Climate, Shocks, Weather and Maize Intensification Decisions in Rural Kenya

Martina Bozzola, martina.bozzola@eui, European University Institute, Florence (IT);

Melinda Smale, msmale@msu.edu, Michigan State University, East Lansing, MI (USA);

Salvatore Di Falco, Salvatore.DiFalco@unige.ch, University of Geneva (CH)

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2016 AAEA Annual Meeting, Boston, Massachusetts, July 31-August 2, 2016

Abstract

We explore how climate, climate risk and weather affect maize intensification among smallholders in Kenya. We find that each plays an important role in maize intensification choice. The economic implications of this choice are also analyzed. We find that the share of maize area planted to hybrid seeds contributes positively to expected crop income, without increasing exposure to income variability or downside risk. The promotion of maize hybrids is potentially a valuable adaptation strategy to support the well-being of smallholder farmers, especially if these prove tolerant to a wide range of conditions.

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

JEL Codes: D81, O13, Q12, Q18

The farm household data used in this work was collected and made available by the Tegemeo Institute of Agricultural Policy and Development of Egerton University, Kenya. However, the specific findings and recommendations remain solely the authors' and do not necessarily reflect those of Tegemeo Institute.

The research leading to these results has received funding from the European Union's Seventh Framework Program FP7/2007-2011 under Grant Agreement Number 290693 FOODSECURE, as well as the US Agency for International Development and Michigan State University. The authors alone are responsible for any omissions or deficiencies. Neither the FOODSECURE project nor any of its partner organizations, nor any organization of the European Union, the European Commission, the US Agency for International Development or Michigan State University are accountable for the content of this paper.

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 - e.g. 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 several of the major maize-growing agro-ecologies, suggested that the use of hybrids in maize production not only enhanced mean yields 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). Ochieng, Kirimi and Mathenge (2016) estimated the effects of climate variability and change in crop revenue on maize and tea revenues earned by smallholder farmers in Kenya, finding differences between the two crops; temperature affected crop revenues negatively in maize but positively in tea production, while rainfall had a negative effect on income from tea. An analysis by Wineman et al. (2016) explored the channels through which exposure to extreme weather in Kenya affects the well-being of smallholder farm households, based on longitudinal and spatial analysis of income- and calorie-based measures of welfare. The authors found that extreme weather generally affects household welfare via crop production, recommending the development of new varieties with enhanced tolerance of dry and moist extremes.

Here, we focus on variety choice. Climate and soil characteristics are rarely incorporated into micro-economic analysis of 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. We measure intensification as the share of maize area per farm allocated to hybrid seeds. While controlling for relevant covariates as noted above, we differentiate and test the separate effects of climatic shocks, climate and weather on hybrid area shares. *Climate shocks* refer to the number of times during the previous decade that each village experienced a serious drought. The term *climatology* refers to climate normals. Climate normals are measured as average weather conditions over a 30-year period (1971-2010). *Weather* indicates the rainfall and temperature registered during the main rainfall season of the corresponding data collection year.

Second, we ask whether and how allocating a higher share of maize area in hybrid seeds per farm affects the vulnerability of smallholder income, expressed in terms of expected crop income, crop income variability and downside risk. Maize is the primary staple food grown by all smallholder farmers in the sample, across a wide range of livelihood types and farming systems. Mathenge et al. (2014) report that maize accounts for about 28% of gross farm output in the small-scale farm sector and that, outside the semi-arid areas, 98% of households grow maize. Tegemeo Institute data, used by Mathenge et al. (2014) and here, show that the share of crop income in household income averages 45%, varying only between 44% and 48% over the years of the survey.

With reference to the portfolio theory of decision-making, we address the second question by 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 in the major agricultural regions of Kenya, controlling for time-invariant heterogeneity by applying the Mundlak-Chamberlain procedure. We are interested in examining both the maize intensification decision and the relationship of maize intensification to income vulnerability in our two-stage econometric modeling. We also consider the potential endogeneity of input choices in crop income outcomes.

We contribute to the existing literature in several directions. First, from a methodological perspective, we differentiate the roles of climatology, climate shock and weather on input choices in a micro-economic context. Second, we explore the intensification of staple food production through the dimension of hybrid seed. 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.

Third, in the second stage of the estimation procedure, we include, along with intensification variables, climatology, climate shocks and weather as explanatory factors, gauging the impact on crop income and risk across agro-regional zones. The inclusion of both climate and weather variables 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.

Finally, we include detailed information on environmental production conditions, such as climate and soil characteristics at the village level, and separate the main rainfall season and short season rainfall. The incidence of seasons and their length vary across Kenya's agro-regional zones, and across 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) with higher mean yields as compared to more traditional farmers' techniques (local maize, no mineral fertilizer).

