizer to maize. Asset values are logged to smooth the skewness of the observed distribution. To control for credit access, we use the frequency of credit recipients in the village during the relevant survey season. Dairy production is treated as a long-term farm investment that is recursive in the labor allocation and fertilizer use decisions on tea, vegetables, and maize. That is, decisions in dairy production are taken in over a distinct production cycle (time period) and may thus be treated as exogenous in the demand functions for these crops.

Market characteristics are measured by the farm wage rate (w) and fertilizer prices (***P***), calculated as the village averages. The fertilizer prices are weighted by share of type in total kgs applied, which differs by farmer and by crop. Maize seed and output prices include large number of missing observations, and imputing these at the village level introduces strong correlations among all four prices. Vegetable units are too variable to permit us to assign a meaningful price across commodities. The tea price, on the other hand, varies too little to include as a separate regressor. Thus, we rely on the directly affected input prices, in effect treating the output prices as likely to vary in proportional to fertilizer prices at the village scale. Prices are in logarithmic form to smooth their distributions.

Other market characteristics include distance to source of fertilizer, which 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 (the

Boserupian hypothesis) as well as the “push-pull” pressures to work off own farms (Barrett, Reardon, and Webb 2001).

Agro ecological conditions 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 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 that 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 also included.

As is needed with either FE2SLS or the Tobit-Tobit CFA approach, the first stage regression of farm earnings contains two instrumental variables. The first, nonfarm share, is calculated as the total amount of nonfarm earnings in each location 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. This second is the distance of households to the nearest source of electricity, calculated as the median distance (km) from the households in the sample villages. This variable represents the presence of physical infrastructure related to nonfarm employment opportunities, but not necessarily to the choice variables of individual households.

## 4. Results

### 4.1. Descriptive Statistics

Fertilizer use and application rates per ha are shown in Table 2 for maize, vegetables and tea, by year. About two-thirds of maize growers applied fertilizer over the survey years. Fertilizer was applied by all vegetable and tea growers. Year differences in applications rates per ha are perceptible for all crop categories, but appear to be more pronounced for vegetables, where they decline sharply over time.

**Table 2. Fertilizer Use, by Crop and Year**

| | | Maize | Vegetables | Tea |
|---|---|---|---|---|
| 2000 | % use | 63 | 100 | 100 |
| | Ave. kgs/ha | 70.8 | 193 | 234 |
| 2004 | % use | 66 | 100 | 100 |
| | Ave. kgs/ha | 72.8 | 169 | 197 |
| 2007 | % use | 69 | 100 | 100 |
| | Ave. kgs/ha | 67.4 | 118 | 207 |
| 2010 | % use | 68 | 100 | 100 |
| | Ave. kgs/ha | 72.1 | 125 | 175 |
| All years | % use | 66 | 100 | 100 |
| | Ave. kgs/ha | 70.8 | 152 | 197 |

Source: Authors

This decline could reflect the changing profitability of vegetable crops, and the shifting combination of crops included in the category over survey years. As might be expected for a traditional export crop with a vertically integrated value chain, mean quantities applied to tea are highest and more stable across the years studied than for either of the other crops. Mean application rates on tea overall are around 200 kgs/ha in three of the four survey years, compared to a high average of 193 kgs/ha on and a low average of 118 kgs/ha on vegetables. Mean application rates on maize vary almost imperceptibly between 67 and 73 kgs/ha across survey years.

General statistics on nonfarm income are shown by crop and type in Table 3. The percentage of farmers earning income from each source does not differ meaningfully among growers of maize, vegetables, or tea. Over 60% of growers in each group reported income from salaries, and over 80% reported some kind of nonfarm income. The percentage of growers reporting income from self-employed businesses was 48% among tea growers, as compared to over 50% for maize and vegetable growers. Meaningful differences between the mean shares of total household income earned from each nonfarm source were apparent only for tea-growing households as compared to other groups. Tea growers reported income from salaries and remittances that averaged only 8% of total household income, as compared to 13% for either maize- or vegetable-growing households. All nonfarm income represented a mean share of only 21% among tea-growing households, as compared to 31% for either maize- or vegetable-growing households. Thus, our data indicate that on average, income from farming constituted an average of just over two-thirds of total household income among smallholders in Kenya, but only about one-fifth rely entirely on income from their own farms.

