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Article

Climate Change and Economic Growth in Africa: An Econometric Analysis

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Abstract

The economic landscape of most African countries depends essentially on the dynamics of climate change. Key sectors driving their economic performance and livelihoods such as agriculture, forestry, energy, tourism, coastal and water resources are highly vulnerable to climate change. This article examines the empirical linkage between economic growth and climate change in Africa. Using annual data for 34 countries from 1961 to 2009, we find a negative impact of climate change on economic growth. Our results show that a 1°C increase in temperature reduces gross domestic product (GDP) growth by 0.67 percentage point. Evidence from sensitivity analysis shows the two largest economies in the Sub-Saharan Africa (Nigeria and South Africa) play a significant role in ameliorating the negative economic impact of climate change in the region. In addition to impact on Africa, this article provides estimates of the impact of climate change on GDP growth of these 34 countries, which can be valuable in appraising national adaptation plans. We do not find evidence that average long-run temperature changes affect long-run economic growth as measured by 5 year averages.

Key words: climate change, economic growth, econometrics, Bayesian analysis, agriculture

JEL classification: Q54, O47, C01, C11, O13

1. Introduction

Climate change has been identified as one of the most daunting challenges facing the world in the twenty-first century and it is particularly more serious in Africa largely due to its geographic exposure, low incomes, greater reliance on climate-sensitive sectors and weak capacity to adapt to the changing climate.[1] In fact, the economic landscape of most African countries

1 Climate change manifests itself with temperature increases, changes in precipitation, a rise in sea levels thereby increasing the intensity of such natural hazards as storms, floods and droughts. For detailed analysis of the various dimensions of climate change, their severity and implications on Africa's development, see IPCC (2007a,b).

depends essentially on the dynamics of climate change. The vulnerability of the overall economy and key sectors driving economic performance such as agriculture, forestry, energy, tourism, coastal and water resources to climate change has been acknowledged to be substantial.[2] The geographical location of most African countries on the lower latitudes has already put the region at a disadvantage where about 80% of damages from climate change are concentrated. Any further warming would seriously affect productivity (Mendelsohn, 2008). Yet, Africa contributes a small proportion to the global greenhouse emissions. As articulated by UNDP (2006), it is less than 5% of total carbon dioxide-equivalent emissions and this share is unlikely to grow substantially in the nearest future. To this end, Africa shows a good example of climate change paradox.

Over the past five decades (1960–2009), many countries in Africa (e.g., Sudan, Chad, Uganda, Botswana and Tunisia) have experienced a substantial rise in temperature—ranging from 1 to over 3°C. The increasing knowledge that the continent contributes least to carbon footprint but experiences the most severe impact of climate change provides incentives for Africa to understand the costs of climate change to its economy and development prospects. This is not only as a result of losses to the economy that might be linked to reduced agricultural productivity but also from increases in morbidity, mortality and social instabilities. These indirect impacts such as death and disabilities associated with climate change have irreversible economic and welfare consequences. When countries spend some resources to adapt to climate change, they incur opportunity costs of not spending it on research and development and capital investment (e.g., infrastructure) that is a binding constraint to growth and development in the continent.

However, there is limited empirical analysis on the damaging effects of climate change on the African economy both collectively and at individual country levels. Because of dearth of the literature on this issue in the continent, there is yet to be a convergence on the magnitude of its impact on economic growth both at the regional and country specific levels. This article aims at quantifying the implications of climate change on economic growth in Africa. Specifically, the article seeks to answer the following questions: Does temperature matter in predicting economic growth in Africa? And is there any heterogeneity in the impact of climate change on the economic growth of African countries?

This article is organised into five sections. Following this introduction is Section 2 that examines the linkages between climate change and economic growth and frames this article in the context of other articles in the literature. Section 3 presents the model and how the parameters of interest are estimated while Section 4 describes the data and analysis of key findings. Section 5 concludes the article.

2. What does the literature say about the link between climate change and economic growth?

The literature is replete with the potential ways through which temperature could affect economic activity. The damaging effect of changes in temperature on growth rate of GDP is informed by both theoretic and empirical evidences. First, the destruction of ecosystems from erosion, flood and drought, the extinction of endangered species and deaths resulting from extreme weathers cause permanent damages to economic growth. Second, the resources required to counter the impact of warming would reduce investment in economic and physical

2 See Dell *et al.* (2012) for the economy-wide impact and Boko *et al.* (2007) for sector-specific effects.

infrastructures, research and development and human capital thereby reducing growth (Pindyck, 2011; Ali, 2012).