However, the approach has been far less commonly applied in the analysis of natural resource management. We apply it 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 climate-related risk in agricultural production (Koundouri et al., 2006; Di Falco and Chavas, 2009). Notably, we assume that a farm family will maximize the following function:

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

where the family chooses to allocate the maize area share of α_t to the riskier hybrid seeds at time *t* and the other terms are defined as follows: R_{t+1} is the return to hybrid maize, from time t to time t+1; $R_{f,t+1}$ is the return to local maize, from time t to time t+1; E_tR_{t+1} is the conditional mean (conditional on the farmer's information at time t, thus they are written with t subscript) of the maize area planted with hybrid seeds and σ_t^2 is the conditional variance of the maize area planted with hybrid seeds.

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 farmers who hold less hybrid seeds.

We extend the standard mean variance model by adding skewness, defined as:

$$\gamma_t = E\left(\frac{X-\mu}{\sigma}\right)^3 = \frac{\mu^3}{\sigma^3} \qquad (1)$$

Given the definition of α_t we can re-define the overall variance of (maize) 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 seeds portfolio) is a linear combination of the simple returns of the riskier and less risky inputs. By definition, the input that generates higher means (in this case, the intensifying input, hybrid seeds) also generates greater variance. One of the factors that can contribute to increasing the vulnerability of modern agricultural production systems is the utilization of a narrow range of genetic material in plant breeding, so that the different varieties grown by farmers are in fact closely related; another is the slow turnover of modern varieties in farmers' fields, although we have no evidence of such a situation in Kenya (Smale and Olwande, 2014).

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 farm family 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 of returns from inputs, with a positive weight on the mean and a negative weight on the variance. The farm family is averse to results skewed in a specific direction ($\gamma_t < 0$).

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

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

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 also can be written as:

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

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

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

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 (maize) land on which the farmer is willing to plant riskier inputs (hybrid seeds). This share is equal to the risk premium divided by the conditional variance times a coefficient representing the risk aversion of the farm family plus a term capturing aversion to negative outcomes of the distribution of skewness. By including skewness in the model, we can approximate downside risk exposure. Increased skewness of yield (income) implies lower exposure to downside risk. Downside risk refers to the probability of zero or negative crop income for a smallholder farming family, which is potentially disastrous (Di Falco and Chavas, 2009). Reducing downside risk decreases the asymmetry of the yield (income) distribution by shifting it toward higher outcomes, holding both means and variances constant (Menezes at al., 1980; Di Falco and Chavas, 2009). We can view the short-term decision of a farming family as intended to avert negative outcomes or yield fluctuations in a specific direction.

Figure 1 illustrates the result of the farmer's maximization problem presented in Equation (4). The figure shows the optimal share of (maize) 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 the skewness of the yield does not matter in defining the share of land allocated to the risky inputs α_t, as indicated by the almost vertical boundary lines for values in the range from α_t,=0.1 to α_t=0.4. However, as variance decreases or expected crop income increases (i.e., as we move to the right along the horizontal axis), the distribution of yield skewness (captured by γ_t) becomes increasingly relevant in determining the family's allocation to the risky input, up to a point where the variance is very low and only extremely adverse distributions of outcomes matter.

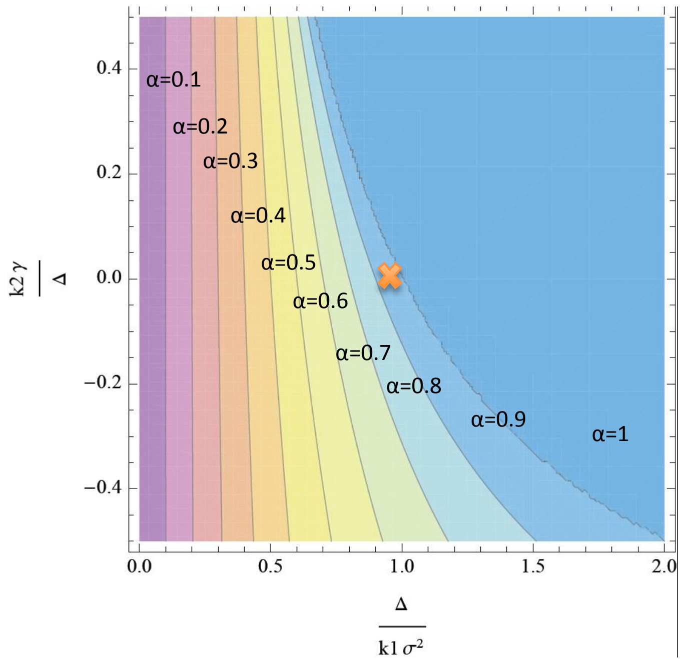

Figure 1: Optimal (maize) land partition

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

If skewness increases to high enough positive outcomes, holding the variance constant will cause the share α_t to increase to 1. However, as the distribution of skewness assumes negative outcomes (and the farm family fears crop failure), the share of cropland allocated to the intensified input decreases. Under downside risk aversion, farm families are adversely affected by downside risk (e.g., risk of negative crop income). We expect that 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). Our research interest in capturing how inputs contribute to the skewness of the crop income distribution is greatest when variance is neither too low (and thus there is very little risk associated with the second moment of the distribution of crop income), nor is variance extremely high.