**Table 3. Non-farm Earnngs by Source and Crop (All Years)**

| | Maize | | | Vegetables | | | Tea | | |
|---|---|---|---|---|---|---|---|---|---|
| | % of growers | mean (KES) | mean share of total income | % of growers | mean (KES) | mean share of total income | % of growers | mean (KES) | mean share of total income |
| Salary | 60.2 | 45097 | 0.139 | 60.4 | 45838 | 0.139 | 60.6 | 46785 | 0.084 |
| Business | 52.4 | 33844 | 0.176 | 53.0 | 34512 | 0.175 | 48.2 | 35076 | 0.134 |
| All Nonfarm | 84.2 | 78941 | 0.315 | 84.2 | 80350 | 0.314 | 81.9 | 81861 | 0.218 |

Source: Authors

### 4.2. Regression Results

Table 4 shows diagnostic statistics for all models by crop. In the FE2SLS regressions, the significance of the F statistics and the lack of significance of the Hansen-J statistics support the validity of the instruments in each model (tea, vegetables, and maize; salary, business, and any nonfarm income source). The null hypothesis of exogeneity is rejected for all sources of nonfarm earnings among maize and vegetable growers, but cannot be rejected among tea-growing households (results of the first stage regressions for maize and vegetables are reported in the annex).

Both maize and vegetable production demand family labor at peak periods, and are labor-intensive. Planning for labor allocation to nonfarm activities for these farmers is more likely to be undertaken simultaneously with plans for farm work. Maize is the major staple for all households included in the survey and occupies family labor at the same time of the season that household members would seek wage labor on neighboring farms. The complementary nature of family labor and fertilizer use in maize production explains this result. By contrast, tea growing involves a longer planning horizon. Our findings are consistent with the notion that decisions regarding family labor allocation— farm and nonfarm in this case—are recursive or independent.

**Table 4. Diagnostic Tests by Crop and Activity Type**

| | Tea (dof=209) | Vegetables (dof=1381) | Maize (dof=3571) |
|---|---|---|---|
| Salary | | | |
| F (2), excluded instruments | 7.16*** | 5.55*** | 22.6*** |
| Kleibergen-Paap rk LM, Chi-sq (2) | 12.8 | 10.9** | 43.9*** |
| Hansen-J (over-identification), Chi-sq(2) | 2.52 | 4.18 | 0.287 |
| | (p=0.496) | (p=0.518) | (p=0.591) |
| Exogeneity, Chi-sq (1) | 0.823 | 7.774** | 4.47** |
| | (p=0.342) | (p=0.005) | (p=0.035) |
| Business | | | |
| F (2), excluded instruments | 4.38** | 5.35*** | 13.9*** |
| Kleibergen-Paap rk LM, Chi-sq (3) | 11.8** | 10.5*** | 26.7*** |
| Hansen-J (over-identification), Chi-sq(2) | 1.62 | 0.083 | 0.155 |
| | (p=0.576) | (p=0.773) | (p=0.694) |
| Exogeneity, Chi-sq (1) | 2.05 | 8.025*** | 5.01** |
| | (p=0.329) | (p=0.005) | (p=0.025) |
| All Nonfarm | | | |
| F (2), excluded instruments | 9.89*** | 11.11*** | 36.5*** |
| Kleibergen-Paap rk LM, Chi-sq (3) | 27.9*** | 21.6*** | 67.8*** |
| Hansen-J (over-identification), Chi-sq(2) | 2.74 | 0.293 | 0.237 |
| | (p=0.632) | (p=0.588) | (p=0.626) |
| Exogeneity, Chi-sq (1) | 0.789 | 7.84** | 4.84** |
| | (p=0.424) | (p=0.0051) | (p=0.0278) |

Source: Authors. *** p<0.01, ** p<0.05, * p<0.1; including all years, n=703 for tea, 4512 for vegetables, 4807 for maize.

