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How do African Farm Households Adapt to Climate Change? A Structural Analysis from Malawi

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Abstract

Using three waves of national representative household level panel data from Malawi, we examine two forms of adaptation to climate change: 1) adopting improved maize varieties and 2) adjusting input quantities and income sources. Our results indicate that climate change induces both forms of adaptation, though only the second appears relevant in determining climate change impacts on net revenue. Adverse trends in climate variables (increased temperature and rainfall variability, and reduced growing season rainfall) increase farmers' reliance on income from subsistence maize production. Assets enhance a household's capacity for adaptation to climate change by reducing reliance on maize-income.

Introduction

Most scientists agree that the earth's climate is changing, and the Intergovernmental Panel on Climate Change (IPCC) projects that sub-Saharan Africa (SSA) will be one of the most severely affected regions. Temperatures across SSA are projected to increase 3-4° Celsius over the course of the 21st century, which isabout one and a half times greater than the expected global temperature increase (IPCC 2007). In addition, while rainfall projections are not uniform across the continent, southern Africa is expected to receive, on average, less precipitation and more rainfall variability in the future. The changing climate will have a major impact on rain-fed agriculture, which will in turn affect the welfare of hundreds of millions of people in SSA as up to 90% of the population in some countries is engaged in farming activities.

Given the potential ramifications of climate change on human welfare, it is critical to precisely quantify its effects on agriculture, so that policy makers can understand the benefits of climate policies or, conversely, the cost of inaction. While there is a growing literature on how households may or may not adapt to climate change in developing countries, scientists' understanding of adaptation mechanisms and the factors that facilitate or inhibit farmers' ability to adapt remains limited.

With these considerations in mind, the objective of the present study is to estimate smallholder farm households' behavioral response to climate change and its resulting impact on households' welfare, measured as net income. Moreover we measure the influence of a household's assets on their adaptation capabilities, which is important to understand in a developing country context as financial constraints caused by market frictions and failure are prevalent. We do this by developing a structural model where farm households can adapt to climate change by adjusting i) maize varieties that they plant, ii) production inputs like inorganic

fertilizer and hired labor, and iii) income sources, by moving from on-farm to off-farm income generating activities and visa versa. The present study uses three waves of nationally representative farm household panel data from Malawi to estimate the impacts of climate change and the adaptation strategies prompted.

Malawi makes an excellent case study to measure the impact of farm household adaptation to climate change, because the majority of its population is engaged in subsistence agriculture, focused on maize production. Furthermore, climate change is a major issue in Malawi, as Tadross et al. (2009) observe a substantial decrease in the duration of the growing season between 1960 and 2005 in that country, along with significant trends toward higher temperature, longer mean durations of dry spells[1] and fewer rain days[2] during the growing season.

The present study makes three important contributions to the existing literature on climate change. First we explicitly model input demands and output supplies to determine how adaptation takes place along the production frontier as well as the way in which that frontier is affected by major management practices and socio-economic factors. This results in estimation of climate change impacts, explicitly controlling for economic conditions that the household faces, such as prices for inputs and outputs. Second, we utilize panel data and consider continuous adaptation variables which allow for a richer description of adaptation behavior at the margin. Specifically, this combination permits accounting for the *intensity* of adaptation rather than treating adaptation as a binary outcome or a multinomial choice. In addition, using panel data with continuous measures of adaptation also allows us to estimate our models via household fixed-effects, where we can control for time-constant unobserved factors like farmer motivation and ability, which may affect both the household's ability to adapt to climate change and their

welfare. Third, both adaptation avenues (adoption of a major management practice and reallocations of inputs and outputs along the frontier) are allowed to vary across asset levels incorporating inherent differences in adaptation possibilities across the wealth spectrum.

Table 1 illustrates how the present study contributes to and builds upon the existing literature on climate change and adaption to it. To our knowledge, nearly all previous studies estimating the impact of climate change on household outcomes, measured as productivity or net income, can be broadly classified in three categories: i) agronomic, ii) Ricardian, and iii) structural Ricardian. The first column of table 1 displays the desirable methodological attributes that different classifications of previous studies possess, and the table compares the different approaches on the basis of these attributes. A plus (minus) sign indicates that a methodology does (does not) exhibit such attribute.

The first segment of the existing literature approaches the estimation of climate change impacts on agricultural production from an agronomic point of view (Adams, 1989; Easterling et al., 1992; Rosenzweig and Parry, 1994; Schlenker and Roberts, 2006; Deschenes et al., 2007; Schlenker and Lobell, 2010; Di Falco et al., 2011; Di Falco and Veronesi, 2013). With exceptions (Di Falco et al., 2011; Di Falco and Veronesi, 2013) these studies did not explicitly consider possible adaptation mechanisms which hinders assessment of potential barriers to adaptation that can be removed through policy.

In an attempt to overcome these limitations, and following Mendelsohn et al. (1994), researchers have employed a Ricardian framework to estimate the welfare implications of long-run climate change after farmers have adapted to such change (Sanghi and Mendelsohn, 2008; Wang et al., 2009). This approach does not reveal information about the adjustment process—only the final outcome is observed; hence the negative sign for this approach in the "Adaptation"

row from table 1. More recently, a 'structural Ricardian' framework has been developed for the purposes of modeling adaptation explicitly (Seo and Mendelsohn, 2008; Seo 2010a; Seo 2010b; Hassan and Nhemachena, 2008; Deressa et al., 2009; Deressa et al., 2011; Fosu-Mensah et al., 2012; Di Falco and Veronesi, 2013).

While studies using the structural Ricardian approach have overcome some of the limitations of other approaches, they have not recognized the potential influence that climate change may have on more subtle, but equally important, adaptation mechanisms such as adjusting input quantities or reallocating time invested in alternative income sources. These readjustments in inputs and outputs may be more prevalent among disadvantaged farmers as they do not involve large investments. Consequently, these adaptation measures are less likely to be limited by market barriers. These decisions are, in a structural sense, simultaneously made as inputs and outputs are typically non-separable in production. Moreover they may be conditional on other management practices, so appropriate identification of structural behavior requires modeling of price effects. Failure to control for changing economic conditions, such as input and output prices, increases the risk of omitted variable bias as prices may be correlated with right and left hand side variables.[3]

The present study contributes to our understanding of adaptation by estimating a structural model of households' behavioral response to climate change in Malawi. This model displays all of the desired attributes listed in Table 1. The rest of the article is organized as follows: the next section defines how we measure climate change adaptation and discusses the Malawian context. This is followed by the conceptual framework and empirical model. Subsequent sections present the data, results and conclusions.

[Table 1 Here]

Defining Climate Change

The behavioral premise behind the choice and measurement of climate variables is that farmers' form expectations of conditions in the upcoming growing season based on their perceptions of long term climate trends in the past. In turn, this expectation informs their production decisions. We measure climate using three variables, i) historical average growing season precipitation (GSP), ii) historical coefficient of variation of monthly growing season precipitation (CVMP), and iii) historical average growing season temperature (TEMP).[4] Data for the climate change variables come from historical weather station data that is recorded across Malawi, and interpolated to match the location where the households reside (the source of the climate data is discussed in the data section).

The timeframe based on which a farmer forms his or her climate expectation is adjusted by his or her age in this study. We reason that a household head's memory is likely to include more than just the last few years, but will be weaker in the earliest years of his or her life. As a result, our climate variables GSP, CVMP, and TEMP are defined over specific time-frames based on the age of the household head. In particular we assume a household head will have constructed expectations based on historical weather information going back to the time when he or she was 17 years old. However, a lower bound and an upper bound on households' memory is put in place. If a household head is older than 37 years of age, a maximum memory of 20 years of weather history is allowed and used to construct the climate variable. If a household head is younger than 24 years old, a minimum of 7 years of weather memory is assumed and used to construct the climate variables.

For household's whose head is 37 years of age or older at the time of the survey, we track the full climate history going back 20 years. For household's whose head is 36 years of age at the time of the survey, we define the climate variable for that household going back 19 years. For households 35 years of age, the last 18 years are used to construct climate variables, and so forth. We proceed in this way for all households in which the age of the household head fell between 24 and 36 at the time of the survey. For household heads aged 23 or less at the time of the survey, we define climate over the previous 7 growing seasons, giving every household at least 7 years of growing season weather history.

Establishing a maximum memory of 20 years allows us to incorporate a longer range of relevant information in the decision making process. Such information is, in addition, only relevant to the subsample of older farmers, whose decisions and well-being have been directly impacted by such climate history. Lowering the upper bound of maximum memory may result in artificial shrinking of the informational set of older farmers. Similarly, establishing a lower bound of 7 years to climate memory avoids artificially shrinking the informational set of younger farmers. We contend that allowing for a large informational set is an appropriate starting point for this analysis. Robustness of our results to memory truncation are discussed in the results section of the article.

