Input Intensification, Climate Shocks and Climate Change among Smallholder Maize Growers in Kenya

Bozzola Martina[1], Melinda Smale[2], Salvatore Di Falco[3], Timothy Swanson[4]

Abstract

This paper explores how climate risk affects maize intensification among smallholders in Kenya and tests the effects of this strategy on income vulnerability. We apply a comprehensive econometric strategy that differentiates weather shocks from climate change. We conclude that although farmers may not be adapting optimally to climate change, use of hybrid seed and fertilizer in maize production contributes positively to crop revenues, also reducing exposure to revenue variability. Finally, we find that maize intensification is driven by weather realizations in the near past. In this win-win situation, both maize intensification and adaptation strategies could be promoted by the Government of Kenya to support the well-being of smallholder farmers.

Keywords: Climate Change, Maize, Smallholder farmer, Vulnerability, Kenya

JEL Codes: D81, O13, Q12, Q18

[1] PhD, Graduate Institute of International and Development Studies (CH); Research Associate, CIES, Graduate Institute of International and Development Studies (CH). martina.bozzola@graduateinstitute.ch.

[2] Corresponding Author, Professor of International Development, Michigan State University, East Lansing, MI. msmale@msu.edu

[3] Professor of Environmental Economics, University of Geneva (CH). Salvatore.DiFalco@unige.ch

[4] Professor of International Economics, Graduate Institute of International and Development Studies (CH). Timothy.swanson@graduateinstitute.ch

1. Introduction

Farmers in Africa are among the most vulnerable to climate change. On the African continent, multiple stresses occur at multiple scales; African smallholder farmers, who are among the world's poorest, have limited capacity for adaptation (Boko et al., 2007). Kenya is heavily exposed to changing climatic patterns, with serious repercussions for the well-being of farming households (Oremo, 2013). Many areas of the country have registered rising seasonal mean temperatures over the last 50 years. Regional climate model studies suggest drying over most parts of Kenya in August and September, although climate impacts are likely to be unevenly distributed across the country (Niang et al., 2014).

Smallholder farm families pursue various adaptive strategies to cope with climate change, but intensification of production—increased use of hybrid seed and mineral fertilizer—is not generally considered to be one of them. Since the Green Revolution in Asia, researchers have debated whether the yields of improved varieties and hybrids are higher but also more variable, exposing poor farmers to greater risk (e.g., Anderson and Hazell 1989). In general, empirical evidence on this point depends on the counterfactual (which varieties/hybrids are compared) and the geographical scale of analysis. In the major agricultural regions of Kenya, farm families depend on maize as a food staple and ready source of cash. Maize growers have high adoption rates and a history of growing maize hybrids with and without fertilizer (Mathenge et al., 2014). They have limited access to credit and no access to insurance, so they have a strong incentive to plant seed that reduces the variance of yields and limits their exposure to downside risk. Preliminary research by Jones et al. (2012), who considered only some of the major maize-growing agro-ecologies, suggested that use of hybrids in maize production was not only mean-enhancing but also reduced downside risk, with no significant effect on yield variance.

Smallholder agricultural production in rainfed agriculture, like that found in Kenya, relies on environmental production conditions that are "exogenously" determined - largely outside the control of farm families (Sherlund et al., 2002). Yet, climate and soil characteristics are rarely incorporated into micro-economic analysis of crop and variety choice. Mutiso (1996) showed that farmers in southeastern Kenya follow local knowledge systems when choosing the time to prepare land and plant. Other agronomic factors also guide planting decisions, especially in areas with sparse rainfall (Sacks et al., 2010). Thus, it is important to account not only for environmental conditions, including climate and soil quality, but also for factors influencing farm management choices and adaptation options, such as human capital (labor supply and quality), financial and physical capital (assets, access to credit, farm size and tenure).

We address two research questions in this paper. First, we ask how climatic shocks, weather and climate change affect smallholder decisions to *intensify* maize production. While controlling for relevant covariates as noted above, we test the separate effects of climatic shocks, weather. *Climatic shocks* refer to the number of times during the previous decade that each village experienced a serious drought. *Weather* indicates the rainfall and temperatures values registered during the main rainfall season of the corresponding data collection year. *Climate* refers to climate normals (also referred as climatologies): each village's weather averaged over a 30-years period (1971-2010).

Second, we ask how these variety and seed decisions (maize intensification) affect smallholder vulnerability. With reference to the portfolio theory of decision-making, we address this question by examining the mean, variance and skewness of crop revenues using Antle's (1983) method of moments.

Our econometric strategy reflects the structure of our data-generating process and conceptual frame. We apply our model to four waves of panel data collected the major agricultural regions of Kenya, controlling for time-invariant heterogeneity by applying the Mundlak-Chamberlain procedure. We consider the potential endogeneity of input choices in revenue outcomes.

We contribute to the existing literature in several directions. From a methodological perspective, we differentiate the role of climatic shocks, weather and climate on input choices in a micro-economic context, isolating their separate effects econometrically. We explore the intensification of staple food production through the dimension of hybrid seed and fertilizer use. The Boserupian hypothesis (Boserup, 1975) suggests that population pressures on a declining environmental base generate incentives for intensifying food production. In a volatile environmental context, input intensification could aggravate smallholder vulnerability. We test this hypothesis.

Further, in the second stage of the estimation procedure we include, along with intensification variables, climatologies and weather as explanatory factors, gauging the impact on agricultural revenue and farm risk across agro-ecologies. The inclusion of both climate and weather allows us to capture the full extent of underlying adaptation decisions (Bezabih et al., 2014). Thus, our work contributes to illuminating an ongoing debate concerning the appropriate measurement methods in adaptation studies. We also include detailed information on environmental production conditions, such as climate and soil characteristics at village level, and separate main and short season rainfall, which varies across Kenya's agroecologies, within years. Sherlund et al. (2002) have demonstrated the potential bias in production models of failing to control for soil quality. In terms of measurement techniques, we utilize the most advanced drought index available (SPEI). The SPEI is a multi-scalar drought index that accounts for the fact that the impact of rainfall on the growing cycle of a plant depends on the extent to which water can be retained by the soil.