Table 5 indicates that while salaries and overall nonfarm earnings have no statistically significant effect on fertilizer application rates in tea production, earnings from nonfarm businesses has a statistically weak (<10% significance) but positive effect. Over time, tea-growing households have more consistent expectations about their input supply and product market, leading to a more stable environment in terms of decisions about farm investments and labor allocation between farm and nonfarm activities. Nonfarm business earnings, compared to salaries, are more likely to be local, informal, and variable in magnitude and thus, they may not be included in the planning horizon. Other than fertilizer prices, which are negatively associated with intensify of fertilizer use as is predicted by economic theory, only year effects and rainfall are significant factors. Distance to fertilizer source is not statistically significant, since inputs are supplied through the services of the Kenya Tea Development Authority. The finding that household characteristics are not significantly associated with N nutrient kgs/ha is consistent with the perspective that most of these growers are commercially oriented. Long-term average rainfall is negatively associated with fertilizer use, but tea is generally grown in areas with greater moisture.

**Table 5. Effects of Nonfarm Earnings on Nitrogen Nutrient Kgs/ha for Tea (FE2SLS)**

| | Salary | Business | All Nonfarm |
|---|---|---|---|
| Income source | 3.63e-07 | 7.69e-07* | 5.52e-07 |
| | (6.08e-07) | (4.33e-07) | (3.63e-07) |
| Women's education | 0.115 | 0.117 | 0.111 |
| | (0.0884) | (0.0879) | (0.0871) |
| Men's education | -0.0611 | -0.0663 | -0.0671 |
| | (0.0606) | (0.0600) | (0.0599) |
| Land per capita | -0.0341 | -0.0307 | -0.0380 |
| | (0.0472) | (0.0464) | (0.0458) |
| Assets | 0.0789 | 0.0614 | 0.0613 |
| | (0.116) | (0.118) | (0.117) |
| Dairy | -0.104 | -0.106 | -0.107 |
| | (0.122) | (0.122) | (0.122) |
| Farm wage | 0.236 | 0.214 | 0.225 |
| | (0.327) | (0.320) | (0.324) |
| Fertilizer price | -1.249*** | -1.314*** | -1.268*** |
| | (0.462) | (0.469) | (0.468) |
| Credit | 1.334 | 1.289 | 1.322 |
| | (1.073) | (1.056) | (1.065) |
| Distance to fertilizer | 0.0446 | 0.0411 | 0.0458 |
| | (0.0373) | (0.0380) | (0.0372) |
| Rainfall | -0.000991* | -0.00102** | -0.00103** |
| | (0.000509) | (0.000497) | (0.000501) |
| Population density | 0.00107 | 0.00114 | 0.00119 |
| | (0.000883) | (0.000878) | (0.000886) |
| 2004 | 0.123 | 0.163 | 0.151 |
| | (0.440) | (0.447) | (0.443) |
| 2007 | 0.742** | 0.785** | 0.752** |
| | (0.368) | (0.376) | (0.369) |
| 2010 | 0.867* | 0.950* | 0.876* |
| | (0.504) | (0.516) | (0.504) |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; N=703 tea grower observations (all years).

Vegetable models are presented in Table 6. Regardless of source, nonfarm earnings detract from fertilizer use rates on vegetables in a statistically significant way. As was the case for tea, the largest coefficient is associated with self-employed business—but in the opposite direction. In this regression, growers are also responsive to fertilizer prices, responding negatively as they increase. Again, household characteristics are generally insignificant (education of either men or women), but assets figure strongly and positively in the intensity of fertilizer use on vegetables. Population density is positively correlated with intensification, consistent with the Boserupian hypothesis. The first-stage regression predicting nonfarm earnings among vegetable growing households is included in Appendix 1. In that regression, human capital (for either men or women or both) and assets are strongly related to the magnitude of nonfarm earnings. Men's education appears particularly strong in the salary earnings, while women's education appears more strongly in business earnings.