Defining Adaptation to Climate Change

Adaptation measures that appear most frequently in previous studies and constitute responses to long-run changes in growing season conditions fall broadly into four categories: 1) switching crop varieties (Molua, 2002; Behnin, 2006; Maddison, 2007; Below et al., 2010), 2) diversifying production between on-farm and off-farm activities (Shewmake, 2008; Molua, 2011; Fosu-

Mensah et al., 2012; Silvestri et al. 2012), 3) diversifying production between crop and livestock activities (Thomas et al. 2007; Hassan and Nhemachena, 2008; Seo, 2010a; Seo 2010b) and 4) diversifying among multiple crops (Dinar et al. 2008; Kurukulasuriya and Mendelsohn, 2008; Seo and Mendelsohn, 2008; Mertz et al., 2009). In the present article we concentrate our attention on changes in varieties and reallocations in production inputs and income sources.

Using adoption of improved maize seed varieties as a climate change adaptation strategy is extremely relevant in Malawi because these improved varieties generally mature more rapidly than local varieties, rendering them less vulnerable to dry growing season conditions (Smale and Jayne, 2009).[5] Pauw et al. (2010) find that shifting 10% of cultivated area from local maize varieties to commercial varieties fully offsets the yield losses associated with a mild drought (a drought that would recur every five years on average) and partially offsets those associated with more severe droughts (those with return periods of 10 years or more). It is therefore reasonable to expect a shift from local varieties to improved varieties as Malawi's climate becomes hotter and drier, provided that farmers have proper weather information and access to these improved seeds.

Diversifying income sources away from subsistence maize production represents a second relevant climate change adaptation strategy for households in SSA. Household may diversify into other crops. For example, tobacco is the main cash crop for smallholders in Malawi. Raising livestock is another option for smallholders, although it is fairly limited in Malawi. Working off-farm, either by running or working for a micro-enterprise or working as an agricultural laborer on another farm is also an important income diversification source for smallholder households. Agricultural labor income (called *ganyu* in Malawi) makes up 10.1 % of household income, while non-farm income makes up 25.6% of household income in 206/07

(Jayne et al., 2010, p. 34). Therefore considering the decision to work in activities other than maize production is a very important adaptation strategy to model in our context.

Altering the intensity of input utilization constitutes a third means by which farmers reduce production risk in the face of climate change in Malawi. Downing et al. (1997) list 'incremental adjustment in inputs' among potential response strategies to climate change in Africa. Specifically, Behnin (2006) find that farmers in South Africa increase the application of chemicals and manure in order to reduce soil moisture loss and maintain fertility.

The adaptation mechanisms examined in this article are interdependent which calls for structural modeling of farmers' behavior. First, the decision on the amount of time allocated to on-farm labor is taken simultaneously with the quantity of other inputs used in production which can be substitutes or complements to on-farm labor. Second, the marginal value product of production inputs may be influenced by the type of variety planted. Therefore we develop a structural model describing the sequential optimization problem solved by the farmer. First the farmer decides on a management practice, such as area planted with improved maize varieties, and they then subsequently decide on the input/output combination as the marginal contribution of the latter to net revenue is conditioned by the variety planted.

Conceptual Framework

We start with a separable farm household model where net revenue (π) is maximized with respect to a vector of input demand and output supply equations. Decisions on inputs and outputs are a function of climate, prices (p), a vector of other variables (z), and adoption of improved maize variety (x^*). This captures the sequential nature of the farmers' decision making process (i.e. the choice of inputs and outputs during the growing season is conditional on the type of

variety planted). Moreover, the share of land planted to improved varieties is in part likely to be a response to the changing climate and economic conditions. Net revenue is also conditioned on exogenous short-run weather events. Therefore, the net revenue expression in (1) can be re-written as:

$$(1) \qquad \pi^* = f\{weather, y^*[climate, p, z, x^*(climate, p, z)]\}$$

Note that climate and weather are defined as different concepts. Climate refers to historical trends in rainfall and temperature, while weather is just an annual occurrence. Therefore climate does not enter the net revenue expression directly, but enters indirectly through its influence on behavior.

We assume farmers are price-takers in input and output markets. Therefore, differentiating π with respect to climate gives the change in net revenue for small changes in climate, which is composed of the indirect partial effect of climate on net revenue through adaptation behavior:

$$(2) \qquad \frac{d\pi^*}{d(climate)} = \frac{\partial \pi^*}{\partial x^*} \times \frac{dx^*}{d(climate)} + \frac{\partial \pi^*}{\partial y^*} \times \frac{dy^*}{dx^*} \times \frac{dx^*}{d(climate)} + \frac{\partial \pi^*}{\partial y^*} \times \frac{dy^*}{d(climate)}$$

As previously noted, an important contribution of this study is to quantify the effect of climate on reallocations of inputs and outputs which are captured by the second and third terms of equation (2). While structural Ricardian models have estimated the effect described in the first term, the effect described by the other two terms has received little attention in the scholarly literature until now. These effects are implicitly captured in structural Ricardian models through changes in net revenue. However explicit modeling and estimation of these effects is informative for policy makers of the market-level impacts of climate change (e.g. the effect of climate change on labor supply, fertilizer demand, and maize supply). It is also informative of the relative importance of alternative adaptation mechanisms; major changes in management

practices which can shift the production frontier versus reallocations of inputs and outputs along the production frontier.

Our empirical strategy consists of estimating $x^*(climate, p, z)$, then inserting that into the system $y^*[climate, p, z, x^*(climate, p, z)]$ which is derived by applying Hotelling's lemma to a specified functional form for π^*in equation (1). The system y^* and equation π^* are estimated simultaneously so that theoretically consistent and efficient estimates of structural parameters are obtained. Such estimation allows us to accurately identify the structure of equation (1) which, due to its differentiability permits estimation of (2).

Empirical Model

Stage one: Linking climate and adoption of improved maize

Prior to estimating a household net income equation, we examine the relationship between climate and the share of cultivated land planted with improved maize varieties z_1. Improved maize share is modeled as a function of long-run growing season rainfall (including means and variances), recent weather shocks, input and output prices, household landholding and value of livestock and durable assets.

We construct the equation for household i at time t as follows:

(3) $$z_{1it} = \beta W_{it} + \alpha_i + \varepsilon_{it}, \quad t = 1, 2, 3$$

Where W_{it} represents a column vector of observed household-specific factors that vary across time including climate variables (GSP, CVMP, and TEMP), while β is a row vector of parameters to be estimated. Time-invariant unobservable, household-specific fixed factors are represented by α_i, while ε_{it} represents unobservable household-specific shocks that vary across time.

We estimate equation (3) via household fixed-effects that de-means the data and removes α_i from the model.[6] Doing so allows us to generate consistent estimates of β even if time-invariant unobservable factors in α_i are correlated with covariates in W_{it} .[7] This study assumes that ε_{it} is distributed iid normal (0, σ^2). Since farmers tend to be risk averse, we expect that the adoption of improved maize varieties will intensify as rainfall variability increases both within and across years. Moreover, since improved varieties are less vulnerable to dry and hot growing season conditions (Smale and Jayne, 2009), adoption may also raise in response to increases in GSP and TEMP.

In addition, a recent occurrence of bad weather might induce the farmer to adopt a crop variety that is more resilient under unfavorable conditions. We account for this by including a binary variable equal to one if the household reported to be severely impacted by an extreme rainfall pattern in the past five years and zero otherwise.

The real 2009 value of household livestock and durable assets are also included in W_{it} as a measure of household wealth. The effect of wealth on the intensity of improved maize adoption could conceivably be positive or negative. If wealthier farmers engage in a more diverse portfolio of activities, they may devote a smaller share of their resources to crops and thus not be particularly concerned about minimizing climate risk in the domain of maize production (Kaliba et al., 2000). Conversely, household wealth might provide greater capacity to learn about and acquire new varieties and also serve as a safety net in case the new practices fail (Sserunkuuma, 2005; Bellon and Risopoulos, 2001; Langyintouo and Mungoma, 2008).

Farmers may perceive or experience changes in the marginal product of production inputs under different varieties. Therefore improved varieties may constitute substitutes or complements to conventional inputs. For instance, Nkonya et al. (1997) finds a positive and

significant correlation between fertilizer application and the area planted to improved maize varieties, lending credence to this hypothesis. Ogunlade et al. (2010) identify lack of access to fertilizer as a barrier to optimizing the benefits of improved maize varieties. To control for such links, input prices for commercially sold maize seed, commercially sold fertilizer, and agricultural wage rates along with output prices for maize are also included in W_{it}.