2. Theoretical basis

A leading paradigm in models of seed-fertilizer adoption since the Green Revolution has been the portfolio theory of investment attributed to Markowitz (1952), articulated by Just and Zilberman (1983) in terms of trade-offs between the mean and variance of yield distributions where the choice variable was the crop area share allocated to new techniques (here, hybrid seed and mineral fertilizer) with higher mean yields as compared to more traditional farmers' techniques (local maize, no mineral fertilizer).

However, the approach is far less commonly applied in the analysis of natural resource management. We apply this approach in the context of intensification choices made under climate change and extend it to include skewness effects, following Antle's method of moments (1983). Recent research has demonstrated the importance of the third moment in analyzing of climate-related risk in agricultural production (Koundouri et al., 2006; Di Falco and Chavas, 2009). By including skewness in the model we can approximate downside risk exposure: if the skewness of yield (revenue) increases then it means that downside risk exposure decreases, that is the probability of disastrous outcomes (non-positive revenue for a smallholder farming family) decreases (Di Falco and Chavas, 2009). Although reducing downside risk does not provide information on the role of adaptation on farmer's welfare, it decreases the asymmetry (i.e., the skewness) of the risk distribution toward higher outcomes, holding both means and variance constant (Menezes at al., 1980; Di Falco and Chavas, 2009). We thus introduce skewness into the myopic portfolio choice to take into account farmers' aversion to yield fluctuations in a specific direction.

Given the definition of α_t as the area share allocated to intensified inputs we can re-define the variance of crop yields as: $\sigma_{pt}^2 = \alpha_t^2 \sigma_t^2$. Similarly, we define the skewness as: $\gamma_{pt}^2 = \alpha_t^3 \gamma_t$.

The return on the input mix (the portfolio) is a linear combination of the simple returns of the riskier and less risky inputs. We assume that the benchmark input set has sufficiently low risk, so that the solution of the problems is almost identical to the standard mean-variance model with a riskless asset. The farmer prefers a high mean and low variance of returns on the mix. As in the standard mean variance model we assume that the farm family maximizes a linear combination of mean and variance, with a positive weight on the mean and a negative weight on the variance. We further assume that farmer is averse to results skewed in a specific direction ($\gamma_t < 0$), he will thus maximize the following function:

$$\max_{\alpha_t} \alpha_t (E_t R_{t+1} - R_{f,t+1}) - \frac{k_1}{2} \alpha_t^2 \sigma_t^2 + \frac{k_2}{3} \alpha_t^3 \gamma_t \tag{1}$$

The terms $k_1$and k_2 are coefficients representing farmers' risk aversion to yield variance and skewness respectively. Higher terms k_1 and k_2 indicate more conservative investors which hold less risky assets.

By solving the first order condition of Equation (1) we can find the optimal share of land to be farmed with the riskier input set.

$$E_t(R_{t+1} - R_{f,t+1}) - k_1 \alpha_t \sigma_t^2 + k_2 \alpha_t^2 \gamma_t = 0 \tag{2}$$

Defining:

$$\Delta = E_t R_{t+1} - R_{f,t+1} \, ; \qquad x = \frac{\Delta}{k_1 \sigma_t^2} \quad ; \qquad y = \frac{k_2 \gamma_t}{\Delta}$$

The solution of the maximization problem can be also written as:

$$\alpha_t = \min\left(\alpha_t = \frac{1 - \sqrt{1 - 4xy}}{2xy} \quad , \qquad 1 \right) \tag{3}$$

In cases where the yield skewness plays a small effect, an approximate solution, up to the first order in γ, is:

$$\alpha_t = \frac{\Delta}{k_1 \sigma_t^2} + \frac{\gamma_t \Delta^2 k_2}{k_1^3 \sigma_t^6} + \cdots 0(\gamma_t^2) \qquad (4)$$

Where $\frac{\Delta}{k_1 \sigma_t^2} > \frac{|\gamma_t| \Delta^2 k_2}{k_1^3 \sigma_t^6}$ and higher orders are expected to be negligible, because of the way we defined the approximation.

Equation (4) indicates the share of land for which the farmer is willing to rely on from his riskier inputs. This share is equal to the risk premium divided by the conditional variance times a coefficient representing the risk aversion of the farmer plus a term capturing aversion to negative outcomes of the distribution of skewness.

Figure 1 illustrates the result of the farmer's maximization problem presented in Equation (4). The figure shows the optimal share of land planted to intensified inputs, for given ranges of variance, skewness and expected returns. Figure 1 has some interesting features: first, we notice that for high values of the variance term σ_t^2 the distribution of yield's skewness does not matter in defining the share of land allocated to the risky inputs α_t, as indicated by the almost vertical boundaries lines for values corresponding to α_t,=0.1 to α_t=0.4. However, as variance decreases or expected revenues increase (i.e., we move on the right along the horizontal axis), the distribution of yields' skewness (captured by γ_t) becomes increasingly relevant in determining land's allocation share to the risky crop, up to a point where the variance is very low and only extremely adverse distributions of outcomes matter.