**Table 6. Effects of Nonfarm Earnings on Nitrogen Nutrient Kgs/ha for Vegetables (FE2SLS)**

| | Salary | Business | All Nonfarm |
|---|---|---|---|
| Income source | -6.51e-06** | -9.35e-06** | -3.86e-06** |
| | (3.08e-06) | (4.33e-06) | (1.60e-06) |
| Women's education | -0.00755 | 0.0534 | 0.0178 |
| | (0.0508) | (0.0838) | (0.0550) |
| Men's education | 0.0689 | 0.00704 | 0.0438 |
| | (0.0587) | (0.0809) | (0.0550) |
| Land per capita | -0.0317 | -0.181 | -0.0935 |
| | (0.0359) | (0.167) | (0.0766) |
| Assets | 0.149** | 0.189* | 0.166** |
| | (0.0685) | (0.104) | (0.0733) |
| Dairy | -0.0345 | 0.0985 | 0.0200 |
| | (0.0905) | (0.144) | (0.0958) |
| Farm wage | -0.198 | -0.0902 | -0.153 |
| | (0.142) | (0.183) | (0.141) |
| Fertilizer price | -0.406* | -0.556* | -0.468* |
| | (0.242) | (0.291) | (0.244) |
| Credit | -0.0358 | 0.155 | 0.0427 |
| | (0.198) | (0.245) | (0.194) |
| Distance to fertilizer | -5.62e-05 | 0.00382 | 0.00157 |
| | (0.0132) | (0.0218) | (0.0144) |
| Rainfall | 0.000298 | 0.000281 | 0.000291 |
| | (0.000223) | (0.000285) | (0.000219) |
| Population density | 0.00134 | 0.00245*** | 0.00179** |
| | (0.000841) | (0.000891) | (0.000737) |
| 2004 | -0.0266 | -0.0803 | -0.0479 |
| | (0.121) | (0.123) | (0.109) |
| 2007 | -0.106 | -0.232 | -0.157 |
| | (0.152) | (0.170) | (0.139) |
| 2010 | 0.398 | 0.142 | 0.294 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; N=4512 vegetable grower observations (all years)

The structural Tobit CFA-CRE models testing the effects of nonfarm earnings on the intensity of fertilizer use in maize are shown in Table 7. The marginal effects of both types of nonfarm earnings are significant at the 1% level, and are again larger in magnitude for self-employed business earnings than for salaried employment. This is evidence of the direct competition for family labor between maize production and nonfarm activities. In these models, however, education of both men and women has a strongly positive influence on fertilizer application rates. Price relationships are strong.

Rainfall, the depth and quality of soils are also complementary to the intensity of N nutrients kgs per ha. Again, assets are a strong positive determinant of fertilizer use, but more land per capita counteracts this effect. The extent of credit use in the village is negatively correlated with average N nutrient kgs applied per ha to maize, since this factor is typically associated with the importance of non-maize farm enterprises. As expected, intensification of maize production is positively associated with population densities. The statistical significance of the residual coincides with the finding of the FE2SLS model that nonfarm earnings are endogenous in fertilizer decisions on maize. Here, year effects are strong.