The precise shape of the cutting lines in Figure 1 depends on the range of values attributed to the expected yields, as well as their variance and skewness. These are determined by the type of crops grown and local environmental conditions. Figure 1 provides intuition concerning 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, although some literature has found it to be crucial (Koundouri et al., 2006; Di Falco and Chavas, 2009; Groom et al., 2008; Di Falco and Veronesi, 2014). For example, skewness and variance effects might be very different across a country like Kenya, which is characterized by the presence of various agro-regional 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, which was 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-regional zones based on agronomic information from secondary data. The panel dataset comprises eight agro-regional 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-regional 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 are from the Climatic Research Unit (CRU) TS3.21 dataset (Harris et al., 2014). We compile climate data to match the main rainy season and the short rains season, taking into account local differences in the length and timing of these two seasons. These data were used to calculate the SPEI Index; as discussed above, this multi-scalar drought index accounts for the impact of rainfall on plant growth in the context of the soil's capacity to retain water. This in turn depends on the characteristics of the soil and on the extent to which sunshine induces evaporation (Harari and La Ferrara, 2014). The indicator, developed by Vicente-Serrano et al. (2010), considers the joint effects of precipitation, potential evapotranspiration (PET) and temperature in determining droughts.

The SPEI index is an extension of the widely used Standardized Precipitation Index (SPI) (McKee et al., 1993), and can be used for determining the onset, duration and magnitude of drought conditions with respect to normal local conditions. Increasingly, the SPEI index is considered an improved measure over similar indexes previously used[1] because it provides a better measure of the effective amount of moisture received by the soil (Vicente-Serrano et al., 2010; Harari and La Ferrara, 2014). We employ a three-month SPEI Index (SPEI3), determined for the last month of the main rainfall season and comprising also the two preceding months, 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

Our analysis is conducted in two stages. In the first stage, we analyze the determinants of maize intensification, paying particular attention to the role of past climatic shocks (captured by the SPEI3 index), access to markets (captured by population density) and the price per kg of fertilizer used on dry maize from hybrid seeds during the main rainfall season[2]. Second, we probe how maize intensification, along with climate and weather, affect farmers' welfare under uncertainty, taking into account the heterogeneity in agro-regional 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 (Antle 1983; Kim and Chavas, 2003). The dependent variables in the second step of the estimation procedure are expected crop income, variance and skewness of crop income.

[1] Examples include the SPI, which is based on rainfall only, and on the assumption that temperature and potential evapotranspiration have negligible variability compared to precipitation, as well as 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.

[2] By dry maize, we refer to maize grown and harvested dry, rather than green. Price is averaged over fertilizer types, of which the dominant type applied to hybrid maize was Diammonium Phosphate (DAP).

We test and control for the potential endogeneity of maize intensification decisions by estimating two-stage least squares. This 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 logarithm of population density at the village level and the price of fertilizer 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 crop income and risk equations (Equation 6).

In the first stage of our estimation, we use Equation (5) to represent the optimal strategy undertaken by the representative farm household:

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

The subscript 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 $\varepsilon_{\mathrm{it}}$ is the household-specific random error term. The dependent variable α_{it} is a continuous variable indicating the share of land planted with hybrid seeds of dry maize.

3.3 Explanatory variables

Definitions for each variable are presented in Table 1. Descriptive statistics of the variables used in this study are presented in Table 2.

Vectors x_{it}^{h}, x_{it}^{f}, include household and other farm characteristics respectively. The human capital resources of the household are measured as the number of adult men and adult women in the household with a secondary education. Financial capital is measured in terms of livestock wealth, access to credit at the village level, and salaries and remittances, which provide liquidity that is uncorrelated with crop income. Farm physical capital is represented by scale of land cultivated, with a dummy variable indicating ownership by deed.

Vector x_{ikt}^{p} includes the farm price for fertilizer applied to hybrid maize grown during the main rainfall season,[3] while the vector x_{rt}^{s} includes soil quality information at the village level. Vector x_{rt}^{v} includes the logarithm of population density at village level.

Of special interest is vector x_{rt}^{CR}, capturing how climatic risk affects intensification decisions. This vector includes a climate risk proxy stemming from the SPEI3 index, determined 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 number of times during the previous decade that the value of the SPEI3 was lower than -1.65. 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-regional zones fixed effects. We include them in the analysis, as we believe that being in a specific agro-regional zone affects significantly the farm management decisions. For examples, the way farmers adapt to climate change might differ significantly depending on whether the farm is located in a zone with a bimodal or unimodal rainfall regime.

The role of variable α_{it}, representing farmers' decisions on the intensification of production, enters the second stage of our estimation strategy via the predictions from the system of Equation (1). Through this second step, we investigate how intensification affect farmers' expected crop income under risk.

In order to capture the full extent of risk exposure, we assess the impact of intensification strategies on the distribution of expected crop income (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 crop income risk equations, climatic variables, maize intensification decisions and other covariates is given by:

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

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

[3] If the household did not buy fertilizer for this crop during the main rainfall season, the village's average is used.