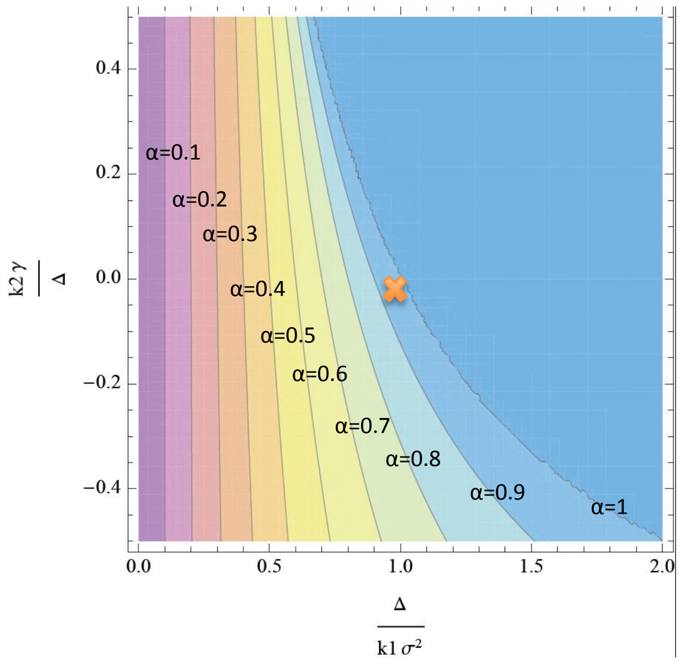

Figure 1: Optimal land partition

For example we can consider an initial land allocation defined by the red-cross in the graph, where 90% of the area is allocated to intensified inputs and 10% to other input set. We assume that the distribution of skewness equals to zero and the ratio $\frac{\Delta}{k_1 \sigma_t^2}$ equals to almost 1.1 for this input choice.

If skewness raises to high enough positive outcomes, holding the variance constant will cause the share α_t to rise to 1. However, as the distribution of skewness takes negative outcome (and the farmer fears crop failure) the share of farmland allocated to the risky variety decreases. Under downside risk aversion farmers are adversely affected by down side risk (e.g. risk of negative revenues). A downside averse decision maker will invest in adaptation strategies to reduce such risk (Menezes et al., 1980; Antle, 1983 and 1987; Di Falco and Chavas, 2009).The interest in going beyond mean and variance effects and capture how inputs contributes to the higher moments of the net revenue distribution increases for higher expected revenues and variance neither too low (when there is very little risk associated to the second moment of the distribution of revenues) nor extremely high. The precise shape of the cutting lines in Figure 1 depends on the values range attributed to the expected yields, their variance and skewness. These are determined by the type of crops grown and several local environmental conditions. This graph might provide an intuition why under some conditions the third moment of the distribution of agricultural yields does not seem to be a key determinant of farmer input choices while some literature found it to be crucial. For example, skewness and variance effects might be very different across a country like Kenya, characterized by the presence of various agro-climatic zones. Notably, hybrid seed would be preferred in areas where the marginal productivity is higher.

3. Empirical approach

3.1 Data sources

We draw on three comprehensive data sources in our analysis. The first source is household survey data collected by Egerton University's Tegemeo Institute of Agricultural Policy and Development with technical support from Michigan State University in four rounds (2000, 2004, 2007, 2010). Argwings-Kodhek (1999) provides a detailed description of the sample design implemented in consultation with the Kenya National Bureau of Statistics (KNBS). Survey instruments are available online (www.tegemeo.org). All non-urban divisions in the selected districts were assigned to one or more agro-ecological zones based on agronomic information from secondary data. The panel dataset comprises eight agro-ecological zones. Within each division, villages and households in that order were randomly selected. The sample excluded large farms with over 50 acres and two pastoral areas. The final dataset used in this study contains detailed farm-level data from 1,243 agricultural households in 22 districts. Certain village-level covariates, such as population density and agro-ecological zones, are included in these data and our analysis.

Second, we associate climate variables developed from the monthly average maximum, minimum and average temperature and monthly cumulative precipitation for 107 villages across Kenya from 1971. These climate data is from the Climatic Research Unit (CRU) CRU TS3.21 dataset (Harris et al., 2014). We compile climate data to match the main and short season, taking into account local differences in the length and timing of these two seasons. These data were used to calculate the SPEI Index. This is a multiscalar drought index that accounts for the fact that the impact of rainfall on the growing cycle of a plant depends on the extent to which water can be retained by the soil. This in turn depends on the characteristics of the soil and on the extent to which sunshine induces evaporation (Harari La Ferrara, 2014). This climate indicator has been developed by Vicente-Serrano et al. (2010) and considers the joint effects of precipitation, potential evapotranspiration (PET) and temperature in determining droughts. This is an extension of the widely used Standardized Precipitation Index (SPI) (McKee et al., 1993). The SPEI index can be used for determining the onset, duration and magnitude of drought conditions with respect to normal local conditions. The SPEI index is increasingly considered as an improved measure over similar indexes previously used (e.g. the SPI, which is based on the rainfall only, and on the assumption that temperature and potential evapotranspiration have negligible variability compared to precipitation, or the Palmer Drought Severity Index (PDSI) (Palmer, 1965), which is based on the soil water balance equation on a fixed temporal scale (between 9 and 12 months)) because it provides a better measure of the effective amount of moisture received by the soil. We include in the regression the SPEI 3 months, determined for the last month of the main rainfall season, taking into account differences between agro-climatic zones in establishing the reference month.

Third, we draw on soils data at the village scale from the Harmonized World Soil Database, a partnership between the Food and Agriculture Organization (FAO) and the European Soil Bureau Network. (FAO, IIASA, ISRIC, ISSCAS, JRC, 2012).