Access to credit is also included in W_{it}. We would expect credit access to help ease any liquidity constraints the household may face and thus enhance adaptive capacity. The vector W_{it} also includes household landholding. This variable is believed to be positively related to adaptive capacity because adopting new technology incurs fixed costs that are more easily absorbed by households with more land.

It is also essential to consider the institutional and political factors that influence improved maize adoption in our model. Malawi has implemented a large scale subsidy program for inorganic fertilizer and improved maize seed during the years of our study. The subsidy was substantial during the second two waves of our survey in 2006/07 and 2008/09. At that time more than half of the smallholder farm population was targeted to receive paper vouchers which entitled them to acquire inputs at a substantially reduced price. We control for the potential effects of the subsidy program by including the quantity of subsidized inorganic fertilizer that a household acquires and the quantity of subsidized improved maize seed that a household acquires as two separate additional covariates in W_{it}. Quantities instead of prices are included because they are regarded as quasi-fixed as a household could only obtain 100 kilograms of inorganic fertilizer at a 66-90% subsidy and 2-4 kilograms of maize seed for free if they were able to participate in the program.[8] A complete list of regressors in equation (3) is included in Appendix A.

Stage two: Structural Model of Net Revenue

Net household revenue (π^*) is measured in Malawi Kwacha/year and is defined as total income from agricultural and non-agricultural sources minus expenditure on production inputs.[9] Income from agricultural sources include: (1) maize production; (2) non-maize income (e.g. tobacco, livestock sales, and livestock product sales), along with agricultural and non-agricultural off-farm work (e.g. work in another farm, selling fire wood, trading, or fishing). Inputs to maize production include fertilizer and labor. The former is the total quantity of fertilizer acquired by the household from subsidized and commercial sources. Labor is the number of days of non-family labor that the household hires in to work on their farm. After input and output optimization, net revenue can be expressed as:

$$(4) \qquad \pi^* = f(\, p_{maize}, \, p_{fertilizer}, \, p_{labor}, Z),$$

where p_{maize} is the price of maize, $p_{fertilizer}$ is the commercial price of inorganic fertilizer, p_{labor} is the price of hired labor, and Z is a vector of control variables.

The vector of control variables includes the share of cultivated land planted with improved maize varieties. Instead of observed shares of improved maize we include predicted shares from the stage one model to represent the optimal level of adoption given climate history. This makes impact estimates more reliable because we account for optimal (though perhaps constrained) behavior with respect to improved maize adoption, while addressing the potential endogeneity of this variable.[10]

The mechanisms through which weather and climate variables affect net revenue are modeled through the interaction terms included in equation (4). Weather variables are included in equation (4) by themselves as opposed to interacted with prices. Subsequent application of Hotelling's lemma eliminates weather from factor demands and output supplies which captures

two facts: 1) growing season conditions influence crop productivity and household income, and 2) weather events such as rainfall occurs after production decisions are made and, thus, do not affect them. Conversely, historical climatic patterns enter the net revenue equation through an interaction with input and output prices, and through a three way interaction with prices and assets. Climate variables then appear, as a corollary of Hotelling's lemma, as explanatory variables of input demands and output supplies and their effects are allowed to depend upon the household's asset holdings.

We specify household net revenue as a translog function due to its flexibility and to the ease with which elasticity of net revenue with respect to climate variables can be calculated. We choose non-maize revenue as the numeraire and normalize all other prices by it. The system formed by the net revenue equation and derived demands and supplies are estimated via seemingly unrelated regression with household fixed effects. A full expression for the translog net revenue function is presented in Appendix B.

Analysis of Climate Change Impacts

The overall impact of climate change on households' well-being is measured by the elasticity of net revenue with respect to climate variables. This can be directly calculated from the estimated translog net revenue function. Taking derivative of net revenue with respect to climate variables in the translog function also reveals the mechanisms through which climate affects households' well-being. Long term climate trends can affect farmers' fertilizer and labor demand, and maize supply both directly and through its effect on adoption of improved varieties. The parametric expressions for these marginal effects and their derivation can be found in Appendices C and D. Upon econometric estimation of parameters, elasticities are calculated by evaluating shares at

their sample medians. Note that valid standard errors are obtained via running all equations within a bootstrap procedure that accounts for the coefficient estimates being obtained through a multiple step estimation process.

Data

Household Survey Data

The data used in this study are drawn from three nationally representative household surveys conducted in Malawi during the 2000s. The first wave of surveys was administered as part of the Second Integrated Household Survey (IHS2) conducted by Malawi's National Statistical Office (NSO) following the 2002/03 and 2003/04 growing seasons. The IHS2 covers 26 districts and 11,280 households in Malawi. The second wave of data comes from the 2007 Agricultural Inputs Support Survey (AISS1) conducted after the 2006/07 growing season by the NSO. The budget for AISS1 was much smaller than the budget for IHHS2 and of the 11,280 households interviewed in IHHS2, only 3,485 of them lived in enumeration areas that were re-sampled in 2007. Of these 3,485 households, 2,968 were re-interviewed in 2007, which gives us an attrition rate of 14.8%.

The third wave of data comes from the 2009 Agricultural Inputs Support Survey II (AISS2) conducted after the 2008/09 growing season by Wadonda Consult. The AISS2 survey had a subsequently smaller budget than the AISS1 survey in 2007, so of the 2,968 households first sampled in 2003 and again in 2007, 1,642 of them lived in enumeration areas that were revisited in 2009. Of the 1,642 households in revisited areas, 1,375 were found for re-interview in 2009, which gives us an attrition rate of 16.3% between 2007 and 2009.

The sample used in this analysis is based on the 2,968 households who were interviewed in wave 1 and wave 2, along with 1,375 households who were interviewed in all three waves.

The Data are considered nationally representative and give broad geographic coverage across Malawi. After removing unrealistic outliers and the 185 observations who experienced negative net revenue, we end up with an unbalanced panel of 6,855 observations used in the analysis.

Climate Data

Locally interpolated time-series data on rainfall and temperature come from the University of East Anglia's Climate Research unit (CRU)-TS 3.1 Climate Database (CRU, 2011; Mitchell and Jones, 2005). We match the household-level information in our dataset with monthly rainfall and temperature totals specified at 44 locations across Malawi. Households are assigned rainfall data according to their spatial proximity to these collection points.

Controlling for Potential Attrition Bias

The rate of attrition between each of the 3 survey waves is between 15-16%. If the households in the survey attrite for non-random reasons, this could bias the coefficient estimates in our analysis. Fortunately our estimation strategy should be robust to most types of attrition bias. By using a household FE estimator we remove any correlation between time constant unobservable factors that affect attrition and the covariates in our model (Wooldridge 2010). Even after running FE estimation we can also run a formal test for attrition to see if any of the unobservable time varying shocks that might affect attrition are correlated with the covariates in our model (Wooldridge 2010a, pg. 837-838). Results of the test indicate that when all households that were surveyed in at least 2 waves are included there is no statistically significant evidence of attrition bias in stage 1 of our model (p-value on the selection indicator = 0.914 for the full sample). This should negate concerns of attrition bias in this study.[11] [12]

Results

Table 2 presents the means and medians of the variables used in the analysis by survey wave. The table indicates that the mean share of area that households plant to improved varieties increases between waves 1 and 2 from 0.392 hectare to 0.45 hectare, then declines in wave 3 to 0.385 hectares. Median share of area planted to improved maize remains constant at 0.33 hectare in wave 1 and 2, then declines to 0.273 hectares in wave 3. Mean maize output increases substantially from 580 kilograms in wave 1 to 703 kilograms in wave 2, then declines to 627 kilograms in wave 3. Median maize production increases throughout the survey ways but is substantially lower than the mean, at 327, 373, 410 kilograms per household in waves 1, 2, and 3 respectively.

[Table 2 Here]

Adoption of Improved Maize Varieties

Table 3 presents results regarding factors affecting share of area planted to improved maize varieties, estimated via household fixed effects. The table reveals that there is evidence of statistically significant relationships between climate variables and the share of land planted with improved maize varieties. This suggests that shifting area to improved maize is a relevant adaptation mechanism used by farmers. The coefficients on the linear, and the quadratic components of TEMP (age-adjusted historical mean temperature during the growing season) are positive and negative respectively, and both statistically significant. An evaluation of the derivative at median TEMP in the sample reveals that the share of area planted to improved maize varieties increases with temperature but also that temperature has a decreasing marginal effect on share of area planted to improved varieties.