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

The subscripts i, t, r and k are defined as in Equation 5. The dependent variable $\ln y_{it}$ denotes the logarithm of crop income for the i^{th} farm household at year t.[4] We incorporate both weather and climate measures as determinants of farm-level crop income and risk, as presented in Equation 6. Therefore, w_{rkt} is a vector of weather variables: temperature (minimum and maximum) and precipitation (monthly cumulative) in year t, while c_{rk} is a vector of climate normals for the mean temperature and cumulative 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 the village level. Z_{a} is a set of agro-regional zone fixed effects. These dummy variables can capture exogenous variables that vary by agro-regional zone but have not been measured.

The coefficients β_w, β_c, μ, φ, , ϑ and ξ represent the vectors of parameter estimates for each associated vector of variables, while 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 (q_i), as follows:

$$\varepsilon_{it} = q_i + u_{it} \quad (7)$$

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 as 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 independent 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

[4] In order to treat the zero values in the sample, which would result into a reduction of the sample size, we add the constant 1 to each variable before taking the natural logarithm i.e.: ln(variable)=ln[1 + (variable)]. By doing this, we ensure that all of the logarithms will exist.

intensification and vulnerability outcomes. However, standard fixed effect models rely on a data transformation that removes the individual effect.

We have previously discussed the importance of including in our framework variables that are by their nature time-invariant regressors, such as climatology 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, 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:

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

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 are 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 the endogenous variable.

4. RESULTS

First-stage regression results for the potentially endogenous variable are reported in Table 3. Frequent past climatic shocks, as manifested by drought incidence, reduce the maize area share per farm allocated to hybrid seeds. Looking at the weather variables, extreme temperature influences maize intensification. Maximum temperature has a negative (insignificant) impact on intensification of production at an increasing rate (significant), while minimum temperatures have the opposite signs with the same significance. Higher rainfall has a significant, positive correlation with hybrid seed use, at a decreasing rate. Farmers in areas where the weather is more favorable tend to allocate more maize area to hybrid seeds; temperatures are lower in the areas with the highest historical adoption rates.

Population density has a positive correlation with maize intensification, consistent with the Boserupian hypothesis. The presence of educated men in the household has a positive impact on the adoption of maize hybrid seeds, since education provides access to information, services and communication, as well as the potential to utilize these more effectively.

Fertilizer price has the expected negative sign but is not a statistically significant determinant of maize area shares planted to hybrid seed. Other research in Kenya has suggested that Kenyan farmers tend to apply non-optimal quantities of mineral fertilizers. Ogada et al. (2010) found that most Kenyan farm households apply insufficient quantities of mineral fertilizers; Sheahan (2011) and Marenya and Barrett (2009) found the opposite. Our empirical model does not enable us to draw conclusions regarding the quantitative response of fertilizer application rates on maize to price variation, but only regarding the jointness of use of mineral fertilizers and hybrid seed. In about 90% of the plots in our dataset where maize hybrid seeds are planted during the main rainfall season, mineral fertilizers were also applied.[5] Also using the Tegemeo dataset, Smale et al. (2015) found a strongly significant and expected negative sign for the relationship between nitrogen nutrient kgs per ha of maize and the fertilizer price.

Wealthier farm families and families with higher human capital resources are more likely to plant a larger share of their land with hybrids. There is no statistically significant evidence that those farmers living in villages with less binding expenditure constraints are planting larger land shares with hybrid seeds. 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). A larger land endowment is negatively associated with the land share allocated to maize hybrid seed planted, suggesting that larger landowners might allocate a larger land share to other crops, such as cash crops, instead of staple crops. Soil quality strongly affects intensification decisions.

Table 4 reports the results for the second stage regressions. We address the issue of the instruments' relevance using an F test of the joint significance of the excluded instruments,

[5] The remaining 10% of observations have missing values regarding the application of mineral fertilizers on the plot; thus, we cannot exclude the possibility that the percentage of the plot farmed with hybrid seeds where mineral fertilizers was applied is even higher.

reported at the bottom of Table 3. The F statistic is greater than 10. This result indicates the strength of the chosen instruments (Staiger and Stock, 1997). 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 expected crop income. Consistent with previous research, a larger share of maize area per farm allocated to hybrid seed tends to positively affect expected crop income (Jones et al., 2012; Mathenge et al. 2014). To capture the full extent of how these management decisions determine risk exposure, we also report both the farm-specific variance function (Column 2) and the skewness function (Column 3) for crop income. We find no evidence that a larger share of land allocated to dry maize hybrid seeds (intensification) increases risk, either in terms of variance (this finding is consistent with Jones et al. (2012)) or skewness of the distribution of crop income. The share of maize area allocated to hybrids has no significant impact on either the variance or the skewness of crop income. Thus, planting a greater area with maize hybrid seed contributes positively to mean crop income, with no statistically significant impact on the other risk equations.