3.2. Estimation strategy

We first analyze the determinants of maize intensification , paying particular attention to the role of past climatic shocks (captured by the SPEI3 index) and access to market (captured by population density). Second, we probe how maize intensification, along with climate and weather, affect farmers' welfare under uncertainty, taking into account the heterogeneity in agro-climatic conditions within Kenya. In this second step, we model the production technology as a stochastic production function, assessing its probability distribution using the sequential estimation procedure (Kim and Chavas, 2003). The dependent variables in the second step of the estimation procedure are expected revenue, the distribution of variance and skewness of revenue.

We address endogeneity concerns by implementing a two-stage procedure that allows addressing the potential endogeneity of decisions on maize intensification by smallholder growers. Two-stage least squares is a robust estimation method that provides a standard starting point for applying instrumental variables (Angrist and Krueger, 2001). In the first stage of the estimation procedure, we use the frequency of climatic shocks, the soil moisture level of the previous years' main rainfall season and the logarithm of population density at village level as instrumental variables for the decision on maize intensification. For identification purposes, some of the variables in the equation determining maize intensification (Equation 5) can be excluded from the revenue and risk equations (Equation 6).

In the first stage of our estimation, we assume that the utility function is state-independent,[1] and we represent the optimal strategy undertaken by the representative farm household by Equation (5):

$$M_{it} = M\left(x_{it}^{h}, x_{r}^{s}, x_{rt}^{p}, x_{ikt}^{f}, x_{rt}^{CR}, x_{rk}^{c}, x_{rkt}^{w}, \mathrm{Z_a};\ \gamma\right) + \varepsilon_{it} \tag{5a}$$

$$F_{it} = D\left(x_{it}^{h}, x_{r}^{s}, x_{rt}^{p}, x_{it}^{f}, x_{rkt}^{CR}, x_{rk}^{c}, x_{rkt}^{w}, \mathrm{Z_a};\ \lambda\right) + \varepsilon_{it} \tag{5b}$$

The subscripts it denotes the i^{th} farm household in year t, while the subscript *r* is used for village-level observations and *k* indexes the rainfall seasons. Terms γ and λ are vectors of parameters, and ε_{it} is the household-specific random error term. The dependent variable M_{it} is a continuous variable indicating the logarithm of the kilograms of hybrid seeds used and F_{it} is the nutrients application rate (i.e., the logarithm of nutrients' application rates in kilograms per hectare) by farmer i at year t.

3.3 Explanatory variables

Vectors x_{it}^{h}, x_{it}^{f}, include household and other farm characteristics respectively while the vector x_{rt}^{s} includes soil quality information at village level. Vector x_{rt}^{p} includes the logarithm of population density at village level. Definitions for each variable are presented in Table 1. Descriptive statistics of the variables used in this study are presented in Table 2.

Of special interest is vector x_{rt}^{CR}, capturing how climatic risk affects intensification decisions. This vector includes climate risk proxies stemming from the SPEI3 index, determined

[1] That is, we depart from the standard assumption in the expected utility theory von Neumann and Morgenstern that the utility in a state depends only on the consumption in that state but not directly on the state itself.

for the last month of the main rainfall season, taking into account differences between agro-climatic zones in establishing the reference month. Notably, we include the first lag of the SPEI3 index, as well as the number of times during the previous decade that the value of the SPEI3 was lower than -1.65 in the last month of the main rainfall season. This value indicates the exposure of the village to serious drought stress. The SPEI3 drought index expresses the incidence of past droughts (climatic shocks) as determinants of input choices. Vectors x_{rt}^{c}, x_{it}^{w} include climate and weather information. Vector $\mathrm{Z_a}$ contains agro-climatic zones fixed effects. We include them in the analysis, as we believe that being in a specific agro-ecological zone affects significantly the farm management decisions. For examples, the way farmers adapt to climate change might differ significantly depending if the farm is located in a zone with bimodal or unimodal rainfall regime.

The role of variables, F_{it} and M_{it}, representing farmers decisions on the intensification of production, enters the second stage of our estimation strategy via the predictions from the system of equations (1). Through this second step, we investigate how intensification affect farmers' expected revenue under risk.

In order to capture the full extent of risk exposure we assess the impact of intensification strategies on the distribution of expected revenue (Equation 6a), its variance (Equation 6b) and skewness (Equation 6c). To do this, we follow Antle's moment-based approach to specify the stochastic structure of the model.

Accordingly, the estimated relationship between farm risk equations, climatic variables, crop diversification decisions and other covariates is given by:

$$\ln y_{it} = \alpha + \beta_w w_{rkt} + \beta_C c_{rk} + \mu\, x_{\mathrm{i,t}} + \varphi s_{\mathrm{r}} + \vartheta \widehat{M}_{it} + \tau \widehat{F}_{it} + \xi\, \mathrm{Z_a} + \varepsilon_{it} \quad (6a)$$

$$\ln \hat{\varepsilon}_{it}^{2} = \alpha + \beta_w w_{rkt} + \beta_C c_{rk} + \mu\, x_{\mathrm{i,t}} + \varphi s_{\mathrm{r}} + \vartheta \widehat{M}_{it} + \tau \widehat{F}_{it} + \xi\, \mathrm{Z_a} + \check{\varepsilon}_{it} \quad (6b)$$

$$\ln \hat{\varepsilon}_{it}^{3} = \alpha + \beta_w w_{rkt} + \beta_C c_{rk} + \mu\, x_{\mathrm{i,t}} + \varphi s_{\mathrm{r}} + \vartheta \widehat{M}_{it} + \tau \widehat{F}_{it} + \xi\, \mathrm{Z_a} + \tilde{\varepsilon}_{it} \quad (6c)$$

The subscripts i, t, r and k are defined as in Equation 5. The dependent variable $\ln y_{it}$, denotes the logarithm of net agricultural revenue for the i^{th} farm household at year t. We simultaneously incorporate both weather and climate measures as determinants of farm-level revenue and risk, as presented in Equation 6. Therefore, w_{rkt} is a vector of weather variables: temperatures (minimum and maximum) and precipitations (monthly cumulated) in year t, while c_{rk} is a vector of climate normals for the mean temperature and cumulated rainfall. Both vectors refer to village r, for the main rainfall season (k=1). Vector x_{it} includes socioeconomic and physical farm characteristic variables at time t. Vector s_{r} contains soil quality variables, available at village's level. Z_a is a set of agro-ecological zones fixed effects. These dummy variables can capture exogenous variables that vary by agro-climatic zone but have not been measured.