Table 3 also shows the coefficients on the linear and squared measure of rainfall variability (CVMP) are negative and positive respectively, and both statistically significant. Evaluation of the derivative at median CVMP in the sample (0.6) reveals a positive effect on share of area planted to improved maize varieties. Such effect becomes substantially stronger when CVMP is evaluated at higher percentiles due to the strong convex nature of the effect of CVMP on planting decisions. These results suggest that as TEMP and CVMP increase, improved varieties become more attractive than local varieties for the majority of farmers in our sample. Moreover, results indicate that farmers' adoption of improved varieties is more sensitive to long term changes in variability of monthly precipitation than they are to long term changes in the mean. This is consistent with analyses of past climatic trends in Malawi (Gama et al., 2014).

[Table 3 Here]

Climate Change Impacts

Results from the simultaneous equations estimation are reported in table E1 in Appendix E. Results in table E1 show that the share of land planted with improved varieties does not influence farmers' choice of inputs and outputs revealing the homothetic nature of its impact (i.e. relative productivities are not affected by varieties). Therefore, we conclude that these adaptation strategies are "separable" decisions in production in the sense that improved maize share does not affect the expected marginal productivity of other inputs (or that is, at least, the perception of the farmers).

Based on parameter estimates in table E1, we compute the elasticity of net revenue, maize supply, fertilizer demand, labor demand, and non-maize output supply, with respect to climate variables. Elasticities derived from the translog specification need to be evaluated at a given point with respect to the natural logarithm of prices and assets. The median is, in this case,

a more appropriate measure of central tendency due to the asymmetric nature of the logarithmic transformation and the strong positive skewness of the distribution of asset levels (Table 2).

Table 4 presents these elasticity estimates along with bootstrapped p-values.[13] Results from rows i), ii) and iii) of table 4 reveal that as growing seasons become drier (GSP), warmer (TEMP), and monthly rainfall becomes more volatile (CVMP), farmers' net income is reduced.[14] Therefore, adverse climatic trends seem to have a sizable and negative effect on farmers' well-being. This is an important result, as it underscores the fact that, while farmers can and do respond to climate change, adaptation strategies can only partially alleviate its adverse effects.

Results from table 4 confirm our expectations that reallocation of inputs and revenue sources are an important part of farmers' response to changes in climate. Rows iv) – vii) show that a history of drier growing seasons induces farmers to reduce labor hiring. Farmers our also found to increase their application of inorganic fertilizer which is consistent with results in Behnin (2006). The additional fertilizer applied does not outweigh the reduction in labor, and maize production declines. Non-maize income also decreases as growing seasons get drier, and they do so more than proportionally to the reduction in maize income. This results in an increased reliance of the median farmer on maize production.

Rows viii) – xi) of table 4 present the impacts of rainfall variability (CVMP) on farmers' behavior. We find evidence that the median farmer reduces fertilizer and on-farm labor hiring (presumably due to reduced marginal productivity). Both maize and non-maize income are reduced by a higher rainfall variability. Subtracting the elasticity of net income with respect to CVMP from the elasticity of maize supply with respect to CVMP reveals that a one percent increase in CVMP increases the share of the median farmer's income coming from maize production by 0.42%. By a similar calculation, it can be shown that the share of non-maize

outputs in the median farmer's net income remains unchanged. Therefore the median farmer's response to an increase in historical rainfall variability seems to result in increased reliance on maize income. Behavioral responses are not sufficient to completely offset the harming effects of increased rainfall variability, so net income is reduced.

Rows xii) – xv) in table 4 present the impacts of growing season temperature (TEMP) on output supply and input demand. The response of the median farmer to warmer growing seasons are the largest in magnitude. In response to increased temperature, the median farmer reduces both fertilizer use and hiring of on-farm labor. Both maize and non-maize income sources are reduced revealing an overall reduction in productivity and income opportunities.

High elasticities of input demands and income sources with respect to climate variables also reveal that farmers do tend to use these subtle, yet critical, simultaneous changes in inputs and outputs as a mechanism to protect their income from the adverse effects of climate change. This is a very important result given the fact that these mechanisms have been overlooked by much of the previous literature. Failure to at least implicitly account for this behavioral responses (such as in the agronomic approach cited in Table 1) may result in overestimation of damages from climate change. Failure to explicitly account for behavioral responses (as in the Ricardian approaches depicted in Table 1) precludes quantification of the relative importance of different adaptation mechanisms which hinders our ability to design policy aimed at reducing barriers to adaptation. It also limits our capacity to anticipate market-level effects of climate change.

Relationship between climate change impacts and wealth

Computation of net revenue, input demand and output supply elasticities in response to climate change for the median farmer may disguise a substantial degree of heterogeneity in

farmers' ability to adapt and mitigate the effect of climate change on net revenue across the wealth spectrum. We hypothesize that richer farmers, measured as those who have a higher value of livestock and durable assets, have greater adaptation capabilities which allows them to better protect their income against the harming effects of climate change.

While assets do not have a statistically significant influence on the adoption of improved maize varieties, they do influence farmers' choice of production inputs and income sources. Coefficient estimates reported in table E.1 reveal interesting insights in regards to the link between asset ownership, adaptation capabilities, and the resilience of net income to climate change. The interaction of assets and temperature has a negative and significant coefficient in the fertilizer demand equation; coefficient is -0.28 with a p-value of 0.05. This indicates that the negative impact of temperature on farmers' fertilizer demand is smaller for wealthier farmers. Since labor supplied to activities other than maize production is calculated residually from the SUR system including fertilizer demand, our results also show a smaller effect of temperature on non-maize products supply for wealthier farmers.[15]

Figure 1 shows how assets shape the effect of temperature on net revenue. This relationship is calculated by simulating equation (C.1) in Appendix C for a range of asset values. This figure reveals that the magnitude of temperature-induced income loss is inversely related to asset levels. The absolute value of the temperature effect gets smaller as the value of household assets increases. Figure 2 illustrates the main mechanism behind this negative relationship. The relationship plotted in Figure 2 is obtained by simulating equation (D.5) in Appendix D for a range of asset values. Relatively richer farmers reduce non-maize supply but to a lesser extent. Therefore we observe that the tendency to concentrate incomes in maize production as temperature increases is weaker for households with greater asset stocks. This finding suggests

that well-endowed households have access to mechanisms for income diversification not available to poorly-endowed households, and these alternative income sources are particularly important in shaping the welfare impact associated with higher temperature.

[Figure 1 here]

The statistically insignificant effect of assets on adoption of improved varieties jointly with its significant and quantitatively relevant effect on input/output allocations and net revenue, underscores the importance of our structural modeling approach. Relatively wealthier farmers are better able to adapt to changes in climate. This, however, is not attained through adoption of new management practices (represented here by planting improved maize varieties) but by a less constrained readjustment of inputs and revenue sources.

[Figure 2 here]

Previous studies (Rao et al., 2011) have suggested that 10 years may be a more appropriate bound for maximum memory. Upon examination of the robustness of our results to a change in maximum memory, we find that results with the 10-year model are generally consistent with those of the 20-year model. Both the 10 and 20-year models suggest a similar behavioral response to climate change. The only coefficient that changes sign at the median in Table 4 is on-farm labor demand. Despite this small difference, our main insights are robust to changing climate recall from 20 to 10 years. Net revenue is still negatively affected by adverse climatic trends, and farmers (especially so poor farmers) rely more on maize income. Results of the 10-year recall specification are available upon request.

Our results point to the need for further investigation into the mechanisms by which assets steer behavioral responses and welfare outcomes. Our data set is not sufficiently detailed to determine the exact nature of these mechanisms, though we offer two possible explanations of

how this might occur. First, the ownership of assets may signify a higher degree of market access, including opportunities to earn income outside of the agricultural sector that would allow the household to increase participation in less climate sensitive activities. Greater access to alternative income sources through diversification of maize and non-maize labor supply allocation would make households better able to minimize the damages associated with climate variability.

Second, since our household income variable includes income derived from sales of livestock or livestock products (captured in our net household income variable, though not explicitly modeled in production due to the lack of price information) assets may represent a direct source of income or consumption that is not so dependent on weather outcomes. More detailed examination of the role of livestock and off-farm income opportunities as a buffer against climate variability would be required to identify promising policy alternatives in this area. Understanding the characteristics of these specific activities would facilitate a more precise estimate of the relevance of these barriers to climate change adaptation.

The results of our study have three other caveats. First, the use of a linear model to describe changes in the share of cultivated land planted with improved maize varieties generates some predicted values outside the zero-one interval. A logistic curve would have been more appropriate for modeling a limited dependent variable such as improved maize share. However, it is impossible to compute predicted values from a non-linear estimator and include the predicted values in the second stage structural model. Second, while we believe that the use of panel data is a substantial improvement over cross-sectional methods, longer time-series data sets would greatly enhance the reliability of the relationships we uncovered between long-run characteristics of growing season rainfall and net revenue. Third, our rainfall data includes only

monthly totals, and the performance of maize is highly dependent on the timing of rainfall relative to its phase in the growing cycle (Tadross et al. 2009). The coarseness of the rainfall data prevents us from drawing any conclusions about these agronomic issues.