In general, long-term impacts are larger than short-term effects, 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 with expected crop income, whereas higher minimum temperature is beneficial. Furthermore, higher diurnal temperature is associated with crop failure. 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 crop income. Looking at the crop income equation (Column 1) we also notice that the coefficients associated with temperatures are much larger than the coefficients associated with rainfall. 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, but not climate, has an impact on the third moment of the distribution of crop income.

The impacts of climate normals on expected crop income are very similar, generally larger than the impacts of weather, but not statistically significant. An increase in rainfall climatologies enhances the risk associated with the variance of the distribution of agricultural yields, as well as the risk of crop failure. 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.

Soil quality is an important determinant of farm crop income. Higher values associated with 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 with 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 with 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 with alkaline soils) is negatively correlated with crop income. Furthermore, farmers in Kenya tend to apply DAP as the main fertilizer type on dry maize from hybrid seeds, when they need to increases the soil pH. This application might, however, also increase acidity of the land over the medium to long-term.

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

Whether the family has a deed title over the land it operates is not statistically significant on expected crop income. However, the associated coefficient is negative, indicating that land tenure insecurity could be detrimental to crop income. 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. The presence in the household of women with secondary education is positively correlated with crop income and reduces the risk of crop failure. This result highlights the importance of human capital in efficiently managing agricultural technology.

5. CONCLUSIONS AND IMPLICATIONS

In this paper, we have analyzed two major research questions. First, we have explored how climatology, weather, and climate shocks affect maize intensification, other factors held constant. Second, we have tested whether maize intensification affects the vulnerability of smallholder farmers to crop income variability and downside risk, in the presence of these factors. We have defined maize intensification as the maize area share per farm allocated to hybrid seed (much of which is fertilized). 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 income 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 in Kenya. In order to include time-invariant variables such as soils and agro-regional fixed effects, while addressing endogeneity, we estimate a random effects model while controlling for unobserved heterogeneity using the Mundlak-Chamberlain approach (referred to as the pseudo-fixed effects model). 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.

Our approach enables us first to demonstrate that maize intensification is strongly affected by weather, climate shocks and climatology, in addition to commonly cited, household-farm characteristics such as education, wealth, access to credit and off-farm earnings. Next, we find that maize intensification has a positive effect on expected crop income but has no significant effect on crop income variability or downside risk. Moreover, relying on a higher proportion of hybrid seed use, which is negatively associated with persistent climatic shocks, is not enough to statistically significantly reduce the likelihood that crop income falls below a given threshold (downside risk). Importantly, cropping system decisions are related to longer-term investment choices, while decisions on specific hybrid types are, rather, annual decisions.

Thus, maize intensification is not in and of itself an effective strategy in the face of climate change and climate shocks. Further, our results suggest 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 and information asymmetries.

In addition to these major findings, our empirical analysis confirms the need to account for agro-regional zones and soil quality variables in microeconomic models of input use and adaptation strategies. Omission of these factors could cause biased estimates of included coefficients. Regression results 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 crop income, indicating changing dynamics of income in rural communities as Kenya urbanizes.

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. In Kenya, multiple market failures include poor or non-existent insurance, so that farmers use other risk-coping mechanisms, which can be weak (Fafchamps, 1992; Kurosaki and Fafchamps, 2002). Safety nets typically provide only limited support (Dercon and Krishnan, 2000; Dercon, 2004), while off-farm income that is not covariant with agricultural shocks is limited in more remote rural areas. In this context, smallholder maize growers need other adaptation mechanisms than the use of hybrid seed as a strategy to buffer against downside risk. Not only do smallholders need continued improvement of access to well-adapted hybrid seed and other inputs through decentralized, competitive markets but also effective, widely-diffused market information services and other insurance mechanisms. Helping farmers learn about weather, climate, production and post-harvest handling, as well as other adaptation strategies, would be beneficial.

Acknowledgements

The farm household data used in this work was collected and made available by the Tegemeo Institute of Agricultural Policy and Development of Egerton University, Kenya. However, the specific findings and recommendations remain solely the authors' and do not necessarily reflect those of Tegemeo Institute.

We are grateful to Jean-Paul Chavas, Robert Finger, Nick Hanley, Mary K. Mathenge, Michele Redi, Timothy Swanson and Cédric Tille for their thoughtful comments. We are also indebted to Simone Fatichi for assistance with the climate and soil quality data, to Xavier Vollenweider for his support in preparing the SPEI index and to Mark Schaffer, for sharing the user written stata command xtivreg3.

The research leading to these results has received funding from the European Union's Seventh Framework Program FP7/2007-2011 under Grant Agreement Number 290693 FOODSECURE, as well as the US Agency for International Development and Michigan State University. The authors only are responsible for any omissions or deficiencies. Neither the FOODSECURE project nor any of its partner organizations, nor any organization of the European Union or European Commission, the US Agency for International Development nor Michigan State University are accountable for the content of papers.