The coefficients $\beta_w, \beta_c, \mu, \varphi, , \vartheta, \tau$ and ξ represent the vectors of parameter estimates for each associated vector of variables and ε_{it} is the error term. The composite error term is composed of a normally distributed random error term, $u_{it}{\sim}N(0, \sigma_u^2)$, and an unobserved household specific time invariant component (α_i), as it follows:

$$\varepsilon_{it} = \alpha_i + u_{it} \tag{7}$$

Similarly, $\check{\varepsilon}_{it}$and $\tilde{\varepsilon}_{it}$ are the composite error terms for the variance Equation (6b) and the downside risk Equation (6c) respectively, and have the same distribution properties of ε_{it}.

The panel structure of our dataset necessitates the use of a fixed effect estimator that permits the time-variant regressors to be correlated with the time-invariant component of the error term, while assuming that these regressors are uncorrelated with the idiosyncratic error. This estimation provides consistent parameters even if there is correlation between the independents variables and time invariant unobserved heterogeneity, such as soil quality. The estimation of an instrumental variables model with fixed effect methodology would allow us to test and control for potential endogeneity caused by a correlation between decisions regarding intensification and vulnerability outcomes. However, standard fixed effect models rely on data transformation that removes the individual effect.

We have previously discussed the importance to include in our framework variables that are in their nature time-invariant regressors, such as climate normals and soil quality variables. One way to include time-invariant variables while addressing endogeneity is to estimate a random effects model while controlling for unobserved heterogeneity using the Mundlak-Chamberlain approach (referred to as the pseudo-fixed effects model). Following Mundlak (1978) and Chamberlain (1982 and 1984) the right-hand side of our regression equation includes the mean value of the time varying explanatory variables. This approach relies on the assumption that unobserved effects are linearly correlated with explanatory variables. Thus the unobserved household specific time invariant component in Equation (7) can be specified as:

$$\alpha_i = \zeta\bar{x} + v_i$$

where $\bar{x}$ is the mean of the time-varying explanatory variables within each farm household (cluster mean), ζ is the corresponding vector coefficient, and v_i is a random error unrelated to the $\bar{x}'$s. The vector ζ will be equal to zero if the observed explanatory variables are uncorrelated with the random effects. The use of the Mundlak-Chamberlain device also addresses the problem of selection and endogeneity bias where these str due to time-invariant unobserved factors, such as household heterogeneity (Wooldridge, 2002). If we failed to control for these factors, we would not obtain consistent parameter estimates. Moreover, estimation of parameters ζ allows us to test for the relevance and strength of the fixed effects via an F test, performed for each endogenous variable.

4. Results

First-stage regression results for each potentially endogenous variable are reported in Table 3.

Frequent past climatic shocks reduce intensification in the use of maize hybrid seeds but have no statistically significant impact on N nutrients applied per hectare. Farmers who benefited from greater soil moisture in the previous year's main rainfall season tend to apply higher rates of nutrients but plant less hybrid seed. This result is supported by the evidence that weather, but not climate, affects intensification decisions.

Looking at the weather variables, temperature influences maize intensification. Notably, maximum temperature has a positive impact on intensification of production while minimum temperatures have the opposite sign, but it is statistically significant only in rates of hybrid seed use. Higher rainfall has a positive correlation with hybrid seed use. Farmers in areas where the weather is more favorable tend to apply more hybrid seeds.

Population density has positive correlation with maize intensification, consistent with the Boserupian hypothesis. Women's headship has no statistically significant impact on maize intensification of production, consistent with some earlier analysis of these data. This result is not surprising, given that headship fails to consider the composition (number of male and female adults) in the household (Doss, 1999). As household head is defined in these data, only a fifth of households are headed by women and most are widows (Smale, 2011). Wealthier farmers and those living in villages with less binding expenditure constraint are more likely to plant hybrids and apply more nutrients. Credit is not provided directly for maize production in Kenya, but farmers who obtain credit for other purposes may also be more likely to plant hybrids (such as tea growers in the highlands). Earnings from off-farm work diminish rates of N nutrients applied per hectare because labor demands outside the farm compete with fertilizer activities, as shown by Mathenge et al. (2014). A larger land endowment is positively associated with the amount of hybrid seed planted while is not correlated in a statistically significant way with N nutrient application, suggesting neutrality to scale. Soil quality strongly affects intensification decisions.

Table 4 reports the results for the second stage regressions. We address the issue of instruments' relevance using an F test of the joint significance of the excluded instruments, reported at the bottom of Table 3. The F statistic is greater than 10 for both variables related to intensification of production (kilograms of maize hybrid seeds and nutrien. These results indicate the strength of the chosen instruments. The choice of instruments seems appropriate and we turn to discussing our main regression results.

Column (1) reports the impact of intensification of production on net agricultural revenues. Hybrid seed use positively affects farm revenue (Jones et al., 2012; Mathenge et al. 2014), but not rates of N nutrients applied. The latter result could reflect either the findings of Ogada et al., (2010) who argue that most Kenyan farm households apply insufficient quantities or with Sheahan (2011) and Marenya and Barrett (2009), who found the opposite. These results are sensitive, however, to pricing assumptions; the extent to which farm families are net sellers vs. net consumers influences the relevant decision price.