Conclusion

Much of the research on climate change considers adaptation in terms of the introduction of entirely new farm practices (e.g., switching crop varieties, adopting water conservation techniques, planting trees, etc.). Little quantitative work has been undertaken to determine the relevance of simpler methods of adaptation such as adjusting the use of existing inputs or reallocating production among existing activities. Employing a structural adaptation model, we test for the relevance of this adaptation mechanism and examine the importance of assets in facilitating these types of adjustments.

First, we find that climate change induces behavioral responses from farmers, causing them to plant a larger share of land to improved maize varieties, reallocate fertilizer and labor inputs, and change income sources. This confirms our *a priori* expectation that these are all important climate change adaptation mechanism that should not be ignored in future work on climate change adaptation and impacts.

Second, all adverse climatic trends considered here (higher temperatures, higher precipitation variability, and lower mean rainfall) have a significant and negative effect on smallholder net revenue, as we would expect *ex ante*. Climate variables affect the share of land planted to improved varieties, but shifting varieties does not in itself affect farmers' choice of inputs and income sources. Conversely, climate change has a significant direct effect on farmers' input and output decisions. While the impact of mean rainfall and rainfall variability on

net revenue, and input and output decisions are considerable, the effect of temperature is quantitatively much larger.

Finally, our results are consistent with the presence of market barriers to adaptation as the elasticity of net revenue with respect to temperature is sensitive to asset ownership. Interestingly, households with lower asset levels tend to rely more on maize related income than wealthier farmers as temperature increases. This result suggests that wealthier farmers have access to a greater diversity of earning opportunities as crop production becomes riskier. A more limited set of opportunities seem to prompt poorer farmers into maize production perhaps in an attempt to ensure their own food security.

Our finding that households tend to intensify maize production (at the expense of other activities) in response to adverse changes in climate suggests the need for further research into high-yielding maize that produces stable yields under inconsistent moisture and high temperature conditions. This is consistent with other climate policy analyses that call for investment in the development of improved maize cultivars (e.g. Kurukulasuriya and Mendelsohn, 2008). Knowing that households, and especially less endowed farmers, may shift *toward* subsistence maize production on their own farm as climate changes indicates that increasing maize productivity may represent the primary mechanism through which adverse climate impacts can be mitigated.

Appendix A

Regressors in equation (3) include wealth as measured by the value of livestock and durable goods owned by the household, growing season precipitation (GSP), GSP squared, temperature (TEMP), TEMP squared, coefficient of variation of monthly precipitation (CVMP), CVMP squared, a binary variable equal to one if the household reported to be severely impacted by an

extreme rainfall pattern in the past five years and zero otherwise, the previous year's maize price, the price of commercial fertilizer in the current year, the amount of subsidized fertilizer acquired by the household in the current year, the wage rate for off-farm agricultural labor in the current year, a binary variable equal to one if the household purchased inputs with credit during the growing season and zero otherwise, a binary variable equal to one if the household head is female and zero otherwise, household size as measured by adult-equivalent, household landholding, a binary variable equal to one if the household reported to have received useful advice on new seed varieties, the price of improved maize seed, assets interacted with GSP, assets interacted with GSP squared, assets interacted with CVMP, assets interacted with CVMP squared, assets interacted with TEMP, assets interacted with TEMP squared, landholding interacted with GSP, landholding interacted with GSP squared, landholding interacted with CVMP, landholding interacted with CVMP squared, landholding interacted with TEMP, landholding interacted with TEMP squared, the number of improved maize seed dealers in the village, the quantity of subsidized maize seed acquired by the household, the number of fertilizer dealers in the village, a binary variable equal to one if the observation corresponds to the 2003-2004 growing season, a binary variable equal to one if the observation corresponds to the 2006-2007 growing season, and a binary variable equal to one if the observation corresponds to the 2008-2009 growing season.

Appendix B

The translog net revenue function is:

$$\ln \pi' = \alpha_0 + \sum_i \alpha_i \ln p_i' + \frac{1}{2}\sum_i \sum_h \gamma_{ih} \ln p_i' \ln p_h' + \sum_i \sum_k \psi_{ik} \ln p_i' \ln z_k +$$

$$\sum_i \sum_k \sum_j \psi_{ikj} \ln p_i' \ln z_k \ln z_j + \sum_k \theta_k \ln z_k + \frac{1}{2}\sum_k \sum_j \phi_{kj} \ln z_k \ln z_j + \sum_s \delta_{0s} T_s + \sum_i \sum_s \delta_{is} \ln p_i' T_s + \sum_k \sum_s \omega_{ks} \ln z_k T_s \quad \text{(B.1)}$$

where π' denotes normalized net revenue and p_i' denotes normalized prices for maize (i = 1), fertilizer (i=2), and labor (i=3). We impose symmetry of net revenue by forcing $\gamma_{ih} = \gamma_{hi}$ for all i and h. Year dummies are denoted by T_s, where s indicates the growing season (2003-04, 2006-07, or 2008-09) treating the 2002-03 growing season as the base year. The vector of exogenous variables, z, includes the predicted share of land planted with improved maize variety, the cumulative growing season precipitation, the coefficient of variation of monthly precipitation, the value of durable goods and livestock owned, total landholding, the quantity of subsidized fertilizer acquired, GSP, CVMP, TEMP. We derive the share of the ith netput on net revenue by differentiating (B.1) with respect to $\ln p_i'$ (and taking the negative of the derivative for inputs):

$$s_1 = \alpha_1 + \gamma_{11} \ln p_1' + 0.5 \sum_{h \neq 1} \gamma_{1h} \ln p_h' + \sum_k \psi_{1k} \ln z_k + \sum_k \sum_j \psi_{1kj} \ln z_k \ln z_j + \sum_s \delta_{1s} T_s \quad \text{(B.2)}$$

$$s_2 = \alpha_2 + \gamma_{22} \ln p_2' + 0.5 \sum_{h \neq 1} \gamma_{2h} \ln p_h' + \sum_k \psi_{2k} \ln z_k + \sum_k \sum_j \psi_{2kj} \ln z_k \ln z_j + \sum_s \delta_{2s} T_s \quad \text{(B.3)}$$

$$s_3 = \alpha_3 + \gamma_{33} \ln p_3' + 0.5 \sum_{h \neq 1} \gamma_{3h} \ln p_h' + \sum_k \psi_{3k} \ln z_k + \sum_k \sum_j \psi_{3kj} \ln z_k \ln z_j + \sum_s \delta_{3s} T_s \quad \text{(B.4)}$$

We estimate the parameters in (B.1)-(B.4) using a seemingly unrelated regression.

Appendix C

Differentiating (B.1) with respect to the log of our climate variables results in a parametric expression describing the effect of climate change on net revenue:

$$\frac{\partial \ln \pi'}{\partial \ln z_k} =$$

$$\theta_k + \sum_i \psi_{ik} \ln p_i' + 2\psi_{ikj} \ln p_i' \ln z_k + \sum_i \sum_j \psi_{ij} \ln p_i' \ln z_j + \phi_{kk} \ln z_k + \frac{1}{2}\sum_j \phi_{kj} \ln z_j + \sum_s \omega_{ks} \ln z_k T_s + \left\{ \sum_i \psi_{i1} \ln p_i' \frac{\partial [\ln z_1(z_k)]}{\partial [\ln z_k]} + \theta_1 \frac{\partial [\ln z_1(z_k)]}{\partial [\ln z_k]} + \sum_j \phi_{1j} \ln z_j \frac{\partial [\ln z_1(z_k)]}{\partial [\ln z_k]} + \sum_s \omega_{1s} T_s \frac{\partial [\ln z_1(z_k)]}{\partial [\ln z_k]} \right\} \qquad z_k \in \{GSP, TEMP, CVMP\} \quad \text{(C.1)}$$

where $\frac{\partial[\ln z_1(z_k)]}{\partial[\ln z_k]} = \frac{z_k}{z_1}\frac{\partial z_1}{\partial z_k}$ and the second factor in this expression is directly obtained from the equation estimated in stage one.