Table 1: Variables Definitions

Variable	Description
Farm specific variables (Source: Tegemeo)	
Crop income	Value of crop production minus input and land preparation costs (labor and seeds costs excluded).
Price fertilizer (kes)	Farm price fertilizer for dry maize from purchased hybrids. If the household did not buy fertilizer for this crop category, the village's average is used.
Educated men	No of adult men with secondary education
Educated women	No of adult women with secondary education
Livestock assets (KES)	Total nominal value (KES) of livestock assets
Credit village	Proportion of village households that received credit, by year
Salaries & remittances	Share of salaries and remittance earnings in total household income
Land	total household land area (ha)
Land title deed	=1 if land owned with no title deed, 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-regional zone to which each village belongs) and the two preceding months. 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-regional Zones	
Population density	Village population density (cap/km²)
Agro-regional zone	HPMZ high potential maize zone (26.6%); CHI central highlands (19.4%), WLO western lowlands (12%); WTR western transitional (11.7%); ELO eastern lowlands (11.3%); WHI western highlands (10.3%); CLO coastal lowlands (5.9%); MRS marginal rain shadow (2.7%). Percentages indicate the frequency of farms in our sample in each agro-regional zone.

*We take into account the relevant cropping season: e.g. for villages in the Rift Valley, 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 income	87,911	142,264	0	3,883,123
Hybrid seeds (maize land share)	0.338	0.323	0	1
Price Fertilizer (kes)	37.08	18.03	0.32	700
Educated men	0.89	0.98	0	10
Educated women	0.71	0.81	0	6
Livestock assets (kes)	81,366	217,682	0	8,679,900
Credit village	0.47	0.30	0	1
Salaries & remittances income share	0.18	0.24	0	1
Land	5.80	8.72	0	157
No land title deed 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	28
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	1,245.11

Table 3: Estimation results – First Stage regressions

	share acreage under purchased hybrids	
Droughts_165	-0.0565***	[0.0085]
ln population density	0.3534***	[0.0536]
ln fertilizers price	-0.0163	[0.0104]
Temperature max	-0.2010	[0.1514]
Temperature max squared	0.0059**	[0.0029]
Temperature min	0.0581	[0.0657]
Temperature min squared	-0.0042*	[0.0022]
Rainfall	0.0004*	[0.0002]
Rainfall squared	-2.81e-07**	[1.41e-07]
Temperature average climatologies	-8.2869***	[1.1446]
Temperature average climatologies squared	0.1481***	[0.0257]
Rainfall climatologies	-0.0133***	[0.0039]
Rainfall climatologies squared	6.02e-06**	[2.36e-06]
AWC_mm	0.0008	[0.0030]
Ph top soil	0.0892***	[0.0117]
Gravel top soil	0.0087***	[0.0019]
ln livestock assets	0.0060*	[0.0031]
ln credit village	0.0468	[0.0323]
no land title dee dummy	-0.0045	[0.0092]
ln educated men	0.0267**	[0.0120]
ln educated women	0.0012	[0.0121]
ln salaries & remittances income share	0.0558	[0.0347]
ln land	-0.0466***	[0.0125]
agro-regional FE	Yes	
F test of excluded instruments	F(5, 4041)=30.58	
Observations	4,085	

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) ln_crop Income		(2) Variance		(3) Skewness	
share acreage under purchased hybrids	0.8873***	[0.2615]	-0.4921	[0.4843]	-1.8270	[60.4570]
Temperature max	-3.3191***	[0.4660]	0.9754	[1.0438]	-12.4135**	[6.2528]
Temperature max squared	0.0637***	[0.0091]	-0.0175	[0.0200]	0.2433*	[0.1661]
Temperature min	1.9952***	[0.2060]	-0.4800	[0.4717]	5.3069*	[3.0216]
Temperature min squared	-0.0659***	[0.0071]	0.0146	[0.0150]	-0.1723*	[0.0934]
Rainfall	0.0068***	[0.0006]	-0.0005	[0.0007]	0.0065	[0.0208]
Rainfall squared	-4.42e-06***	[3.82e-07]	-1.41e-07	[4.44e-07]	-4.14e-06	[0.00002]
Temperature average climatologies	-2.6787	[8.1524]	-9.1297	[30.8128]	6.2084	[4944.3]
Temperature average climatologies sq.	0.0826	[0.1686]	0.1458	[0.6034]	0.0967	[100.828]
Rainfall climatologies	-0.0037	[0.0088]	0.0270	[0.0271]	-0.0289	[3.9933]
Rainfall climatologies sq.	5.55e-06	[6.30e-06]	-0.00002*	[0.00002]	0.00003	[0.0029]
AWC_mm	-0.0008	[0.0133]	0.0593**	[0.0273]	0.0228	[0.3569]
Ph top soil	-0.4427***	[0.0447]	0.0831	[0.0689]	0.1851	[1.4567]
Gravel top soil	-0.0449***	[0.0087]	-0.0083	[0.0170]	-0.0250	[1.0743]
ln livestock assets	0.0456***	[0.0096]	-0.0268*	[0.0159]	0.2112	[0.3059]
ln credit village	0.3046***	[0.1029]	0.3764*	[0.2040]	-2.1129	[2.8854]
no land title dee dummy	-0.0365	[0.0273]	-0.0742**	[0.0308]	0.2418	[0.1665]
ln educated men	0.0093	[0.0386]	0.0813	[0.0504]	0.0534	[1.3603]
ln educated women	0.0992**	[0.0462]	-0.1979	[0.1217]	1.2878*	[0.6849]
ln salaries & remittances income share	-1.0519***	[0.1429]	0.5615	[0.4673]	-4.9736	[6.7722]
ln land	0.4596***	[0.0464]	0.1290*	[0.0731]	-0.7405	[2.9065]
Agro-regional FE	Yes		Yes		Yes	
Observations	4,085		4,085		4,085	
Number of hhid	1,166		1,166		1,166	