**Table 7. Effects of Nonfarm Earnings on Nitrogen Nutrient Kgs/ha for Maize (Tobit CFA-CRE)**

| | Salary | Business | All Nonfarm |
|---|---|---|---|
| Income source | -9.47e-05*** | -0.000209*** | -0.000100*** |
| | (9.35e-06) | (1.42e-05) | (7.81e-06) |
| Women's education | 2.209*** | 3.267*** | 2.868*** |
| | (0.244) | (0.261) | (0.257) |
| Men's education | 2.640*** | 2.385*** | 2.756*** |
| | (0.288) | (0.227) | (0.259) |
| Land per capita | -0.589*** | -0.286* | -0.403** |
| | (0.175) | (0.164) | (0.167) |
| Assets | 1.923*** | 4.538*** | 3.098*** |
| | (0.383) | (0.455) | (0.411) |
| Dairy | 1.004** | -2.734*** | -0.463 |
| | (0.494) | (0.603) | (0.530) |
| Farm wage | -0.769 | 2.892*** | 0.284 |
| | (0.631) | (0.627) | (0.613) |
| Fertilizer price | -9.379*** | -12.88*** | -10.93*** |
| | (0.953) | (0.990) | (0.969) |
| Credit | -2.795*** | 0.266 | -1.955*** |
| | (0.671) | (0.688) | (0.666) |
| Distance to fertilizer | -0.0430 | -0.106* | -0.0789 |
| | (0.0583) | (0.0579) | (0.0580) |
| Rainfall | 0.00627*** | 0.0151*** | 0.00872*** |
| | (0.00102) | (0.000924) | (0.000911) |
| Depth | 0.841*** | 0.206 | 0.708*** |
| | (0.118) | (0.130) | (0.116) |
| Soil quality | 5.585*** | -0.969 | 3.686*** |
| | (0.523) | (0.693) | (0.545) |
| Population density | 0.00886*** | 0.00421*** | 0.00770*** |
| | (0.00103) | (0.000917) | (0.000963) |
| 2004 | 2.239*** | 0.652 | 2.608*** |
| | (0.628) | (0.564) | (0.609) |
| 2007 | 4.700*** | 7.722*** | 5.991*** |
| | (0.675) | (0.714) | (0.686) |
| 2010 | 14.25*** | 14.00*** | 16.11*** |
| | (1.064) | (1.005) | (1.079) |
| Residual, stage 1 | -1.205*** | -0.522*** | -0.964*** |
| | (0.0952) | (0.0995) | (0.0941) |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 N=4807 maize grower observations (all years)

## 5. Conclusions

The results of our analysis indicate differences in the effects of nonfarm earnings on fertilizer use across different crop categories and types of nonfarm activity. The emerging picture is that, holding other factors constant, nonfarm earnings from self-employed business activities have a discernibly positive effect on fertilizer use on tea, a traditional cash crop in Kenya. Moreover, there is no statistical support to simultaneity in decision-making about fertilizer use on tea and nonfarm employment. Instead, findings suggest that these decisions are recursive or independent, reflecting the longer-term planning horizon and well-integrated supply chain in which tea growers operate.

By contrast, nonfarm earnings have a strong and negative effect in vegetable and maize production, which are crops produced by a larger number and more heterogeneous population of smallholders for subsistence and for cash. Both sources of nonfarm earnings are negatively associated with the intensity of fertilizer use in these crops, although the coefficient for business earnings is of greater magnitude in both sets of models. Among vegetable and maize growers, in contrast with tea growers, statistical evidence suggests that decisions over labor allocation to nonfarm activities and fertilizer application are interrelated.

The direction of the relationship between nonfarm employment and on-farm investment has important implications for public policy to support rural communities during the process of economic change. Not all of today's smallholder farms 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, and consistent with earlier findings, 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.

This paper provides empirical evidence on the direction of effects of nonfarm work on fertilizer use across different crops. Although maize and vegetables show potential competition in resource commitments by smallholder farm families to farm and nonfarm sectors as Kenya's rural areas develop, the overall picture is mixed as tea depicts a complementary relationshiop. The results generally support the view that nonfarm work may detract from, rather than complement production of staple food crops and emerging, labor-intensive cash crops by drawing labor resources away from the farm. We found the opposite relationshiop for the traditional export crop, which is fairly consistent with its highly structured, vertically-integrated supply chain and predictable investment schedule.