Appendix D

Differentiating (B.2)-(B.4) with respect to the log of our climate variables results in a parametric expression describing the effect of climate change on, respectively, maize, fertilizer, and labor demand:

$$\frac{\partial \ln x_1^*}{\partial \ln z_k} = \frac{\psi_{1k}+\sum_j \psi_{1kj} \ln z_j + 2\psi_{1kk} \ln z_k}{s_1}, \qquad z_k \in \{GSP, TEMP, C\ VMP\} \qquad \text{(D.1)}$$

$$\frac{\partial \ln x_2^*}{\partial \ln z_k} = \frac{\psi_{2k}+\sum_j \psi_{2kj} \ln z_j + 2\psi_{2kk} \ln z_k}{s_2}, \qquad z_k \in \{GSP, TEMP, C\ VMP\} \qquad \text{(D.2)}$$

$$\frac{\partial \ln x_3^*}{\partial \ln z_k} = \frac{\psi_{3k}+\sum_j \psi_{3kj} \ln z_j + 2\psi_{3kk} \ln z_k}{s_3}, \qquad z_k \in \{GSP, TEMP, C\ VMP\} \qquad \text{(D.3)}$$

Let us denote non-maize income by y^*. The derivation of the elasticity of y^* with respect to climate proceeds as follows. Since non-maize income is the normalizing factor and given that input and output shares sum to 1 by definition, non-maize supply is given by:

$$y^* = \pi^* \left(1 - \frac{p_1 x_1^*}{\pi^*} - \frac{p_2 x_2^*}{\pi^*} - \frac{p_3 x_3^*}{\pi^*}\right) \qquad \text{(D.4)}$$

Computation of this elasticity is conducted by evaluating $p_i x_i^* / \pi^*$ at their sample medians. The elasticity of non-maize supply with respect to climate is conducted by taking logarithm on both sides of (D.4) and deriving the resulting expression by lnz_j:

$$\frac{\partial \ln y^*}{\partial \ln z_j} = \frac{\partial \ln \pi'}{\partial \ln z_k}\left(1 - \frac{p_1 x_1^*}{\pi^*} - \frac{p_2 x_2^*}{\pi^*} - \frac{p_3 x_3^*}{\pi^*}\right) \qquad \text{(D.5)}$$

Appendix E

Table E.1 Estimation of net revenue, inputs, and income sources equations

log (net household income)	Coefficient	p-value
log(maize price)	14.147	0.424
log(fertilizer price)	-22.198	0.251
log(labor price)	2.421	0.838

log(maize price)*log(maize price)	-0.041	0.533
log(maize price)*log(fertilizer price)	0.068	0.477
log(maize price)*log(labor price)	0.011	0.777
log(fertilizer price)*log(fertilizer price)	0.005	0.931
log(fertilizer price)*log(labor price)	-0.002	0.955
log(labor price)*log(labor price)	-0.007	0.265
log(maize price)*log(improved maize share)	0.002	0.939
log(maize price)*log(growing season precipitation, current year)	0.711**	0.030
log(maize price)*log(growing season degree days, current year)	-0.996	0.698
log(maize price)*log(cv month grow. season precipitation, current year)	-0.921***	0.002
log(maize price)*log(assets)	-1.522	0.137
log(maize price)*log(landholding)	-0.643	0.818
log(maize price)*log(subsidized fertilizer quantity)	-0.007	0.112
log(maize price)*log(GSP)	-1.410**	0.052
log(maize price)*log(TEMP)	0.146	0.960
log(maize price)*log(CVMP)	1.600**	0.030
log(fertilizer price)*log(improved maize share)	0.008	0.694
log(fertilizer price)*log(growing season precipitation)	-0.774**	0.017
log(fertilizer price)*log(grow season degree days, current year)	-5.995**	0.018
log(fertilizer price)*log(cv mo growing season precipitation)	0.876***	0.008
log(fertilizer price)*log(assets)	3.668**	0.022
log(fertilizer price)*log(landholding)	-4.964	0.323
log(fertilizer price)*log(subsidized fertilizer quantity)	0.009*	0.068
log(fertilizer price)*log(GSP)	1.861*	0.083
log(fertilizer price)*log(TEMP)	7.518**	0.025
log(fertilizer price)*log(CVMP)	-1.474	0.243
log(labor price)*log(improved maize share)	-0.006	0.579
log(labor price)*log(growing season precipitation)	0.008	0.907
log(labor price)*log(growing season degree days, current year)	0.136	0.781
log(labor price)*log(cv mo growing season precipitation)	-0.020	0.776
log(labor price)*log(assets)	-1.012	0.196
log(labor price)*log(landholding)	-0.651	0.448
log(labor price)*log(subsidized fertilizer quantity)	-0.001	0.613
log(labor price)*log(GSP)	0.165	0.732
log(labor price)*log(TEMP)	-0.649	0.643
log(labor price)*log(CVMP)	-0.433	0.568
log(maize price)*log(GSP)*log(assets)	0.042	0.542
log(maize price)*log(GSP)*log(landholding)	-0.042	0.811
log(maize price)*log(TEMP)*log(assets)	0.133*	0.103
log(maize price)*log(TEMP)*log(landholding)	0.123	0.534
log(maize price)*log(CVMP)*log(assets)	-0.106*	0.104
log(maize price)*log(CVMP)*log(landholding)	0.100	0.512
log(fertilizer price)*log(GSP)*log(assets)	-0.102	0.311

log(fertilizer price)*log(GSP)*log(landholding)	0.226	0.385
log(fertilizer price)*log(TEMP)*log(assets)	-0.328***	0.009
log(fertilizer price)*log(TEMP)*log(landholding)	0.379	0.334
log(fertilizer price)*log(CVMP)*log(assets)	0.121	0.368
log(fertilizer price)*log(CVMP)*log(landholding)	0.245	0.428
log(labor price)*log(GSP)*log(assets)	0.009	0.844
log(labor price)*log(GSP)*log(landholding)	0.056	0.256
log(labor price)*log(TEMP)*log(assets)	0.116	0.112
log(labor price)*log(TEMP)*log(landholding)	0.013	0.853
log(labor price)*log(CVMP)*log(assets)	0.024	0.762
log(labor price)*log(CVMP)*log(landholding)	-0.068	0.292
log(improved maize share)	-0.120	0.832
log(growing season precipitation, current year)	1.387***	0.005
log(growing season degree days, current year)	-2.912	0.563
log(cv monthly growing season precipitation, current year)	-1.199***	0.002
log(assets)	0.179***	0.000
log(landholding)	0.067	0.202
log(subsidized fertilizer quantity)	0.004	0.528
yr2003_04	0.051	0.491
yr2006_07	-0.432***	0.000
yr2008_09	-0.023	0.786
maize output supply		
log(maize price)	-0.082	0.533
log(fertilizer price)	0.068	0.477
log(labor price)	0.011	0.777
log(improved maize share)	0.002	0.939
log(growing season precipitation, current year)	0.711**	0.030
log(growing season degree days, current year)	-0.996	0.698
log(cv growing season precipitation, current year)	-0.921***	0.002
log(assets)	-1.522	0.137
log(landholding)	-0.643	0.818
log(subsidized fertilizer quantity)	-0.007	0.112
log(GSP)	-1.410**	0.052
log(TEMP)	0.146	0.960
log(CVMP)	1.600**	0.030
log(GSP)*log(assets)	0.042	0.542
log(GSP)*log(landholding)	-0.042	0.811
log(TEMP)*log(assets)	0.133*	0.103
log(TEMP)*log(landholding)	0.123	0.534
log(CVMP)*log(assets)	-0.106*	0.104
log(CVMP)*log(landholding)	0.100	0.512
fertilizer input demand		
log(maize price)	0.068	0.477
log(fertilizer price)	0.009	0.931

log(labor price)	-0.002	0.955
log(improved maize share)	0.008	0.694
log(growing season precipitation, current year)	-0.774**	0.017
log(growing season degree days, current year)	-5.995**	0.018
log(cv growing season precipitation, current year)	0.876***	0.008
log(assets)	3.668**	0.022
log(landholding)	-4.964	0.323
log(subsidized fertilizer quantity)	0.009*	0.068
log(GSP)	1.861*	0.083
log(TEMP)	7.518**	0.025
log(CVMP)	-1.474	0.243
log(GSP)*log(assets)	-0.102	0.311
log(GSP)*log(landholding)	0.226	0.385
log(TEMP)*log(assets)	-0.328***	0.009
log(TEMP)*log(landholding)	0.379	0.334
log(CVMP)*log(assets)	0.121	0.368
log(CVMP)*log(landholding)	0.245	0.428
labor input demand		
log(maize price)	0.011	0.777
log(fertilizer price)	-0.002	0.955
log(labor price)	-0.014	0.265
log(improved maize share)	-0.006	0.579
log(growing season precipitation, current year)	0.008	0.907
log(growing season degree days, current year)	0.136	0.781
log(cv growing season precipitation, current year)	-0.020	0.776
log(assets)	-1.012	0.196
log(landholding)	-0.651	0.448
log(subsidized fertilizer quantity)	-0.001	0.613
log(GSP)	0.165	0.732
log(TEMP)	-0.649	0.643
log(CVMP)	-0.433	0.568
log(GSP)*log(assets)	0.009	0.844
log(GSP)*log(landholding)	0.056	0.256
log(TEMP)*log(assets)	0.116	0.112
log(TEMP)*log(landholding)	0.013	0.853
log(CVMP)*log(assets)	0.024	0.762
log(CVMP)*log(landholding)	-0.068	0.292

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Table 1. Attributes of methodological approaches in climate adaption literature

Methodological approach / Desired model attributes		Agronomic	Ricardian		Structural Ricardian		The Present Study
			Land price	Net revenue	Land price	Net revenue	
Adaptation	Management practices	+	-	-	+	+	+
	Inputs' applications and reallocation of income sources	-	-	-	-	-	+
Welfare		-	+	+	+	+	+
Controlling for Fixed Effects		-/+	-	-	-/+	-/+	+
Incorporating price effects		-	-	-	-	-	+
Allowing for "partial" adaptation		-	-	-	-	-	+
Heterogeneity in adaptation (e.g. the role of wealth on adaptation behavior)		-	-/+	-/+	-/+	-/+	+

Note: -/+ indicates that some studies using the particular approach have the attribute while others do not.