To capture the full extent of how these management decisions determine risk exposure we also report both the farm-specific revenue variance function (column 2) and the revenue skewness function (column 3). We find no evidence that maize intensification increases risk (consistent with Jones et al. 2012), either in terms of variance or skewness of the distribution of agricultural revenue. Scale of hybrid seed use has no significant impact on the variance of the agricultural revenue, but is positively correlated with skewness. Thus, the more hybrid seed planted (the greater the area planed), the less likely are revenues to fall below a given threshold, also contributing positively to mean revenues. This finding suggests, as we would expect, that larger maize growers are more often in a more favorable economic situation when intensifying input use.

This may have significant policy implications in a country characterized by market failures (credit constraints, information asymmetries and commitment failures) which cause weak insurance and risk coping mechanisms (Fafchamps, 1992; Kurosaki and Fafchamps, 2002). Safety nets typically provide only limited support (Dercon and Krishnan, 2000; Dercon, 2004) while off-farm, non-covariant income is limited in more remote rural areas. In this context, fewer options exist to diversity incomes. In this context, smallholder maize growers have incentives to use hybrid seed as a strategy to buffer against downside risk. This conclusion calls for continued improvement of farmer access to well-adapted hybrid seed through decentralized, competitive markets and effective, widely-diffused market information services.

The negative and statistically significant coefficient associated with fertilizer use (N nutrient kgs/ha) in the variance regression (column 2) indicates that for the average Kenyan smallholder in the major maize-growing regions of Kenya, applying mineral fertilizer to maize generally reduces the variability of agricultural revenue. In sum, our results suggest that maize intensification is an effective strategy even in the face of climate change and climate shocks.

In general, long-term impacts are larger than short terms one, a result also found in Bezabih et al., (2014). Looking at weather, the squared temperature and precipitation coefficients are generally significant. This finding implies that the model is nonlinear. The fact that the squared terms are positive or negative reveals that seasonal effects are convex or concave, respectively. The maximum diurnal temperature correlates negatively to expected revenue, whereas higher minimum temperature is beneficial, up to a maximum of 16.5^{o}C. Several agronomic studies confirm that maize reacts differently to maximum and minimum temperature (Harrison et al., 2011). Rainfall during the current main rain season has a bell-shaped relationship with agricultural revenues.

The impacts of climate normals on expected revenue are very similar, but generally larger. Rainfall climatologies display a bel-shaped relationship with agricultural revenue, which is consistent with the literature (Kabubo-Mariara and Karanja, 2007). However, an increase in rainfall climatologies enhances the risk associated to the variance of the distribution of agricultural yields. This result is probably related to the fact that most of the agriculture in the country (and in our sample) is rainfed and depends strongly on the quantity and distribution of rainfall across space and time. An increase in mean temperature climatologies significantly decreases the variance of agricultural income but it does not have a statistically significant impact on net revenue and higher moments of the distribution of agricultural revenue. Looking at the revenue equation (column 1) we also notice that the coefficients associated to mean temperature climatologies are much larger than the coefficients associated to rainfall climatologies. This result confirms those of Kabubo-Mariara and Karanja (2007), who concluded that in Kenya the temperature component of global warming is much more important than precipitation. Interestingly, weather has an impact on the third moment of the distribution of revenue, but not climate.

Soil quality is an important determinant of farm revenue. Higher values associated to the gravel variable indicate higher percentage of materials in the soil that are larger than 2mm. In areas where this type of soil is predominant, farming is more difficult and plant life is sparser. Notably, the higher the value associated to gravel soil, the lower the ability of the soil to retain moisture, and the lower the presence of mineral nutrients. Henceforth, the negative coefficient associated to this variable complies with our expectations. pH is a measure for the acidity and alkalinity of the soil, measured in concentration levels (-log(H+)). pH between 5.5. and 7.2 (acid to neutral soil) offers the best growing conditions, and the mean value of the sample is in this range. Higher pH (associated to alkaline soils) is negatively correlated with agricultural revenue. The coefficient associated to the available water storage capacity class of the soil unit (AWC_mm), measured in mm/m has the expected sign in the revenue and risk equations (it correlates positively with crop revenue, reduces the variance of the distribution of crop revenues and the probability of crop failure), but it is not statistically significant.

Farm size, as expected, plays an important, positive role in determining agricultural revenue, as does the value of livestock assets. Higher shares of remittances and other salaries in the total household income affect negatively agricultural income, probably because farmers with outside options in terms of income diversification have lower incentives to take management and investment decisions to improve farming conditions.

Whether the family has a deed title over the land it operates is not statistically significant However, the associated coefficient is negative, indicating that land tenure insecurity could be detrimental to agricultural revenue. Since the ratification of the new constitution in Kenya, land tenure and entitlement has been a prominent concern. This finding suggests that land certification could be an effective policy instrument to buffer against climate anomalies.

5. Conclusions

This paper analyzes how maize intensification, defined as the use of hybrid seed and mineral fertilizer relates to farmer's vulnerability. Drawing from and extending the portfolio theory of investment choice, we estimated a two-stage model to identify the determinants of input use and assess the effects of input use on the mean, variance and skewness of crop revenues among smallholder farmers in Kenya. We focus on maize production, considering the importance of this crop not only as a food staple but also an income source for in Kenya. We apply the Mundlak-Chamberlin device to control for unobserved, household heterogeneity and also test and control for endogeneity of crop and variety choices in revenue outcomes.

We extend the portfolio investment approach previously applied to the analysis of input use decisions by incorporating and differentiating the effects of weather, climate change and climatic shocks. We find that long-term impacts are larger than short-term, suggesting that farmers are not adapting optimally to climate change. Suboptimal choices might reflect multiple market failures, such as credit constraints, poor access to input and output markets, information asymmetries and commitment failures.