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## Appendices

**Appendix Table 1. Results of First-stage Regression for Vegetables (FE2SLS)**

| | Salary | Business | All Nonfarm |
|---|---|---|---|
| Women's education | 7,418* | 11,676* | 19,095*** |
| | (3,970) | (6,341) | (7,126) |
| Men's education | 13,303*** | 2,553 | 15,857* |
| | (4,199) | (8,336) | (9,409) |
| Land per capita | -3,122 | -18,151 | -21,273 |
| | (2,877) | (16,513) | (16,455) |
| Assets | 15,447*** | 15,120* | 30,567*** |
| | (5,707) | (8,591) | (10,422) |
| Dairy | -9,924 | 7,253 | -2,671 |
| | (6,727) | (12,472) | (15,360) |
| Farm wage | 7,356 | 16,824 | 24,181* |
| | (11,095) | (10,985) | (14,467) |
| Fertilizer price | -4,833 | -19,568 | -24,402 |
| | (11,964) | (21,560) | (24,913) |
| Credit | -5,943 | 16,392 | 10,448 |
| | (14,754) | (17,921) | (22,465) |
| Distance to fertilizer | 885.5 | 1,070 | 1,956 |
| | (1,014) | (1,203) | (1,649) |
| Rainfall | 16.54 | 10.43 | 26.96 |
| | (17.16) | (23.58) | (28.05) |
| Population density | -101.8 | 45.56 | -56.21 |
| | (62.02) | (68.21) | (89.76) |
| 2004 | 10,908 | 1,510 | 12,418 |
| | (7,540) | (7,694) | (10,213) |
| 2007 | 13,403 | -4,578 | 8,824 |
| | (9,646) | (14,332) | (16,752) |
| 2010 | 48,014*** | 5,203 | 53,217* |
| | (15,414) | (26,792) | (31,107) |
| Nonfarm share | 156,982*** | 109,247*** | 266,229*** |
| | (48,988) | (37,010) | (58,427) |
| Electricity | -1,058 | -1,325 | -2,382 |
| | (1,502) | (1,296) | (1,843) |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; N=4512 vegetable growers (all years).

**Appendix Table 2. Results of First-stage Regression for Maize (Tobit CFA-CRE)**

| | Salary | Business | All Nonfarm |
|---|---|---|---|
| Women's education | 6,457*** | 4,570*** | 11,933*** |
| | (1,311) | (1,670) | (2,154) |
| Men's education | 10,881*** | 3,563** | 13,702*** |
| | (1,347) | (1,534) | (2,230) |
| Land per capita | -1,854** | -124.6 | -1,097 |
| | (880.8) | (1,978) | (2,494) |
| Assets | 9,100*** | 8,596*** | 18,236*** |
| | (1,885) | (2,018) | (2,841) |
| Dairy | -8,083*** | -9,935*** | -17,858*** |
| | (2,742) | (2,809) | (3,875) |
| Farm wage | -8,522** | 4,084 | -3,606 |
| | (3,790) | (3,445) | (4,770) |
| Fertilizer price | -6,917 | -10,197 | -19,238* |
| | (6,203) | (8,435) | (10,844) |
| Credit | 4,383 | 9,672** | 14,264** |
| | (4,202) | (4,345) | (5,843) |
| Distance to fertilizer | 445.6* | 87.79 | 387.9 |
| | (237.9) | (200.5) | (295.9) |
| Rainfall | -1.430 | 20.92*** | 21.39*** |
| | (5.762) | (7.213) | (8.289) |
| Depth | -984.1 | -1,284** | -1,336 |
| | (630.6) | (611.7) | (819.2) |
| Soil quality | 3,087 | -11,201*** | -6,919* |
| | (3,033) | (3,430) | (4,199) |
| Population density | 12.87** | -4.772 | 6.846 |
| | (5.099) | (5.749) | (6.840) |
| Nonfarm share | 92,314*** | 50,335*** | 140,028*** |
| | (9,945) | (10,676) | (13,960) |
| Electricity | -436.9*** | 90.08 | -94.03 |
| | (157.7) | (153.1) | (193.2) |
| 2004 | 7,536** | -1,171 | 9,594** |
| | (2,996) | (3,376) | (4,279) |
| 2007 | 5,408 | 7,567* | 13,676** |
| | (3,739) | (4,535) | (5,558) |
| 2010 | 25,232*** | 9,963 | 43,619*** |
| | (6,219) | (9,282) | (11,774) |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1;  N=4807 maize growers (all years).