Table 2: Descriptive Statistics of Variables Used in the Analysis.

variable	Wave 1 (2002/3 & 003/04) mean	Wave 1 (2002/3 & 003/04) median	Wave 2 (2006/07) mean	Wave 2 (2006/07) median	Wave 3 (2008/09) mean	Wave 3 (2008/09) median
Age-adjusted historical average growing season precipitation in cm (GSP)	9,730	9,455	9,483	9,275	9,919	9,696
Age-adjusted average growing season temperature in degrees Celsius (TEMP)	3,411	3,386	3,426	3,394	3,378	3,292
Age-adjusted average growing season coefficient of variation of monthly precipitation (CVMP)	0.659	0.667	0.652	0.658	0.657	0.673
Share of area planted to improved maize	0.392	0.333	0.450	0.333	0.385	0.273
Maize output household level in kg	580	327	703	373	627	410
Real farm-gate maize price	21	20	14	13	28	30
Real total household income	49,815	26,454	31,239	14,793	67,518	39,813
Days of agricultural labor hired in	14.06	0.00	5.49	0.00	5.13	0.00
Days of agricultural labor hired out	43.05	5.00	10.89	0.00	25.15	0.00
Real value of livestock and durable assets in MK	33,326	10,771	47,300	10,434	56,297	13,600
Household landholding, in Ha	1.32	0.86	1.06	0.81	1.08	0.81
=1 if household experienced a bad weather shock in the past 5 years	0.736	-	0.270	-	0.307	-
Previous year's real retail maize price in Mk/Kg	23	22	22	22	40	40
Real commercial fertilizer price in Mk/Kg	62	61	81	80	139	133
Real off-farm wage rate, in Mk/Day	179	184	207	208	282	278
Quantity of subsidized fertilizer acquired in Kg	12.55	0.00	62.42	50.00	56.15	50.00
Quantity of subsidized improved maize seed acquired in Kg	0.74	0.00	2.81	0.00	2.02	0.00
=1 if household secured a loan for purchasing inputs	0.06	-	0.07	-	0.11	-

Real prices are in 2008/09 Malawi Kwacha (MK); US $1.00 = 140 Malawi Kwacha during 2008/09.

Table 3. Factors Affecting Share of Area Planted to Improved Maize Varieties

Dependent variable: Share of total area planted to improved maize **Covariates**	Coefficient	p-value
Historical average growing season precipitation in cm (GSP)	6.12E-05	(0.876)
GSP squared	1.06E-08	(0.493)
Historical average growing season temperature in degrees Celsius (TEMP)	0.022**	(0.011)
TEMP squared	-2.55E-06*	(0.054)
Historical average growing season CV of monthly precipitation (CVMP)	-20.22*	(0.051)
CVMP squared	15.08*	(0.073)
=1 if household experienced a bad weather shock in the past 5 years	-0.00421	(0.799)
Value of livestock and durable assets in MK	3.49E-08	(0.178)
Household landholding, in Ha	-0.008	(0.166)
=1 if household secured a loan for purchasing inputs	0.039	(0.281)
Previous year real retail maize price in Mk/Kg	0.003	(0.257)
Real commercial fertilizer price in Mk/Kg	-0.001	(0.044)
Real off-farm wage rate, in Mk/Day	-3E-05	(0.001)
Quantity of subsidized fertilizer acquired in Kg	0.0002	(0.116)
Quantity of subsidized improved maize seed acquired in Kg	4.77E-05	(0.515)
Number of observations	6,855	
R-squared (within)	0.05	

Note: *, **, *** indicate that the corresponding coefficient is statistically significant at the 10%, 5% and 1% level respectively. Model includes year dummies and a constant that are not shown. standard errors clustered at household level.

Table 4. Partial effects of climate on net-revenue, output supply, and input demand

Partial Effect		Coefficient	p-value
Net Revenue			
i)	$\frac{\partial ln(net\ revenue)}{\partial lnGSP}$	1.72***	(0.00)
ii)	$\frac{\partial lln(net\ revenue)}{\partial lnTEMP}$	-9.75***	(0.00)
iii)	$\frac{\partial ln(net\ revenue)}{\partial lnCVMP}$	-0.61***	(0.00)
Growing Season Rainfall (GSP)			
iv)	$\frac{\partial ln(maize\ supply)}{\partial lnGSP}$	0.44***	(0.00)
v)	$\frac{\partial ln(fertilizer\ demand)}{\partial lnGSP}$	-0.38***	(0.00)
vi)	$\frac{\partial ln(on-farm\ labor\ demand)}{\partial lnGSP}$	1.32***	(0.00)
vii)	$\frac{\partial ln(non-maize\ income)}{\partial lnGSP}$	0.92***	(0.00)
CV of Growing Season Rainfall (CVMP)			
viii)	$\frac{\partial ln(maize\ supply)}{\partial lnCVMP}$	-0.19***	(0.00)
ix)	$\frac{\partial ln(fertilizer\ demand)}{\partial lnCMP}$	-0.44***	(0.00)
x)	$\frac{\partial ln(on-farm\ labor\ demand)}{\partial lnCVMP}$	-0.40***	(0.00)
xi)	$\frac{\partial ln(non-maize\ income)}{\partial lnCVMP}$	-0.61***	(0.00)
Growing Season Temperature (TEMP)			
xii)	$\frac{\partial ln(maize\ supply)}{\partial lnTEMP}$	-7.86***	(0.00)
xiii)	$\frac{\partial ln(fertilizer\ demand)}{\partial lnTEMP}$	-16.86***	(0.00)
xiv)	$\frac{\partial ln(on-farm\ labor\ demand)}{\partial lnTEMP}$	-10.94***	(0.00)

xv)	$\frac{\partial ln(non - maize\ income)}{\partial nTEMP}$	-26.52***	(0.00)

Note: p-values obtained via bootstrapping at 200 repetitions.

Figure Titles

Figure 1. Relationship between assets and the impact of temperature on net revenue

Figure 2. Relationship between assets and the impact of temperature on non-maize income

[1] The duration of a 'dry spell' is defined as the number of consecutive days with less than 2mm rainfall.

[2] Days in which rainfall exceeds 2mm are considered 'rain days.'

[3] It should be noted that some limitations of previous studies are not inherent to their methodology but are typically associated with data availability.

[4] There was too little variation in the volatility of temperature during our sample period to have any influence in production and consumption decisions. Therefore our regression does not include a variable for the coefficient of variation in temperature.

[5] In this study improved maize seeds are defined as hybrid varieties and open pollinated varieties (OPV). Although smallholder farm households in Malawi report that more than 95% of the improved maize seed they acquire is hybrid, anecdotal evidence from Malawi indicates that most farmers refer to *any* improved seed as hybrid.

[6] Time-constant household characteristics such as age of the household head in the first survey and education of the household head are controlled in the fixed effects regression.

[7] Equation 3 is estimated as a linear model rather than a non-linear fractional probit even though the dependent variable is share of area planted to improved varieties. The reason for this choice is 1) linear estimation allows us to use fixed effects making the analysis less prone to omitted variable bias from unobservable time-constant factors; 2) we can obtain predicted values of share of area planted to improved maize varieties that can be used as a covariate in subsequent models that estimate output supply and net revenue; 3) linear panel methods do not make the restrictive assumption that unobservables are linearly related to the time de-meaned household-level variables (Schlenker and Lobell, 2010).