Our findings lead us to recommend that the Government of Kenya play an active role in encouraging smallholder adaptation to changing climate patterns and climate shocks. Promoting knowledge formation among farmers concerning weather, climate, production and post-harvest handling, and other adaptation strategies, would be beneficial. This conclusion supports findings of previous studies (e.g., Kabubo-Mariara and Karanja, 2007).

Multiple market failures include poor or non-existent insurance, so that farmers use other risk-coping mechanisms. Thus, we find that scale of hybrid seed use, which is negatively associated with persistent climatic shocks, reduces the likelihood that crop revenues fall below a given threshold (downside risk). By contrast, we find that higher soil moisture in the previous growing season determine use of N nutrient kgs/ha in maize production. Notably, N nutrients are used to cope with variability of agricultural income. These findings are consistent with the fact that cropping system decisions are related to longer-term investment choices, and N nutrient use, to annual decisions.

Our empirical analysis confirms the importance of considering agroecological zones and soil quality variables in micro-economic models of input use and adaptation strategies. Omission of these factors could cause biased estimates of included coefficients. Regression results also support the Boserupian theory that rising population density provides incentives for the shift toward more intensive farming systems. Finally, we find trade-offs between nonfarm employment and fertilizer use, and nonfarm employment and crop revenues, indicating changing dynamics of income in rural communities as Kenya urbanizes.

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Annexes

Table 1: Variables Definitions

Variable	Description
Farm specific variables (Source: Tegemeo)	
Crop revenue	Value of crop production minus input and land preparation costs (labor and seeds costs excluded).
Hybrid seeds (kgs)	kg maize hybrid seeds in major rainfall season
Nutrients (kgs/ha)	kg nutrients applied per hectare in major rainfall season
Educated men	adult men with secondary education
Livestock assets (kes)	value (kes) of livestock assets
Credit village	Proportion of village households that received credit
Women's headship dummy	1=reported head of household female, 0 otherwise
Salaries & remittances income share	share of salaries and remittance in household income
Land	total household land area (ha) in current survey wave
No land title dee dummy	dummy 1 if land owned with no title dee 0 otherwise
Village-specific climate characteristics (Source: CRU TS3.21)	
SPEI3 Index	3 months Standardized Precipitation-Evapotranspiration Index (SPEI3) for the last month of the main rainfall season (January, July or August, depending on the division and agro-ecological zone each village belongs to. We calculated the SPEI index manually, using the R routines developed by Vicente Serrano et al. (2010). SPEI index for each location is based on monthly precipitation and rainfall at village level, downloaded from the CRU TS3.21 dataset (Harris et al., 2014) for the period 1971-2012.
Droughts_165	Number of times in the last decade[#] the value of the spei3 was <-1.65 in the last month of the main rainfall season.
Temperature max (°C)*	Monthly average maximum air temperature (°C) during the major rainfall season
Temperature min (°C)*	Monthly average minimum air temperature (°C) during the major rainfall season

Temperature average (°C)*	Monthly average average air temperature (°C) during the major rainfall season
Rainfall (mm/mo)*	Cumulated rainfall (mm/mo) during the major rainfall season
Temperature average climatologies*	Average air temperature (°C) 1971-2010 during the major rainfall season
Rainfall climatologies (mm/mo)*	Cumulated rainfall (mm/mo) 1971-2010 during the major rainfall season
Village-specific soil characteristics (Source: World Soil database)	
AWC_mm	Available water storage capacity class of the soil unit, measured in mm/m
Ph top soil (-log(H+))	pH measured in a soil-water solution. It is a measure for the acidity/alkalinity of the soil
Gravel top soil (%vol)	Volume % gravel (materials in a soil larger than 2mm) in the topsoil (i.e. 0-30 cm) (%vol)
Village level socio economic variables & Agro-ecological Zones	
Pop. Density	Village population density (cap/km²)
Agro-ecological zone Dummies	CLO coastal lowlands; ELO eastern lowlands; WLO western lowlands; WTR western transitional ; HPMZ high potential maize zone; WHI western highlands; CHI central highlands; MRS marginal rain shadow

*We take into account the relevant cropping season: e.g. for villages in the Rift Valley's the reference period is March (year-1) to (August year-1). # Reference Decades: 1989-1999 for 2000; 1993-2003 for 2004; 1996-2006 for 2007; 1999-2009 for 2010.

Table 2: Descriptive Statistics

Variables	Mean	Std. Dev.	Min	Max
Farm-specific variables				
Crop revenue	87,911	142,264	0	3,883,123
Hybrid seeds (kgs)	11.71	27.86	0	600
Nutrients (kgs/ha)	12.94	14.13	0	98.84
Educated men	0.89	0.98	0	10
Livestock assets (kes)	81,366	217,682	0	8,679,900
Credit village	0.47	0.30	0	1
Women's headship dummy	0.21	0.40	0	1
Salaries & remittances income share	0.18	0.24	0	1
Land	5.80	8.72	0	157
No land title dee dummy	0.36	0.48	0	1
Village-specific climatic variables				
Temperature max (°C)	26.56	3.63	19.12	33.47
Temperature min (°C)	14.04	3.76	7.5	23.95
Temperature average (°C)	20.27	3.62	13.3	28.67
Rainfall (mm/mo)	708.75	209.29	145	1154.1
Temperature average climatologies (°C)	19.57	3.69	13.61	27.89
Rainfall climatologies (mm/mo)	708.95	186.32	184.58	946.44
SPEI3 Index	-0.18	1.01	-2.28	2.24
Droughts_165	0.74	0.72	0	2
Village-specific soil characteristics				
AWC_mm	149.42	3.77	125	150
Gravel top soil (%vol)	1.25	4.09	0	21
Ph top soil (-log(H+))	5.75	1.04	4.5	8.9
Village-specific socio economic variables				
Population Density	363.47	214.88	16.43	1245.11