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

References

Anderson, J. R., Hazell, P., 1989. Variability in Grain Yields. London: The John Hopkins University Press.

Angrist, J. A. and Krueger, A. B. Instrumental variables and the search for identification: From supply and demand to natural experiments, Journal of Economic Perspectives, Vol. 15, (2001) pp. 69–85.

Argwings-Kodhek, G, T.S. Jayne, G. Nyambane, T. Awuor, and T. Yamano. 1999. How Can Micro-level Household Information Make a Difference for Agricultural Policy Making? Selected Examples from the KAMPAP Survey of Smallholder Agriculture and Non-Farm Activities for Selected Districts in Kenya. Nairobi, Kenya: Tegemeo Institute, Egerton University.

Antle, J. M., 1983. Testing the stochastic structure of production: A flexible moment-based approach, *Journal of Business and Economic Statistics* 1, 192–201.

Antle, J. M. Econometric estimation of producers' risk attitudes, 1987 *American Journal of Agricultural Economics,* 69, 509–522.

Bezabih M., Di Falco, S., and Mekonnen A., 2014. Is it the Climate or the Weather? Differential Economic Impacts of Climatic Factors in Ethiopia. Grantham Research Institute on Climate Change and the Environment Working Paper No. 148.

Boko, M., et al. "Africa. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change". M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, Eds., Cambridge University Press, Cambridge UK, (2007) pp. 433-467.

Boserup, E., 1975. The impact of population growth on agricultural output. *The Quarterly Journal of Economics* 89(2), 257–270.

Chamberlain, G., 1982. Multivariate Regression Models for Panel Data, *Journal of Econometrics* 1, 5-46.

Chamberlain, G., 1984. "Panel Data" in Handbook of Econometrics, Volume 2, ed. Z. Griliches and M.D. Intriligator. Amsterdam: North Holland, 1248-1318.

Dercon, S. "Insurance Against Poverty" (Oxford: Oxford University Press, 2004).

Dercon, S. and Krishnan, P., 2000. Vulnerability, poverty and seasonality in Ethiopia, *Journal of Development Studies* 36, 25–53.

Di Falco, S. and Chavas, J. P., 2009. "On crop biodiversity, risk exposure and food security in the highlands of Ethiopia", *American Journal of Agricultural Economics* 91, 599–611.

Di Falco, S. and M. Veronesi, 2014 "Managing environmental risk in presence of climate change: the role of adaptation in the Nile Basin of Ethiopia", *Environmental and Resource Economics* 57, 553-77.

Fafchamps, M. 1992. "Cash crop production, food price volatility and rural market integration in the third world", *American Journal of Agricultural Economics* 74, 90–99.

FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012. Harmonized World Soil Database (version 1.2). FAO, Rome, Italy and IIASA, Laxenburg, Austria.

Groom, B., P. Koundouri, C. Nauges, and A. Thomas. 2008. "The story of the moment: Risk averse Cypriot farmers respond to drought management", *Applied Economics*, 40, 315–326.

Harari, M., La Ferrara, E., 2014. "Conflict, Climate and Cells: A disaggregated analysis" IGIER Working Paper n. 461, 2012 (Updated Version: February 2014).

Harris, I., Jones, P.D., Osborn, T.J., and Lister, D.H., 2014. "Updated high-resolution grids of monthly climatic observations" *International Journal of Climatology*, 34, 623-642.

Harrison L. J. Michaelsen, C. Funk, Husak G., 2011. "Effects of temperature changes on maize production in Mozambique" *Climate Research*, 46, 211-222.

Jones, A., Dalton T. and Smale M., 2012. "A Stochastic production function analysis of maize hybrids and yield variability in drought-prone areas of Kenya." Tegemeo Working Paper 49. Tegemeo Institute of Agricultural Policy and Development, Nairobi.

Just, R.E., Zilberman, D., 1983. "Stochastic Structure, Farm Size and Technology Adoption in Developing Agriculture" *Oxford Economic Papers* 35 (2): 307-328

Kabubo-Mariara J., Karanja F. K., 2007. "The economic impact of climate change on Kenyan crop agriculture: A Ricardian approach", *Global and Planetary Change* 57(3–4), 319-330.