[8] Participation in the input subsidy program is not random, and this could lead to inconsistent coefficient estimates if unobservable factors affecting improved seed adoption are related to acquisition of subsidized inputs. The most like source of this endogeneity is from an omitted variable(s), for example more able farmers may be targeted to receive subsidized inputs. Mason and Ricker-Gilbert (2013) used the same dataset as the current study and found that endogeneity of subsidized fertilizer and seed is not an issue after controlling for time-constant unobserved factors. This indicates that in our context it is reasonable to assume that subsidized inputs are uncorrelated with ε_{it} in equation (3) when household fixed effects is used to estimate the equation.

[9] Input costs in agricultural production activities include fertilizer, seed, hired labor, and land rental costs. Households are asked to quantify input costs in livestock and other agricultural activities as well as in non-agricultural activities.

[10] Since we employed a linear model in stage one, 33% of predicted values fall below zero and about 40% exceed one. The mean share is 0.41, while the median share is 0.42, suggesting that the predicted share estimates are not highly skewed.

[11] Inverse probability weights are not valid with FE estimation (Wooldridge, 2010).

[12] Recent studies by Mason and Ricker-Gilbert (2013), use the same dataset as the present study, and both found little or no evidence of attrition bias after controlling for time-constant unobserved factors.

[13] Bootstrapping is necessary as elasticity estimates are constructed based on predicted adoption of maize varieties. This is where the sequential adoption of adaptation strategies comes into play.

[14] Increase rainfall variability means that dry spells become more frequent and lengthy and events of heavy rainfall also become more common.

[15] Coefficients on assets for other climate variables have not been found to be statistically significant so we focus our attention on temperature.

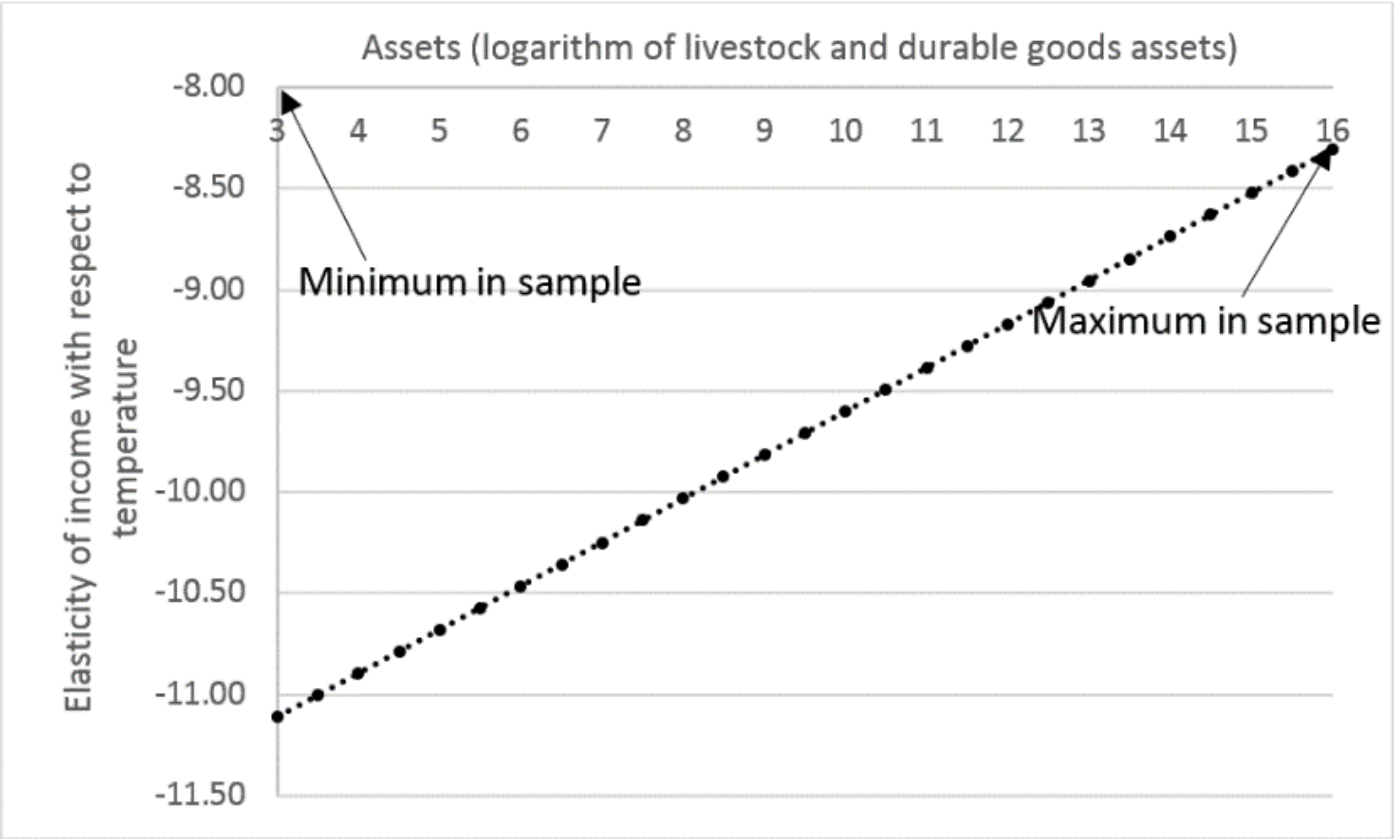

Figure 1. Relationship between assets and the impact of temperature on net revenue

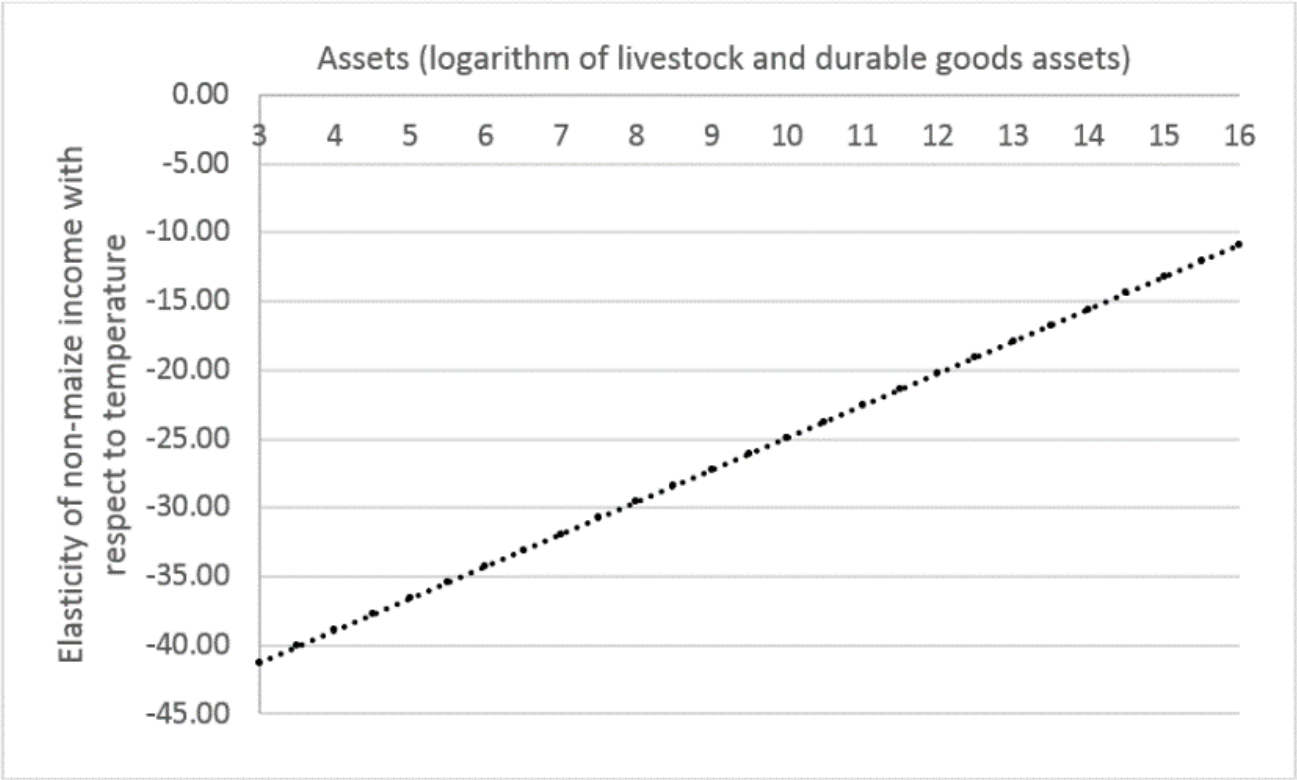

Figure 2. Relationship between assets and the impact of temperature on non-maize income