Table 3: Estimation results – First Stage regressions

	ln Hybrid Seeds (Kgs)		ln Nutrients (Kgs/Ha)	
Droughts_165	-0.1109***	[0.0301]	-0.0242	[0.0333]
First lag SPEI3 Index	-0.0529	[0.0326]	0.0914**	[0.0356]
ln population density	1.4657***	[0.1869]	0.6578***	[0.2151]
Temperature max	1.7570***	[0.4694]	0.5192	[0.4900]
Temperature max squared	-0.0279***	[0.0088]	-0.0100	[0.0090]
Temperature min	-0.6428***	[0.2050]	-0.0020	[0.2061]
Temperature min squared	0.0153**	[0.0066]	0.0022	[0.0065]
Rainfall	0.0030***	[0.0007]	-0.0011	[0.0008]
Rainfall squared	-1.56e-06***	[4.56e-07]	3.45e-07***	[5.29e-07]
Temperature average climatologies	-6.9171*	[3.5300]	-10.4799	[6.7514]
Temperature average climatologies squared	0.1819**	[0.0773]	0.3143**	[0.1446]
Rainfall climatologies	0.0068	[0.0068]	0.0047	[0.0129]
Rainfall climatologies squared	-6.12e-06	[0.00001]	-3.51e-06	[7.79e-06]
AWC_mm	0.0139***	[0.0052]	-0.0011	[0.0039]
Ph top soil	0.1516***	[0.0299]	-0.1248***	[0.0383]
Gravel top soil	0.0151***	[0.0049]	0.0058	[0.0068]
ln livestock assets	0.0272***	[0.0101]	0.0162	[0.0106]
ln credit village	0.5434***	[0.1285]	0.3427***	[0.1280]
Women's headship dummy	-0.0897	[0.0709]	-0.0765	[0.0747]
no land title dee dummy	-0.0425	[0.0356]	0.0225	[0.0394]
ln educated men	0.0837*	[0.0447]	0.1284***	[0.0477]
ln salaries & remittances income share	-0.0098	[0.1108]	-0.2084*	[0.1097]
ln land	0.2170***	[0.0440]	0.0272	[0.0476]
agro-ecological reg. FE	yes		yes	
F test of excluded instruments	F(6, 4750)=32.34		F(6, 4750)=24.01	
Observations	4,797		4,797	

Notes: Pseudo-Fixed effect estimation. Robust standard errors in brackets.*** p<0.01, ** p<0.05, * p<0.1

Table 4: Estimation results – Second Stage regressions (Pseudo Fixed Effects Estimation)

	(1) Crop Revenue		(2) Variance		(3) Skewness	
ln Hybrid Seeds (Kgs)	0.6730***	[0.1524]	-0.5934	[0.3991]	3.7847*	[2.0097]
ln Nutrients (Kgs/Ha)	-0.2191	[0.2524]	-1.6645***	[0.4396]	-1.8735	[2.0581]
Temperature max	-3.7880***	[0.539]	3.1403*	[1.8042]	-26.4563*	[13.952]
Temperature max squared	0.0671***	[0.0102]	-0.0451	[0.0331]	0.4212*	[0.2527]
Temperature min	2.1194***	[0.2322]	-1.0237	[0.8792]	13.7171*	[7.1522]
Temperature min squared	-0.0638***	[0.008]	0.0307	[0.0280]	-0.3653	[0.2224]
Rainfall	0.0048***	[0.0009]	-0.0014	[0.0025]	0.0054	[0.0126]
Rainfall squared	$-3.51e^{-06}$***	[$5.8e^{-07}$]	0.000	[0.0000]	-0.000	[0.0000]
Temperature average climatologies	-16.6317	[21.40]	-205.40***	[22.712]	91.3800	[124.28]
Temperature average climatologies sq.	0.3879	[0.4666]	4.400***	[0.4981]	-1.7472	[2.7057]
Rainfall climatologies	0.0121	[0.0296]	0.288***	[0.0340]	-0.1010	[0.1828]
Rainfall climatologies sq.	-6.53e-06	[0.00002]	-0.0002***	[0.00002]	0.0001	[0.0001]
AWC_mm	0.0054	[0.0107]	-0.0456	[0.063]	0.3188	[0.4242]
Ph top soil	-0.3744***	[0.0881]	-0.4841***	[0.160]	-0.6074	[0.6094]
Gravel top soil	-0.0218***	[0.0078]	0.0123	[0.0266]	0.0836	[0.1444]
ln livestock assets	0.0246**	[0.0104]	0.0044	[0.0249]	0.1240	[0.1297]
ln credit village	-0.4310**	[0.1775]	1.7966***	[0.5199]	-6.6444*	[3.8222]
Women's headship dummy	0.1014	[0.0817]	-0.3994	[0.3070]	2.3731	[2.5357]
no land title dee dummy	-0.0106	[0.0378]	0.0301	[0.0988]	0.0327	[0.5698]
ln educated men	0.0390	[0.0489]	0.2624**	[0.1158]	0.0256	[0.6764]
ln salaries & remittances income share	-0.9777***	[0.1504]	0.0502	[0.5174]	-5.0177	[3.8396]
ln land	0.2433***	[0.0534]	0.2886**	[0.1412]	-1.3563*	[0.7361]
Constant	-19.010	[50.16]	-484.83***	[53.29]	224.121	[283.43]
Agro-Ecological Region FE	Yes		Yes		Yes	
Observations	4,797		4,797		4,797	
Number of hhid	1,220		1,220		1,220	

Notes: Pseudo-Fixed effect estimation. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

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