Kim, K. and Chavas, J-P., 2003. "Technological Change and Risk Management: An Application to the Economics of Corn Production", Agricultural Economics 29, 125-142.

Koundouri, P., Nauges, C., Tzouvelekas, V. 2006. "Technology adoption under production uncertainty: Theory and application to irrigation technology", *American Journal of Agricultural Economics*, 88, 657–670.

Kurosaki, T., Fafchamps, M., 2002. "Insurance market efficiency and crop choices in Pakistan", *Journal of Development Economics*, 67, 419–453.

Marenya, P., Barrett, C. 2009. Soil Quality and Fertilizer Use Rates among Smallholder Farmers in Western Kenya. *Agricultural Economics* 40, 561–572.

Markowitz, H., 1952. "Portfolio Selection". *Journal of Finance* 7, 77-91.

Mathenge, M. K., Smale, M., Olwande, J., 2014. The impacts of hybrid maize seed on the welfare of farming households in Kenya, *Food Policy*, 44, 262-271

McKee, T.B.N., Doesken J., Kleist J., 1993. The relationship of drought frequency and duration to time scales. Eight Conf. On Applied Climatology. Anaheim, CA, Amer. Meteor. Soc. 179-184.

Menezes, C., Geiss C., Tressler J., 1980. Increasing Downside Risk. *American Economic Review* 70, 921-932.

Mundlak, Y., 1978. On the Pooling of Time Series and Cross Section Data. *Econometrica* 46, 69-85.

Mutiso, S.K., 1996. "Indigenous knowledge in drought and famine forecasting in Machakos District, Kenya". Indigenous knowledge and change in African agriculture (ed. by W.M. Adams and L.J. Slikkerveer), pp. 67–86. Technology and Social Change Program, Iowa State University, Ames, IA.

Niang, I., O.C. Ruppel, M.A. Abdrabo, A. Essel, C. Lennard, J. Padgham, and P. Urquhart, 2014: Africa. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional

Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Barros, V.R., C.B. Field, D.J. Dokken, M.D. Mastrandrea, K.J. Mach, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Ochieng, J., L. Kirimi and M. Mathenge 2016. Effects of Climate Variability and Change on Agricultural Production: The Case of Small-Scale Farmers in Kenya. WPS 55/2016 Tegemeo Institute of Agricultural Policy and Development, Nairobi, Kenya.

Ogada, J. M., Nyangena, W., Yesuf, M. 2010. "Production risk and farm technology adoption in the rain-fed semi-arid lands of Kenya", *African Journal of Agricultural and Resource Economics*, 4, 159-174.

Oremo, F. O., 2013. "Small-scale farmers' perceptions and adaptation measures to climate change in Kitui County, Kenya" mimeo, College of Humanities and Social Sciences (CHSS). University of Nairobi digital repository.

Palmer, W.C., 1965. "Meteorological droughts". U.S. Department of Commerce Weather Bureau Research Paper 45, 58.

Sacks, W. J, Deryng D., Foley, J. A., Ramankutty N., 2010. "Crop Planting Dates: An Analysis of Global Patterns." *Global Ecology and Biogeography* 19(5): 607–20.

Sheahan, M.B., 2011. Analysis of fertilizer profitability and use in Kenya. MSc. Thesis, Department of Agriculture, Food and Resource Economics. Michigan State University. East Lansing

Sherlund, S. M., Barrett, C. B., Adesina, A.A., 2002. Smallholder technical efficiency controlling for environmental production conditions, *Journal of Development Economics*, 69, 85-101.

Smale, M. and J. Olwande. 2014. Demand for Maize Hybrids and Hybrid Change on Smallholder Farms in Kenya. *Agricultural Economics* 45*:* 409-420. Article first published online : 23 DEC 2013 DOI: 10.1111/agec.12095.

Smale, M., M. K. Mathenge, and J. Opiyo. 2015. Off-farm Work and Fertilizer Intensification among Smallholder Farmers in Kenya: A Cross-Crop Comparison. Tegemeo Working Paper Series 53, Tegemeo Institute, Nairobi.

Staiger, D., and J. H. Stock. 1997. Instrumental variables regression with weak instruments. *Econometrica, 65*, 557-586

Vicente-Serrano S.M., Beguerìa S., López-Moreno J.I., Angulo M., El Kenawy A., 2010, A global 0.5 gridded dataset (1901-2006) of a multiscalar drought index considering the joint effects of precipitation and temperature, *Journal of Hydrometeorology*, 11(4), 1033-1043

Wineman, A., N.M. Mason, J. Ochieng, and L. Kirimi, 2016. Let it Rain: Weather Extremes and Household Welfare in Rural Kenya. WPS 57/2016. Tegemeo Institute of Agricultural Policy and Development, Nairobi, Kenya.

Wooldridge, J. M. Econometric Analysis of Cross Section and Panel Data (Cambridge, MA: MIT Press, 2002).