Theoretically, the linkage could be established through macroeconomic and microeconomic dimensions. From the macroeconomic side, influence on the *level* of output such as agricultural yields and economy's ability to *grow* (for example by affecting investments or institutions that influence productivity growth) are the two areas that are most emphasised (Dell *et al*., 2012). From the microeconomic analysis dimension, the linkage includes an array of factors such as physical and cognitive labour productivity, conflict and health, all of which could have economy-wide implications (Gallup *et al*., 1999; IPCC, 2007a,b). For instance, increased temperature can lead to political instability, which in turn may impede factor accumulation and productivity growth.

What does the literature say on the empirical linkage between climate change and economic growth? Evidence from Dell *et al*. (2012), using a panel of 136 countries covering 1950–2003, finds the impact of higher temperatures on economic growth to be in three key areas. First, it substantially reduces economic growth in poor countries with a 1°C rise in temperature in a given year reducing economic growth by 1.3 percentage points on average. Second, it does not just affect the level of output, but it also appears to reduce growth rates. Third, higher temperatures have wide-ranging effects, reducing agricultural and industrial output and also increasing political instability.

Using global data for 1950–2004, observe that the impact of climate change on economic growth is not robust. However, the moving average-based measure of temperature for Africa is associated with negative effects—although only at 10% level. Furthermore, Ali (2012), using a co-integration analysis on Ethiopia, finds a negative effect on growth while changes in rainfall magnitude and rainfall variability have long-term drag effects on level of output.

Fankhauser and Tol (2005), using a simple climate-economy simulation model, argue that the capital accumulation effect is important, especially if technological change is endogenous, and may be larger than the direct impact of climate change. The savings effect is less pronounced. The dynamic effects are more important, relative to the direct effects. They conclude that in the long run, for high direct impacts, climate change may indeed reverse economic growth and reduce per capita income. For global warming of 3°C, the direct damages to the economy are estimated to be at least 15% of GDP. When the effect of capital accumulation and people's propensity to save are factored into the damages, the impact could be higher.

Higher growing temperature can significantly affect agricultural productivity, farm income and food security. The effect differs across temperate and tropical areas. In mid and high latitudes, the suitability and productivity of crops are projected to increase and extend northwards while the opposite holds for most countries in tropical regions (Gornall *et al*., 2010). They find that a 2°C rise in temperature in mid and high latitudes could increase wheat production by about 10% while in low latitude regions, it could reduce by the same amount. Their projection, taking the effect of technology into account, finds that rising temperature in Russian Federation could increase wheat yield by between 37 and 101% by 2050s.

In addition, Barrios *et al*. (2008) find the effect of rising temperature on agriculture to be more severe in Sub-Saharan Africa than other developing countries. They observe that if the climatic conditions (rainfall and temperatures) had remained at their pre-1960s level, the gap of agricultural production between Sub-Saharan Africa and other developing countries at the end of the twentieth century would have been only 32% of the current deficit. An econometric analysis on Nigeria (1980–2005) reveals that temperature change generates negative effect while rainfall change exerts positive effect on agricultural productivity (Ayinde *et al.*, 2011).

The Fourth Assessment Report of the IPCC provides some illumination on the impact of climate change on African development. For instance, projected reductions in yields in some countries could be as much as 50% by 2020, and crop net revenues could fall by as much as 90% by 2100, with small-farm holders being the most affected. It will also aggravate the water stress currently faced by some countries—about 25% of Africa's population (about 200 million people) currently experience high water stress. The population at risk of increased water stress in Africa is projected to be between 350 and 600 million by 2050 while between 25 and 40% of mammal species in national parks in sub-Saharan Africa could become endangered (Boko *et al.*, 2007).

The survival of mosquito and malaria parasites is highly sensitive to daily and seasonal temperature patterns. Evidence from Science Daily (2010) reveals that over the past four decades, the spread of malaria to highland areas of East Africa, Indonesia, Afghanistan and elsewhere has been linked to climate change. This was a rare phenomenon in the cooler highland areas about 50 years ago. Tanser *et al.* (2003) also observe that due to changing temperature pattern in Africa, there would be 5–7% potential increase (mainly altitudinal) in malaria distribution with surprisingly little increase in the latitudinal extents of the disease by 2100. Boko *et al.* (2007) also provide some insights into the climate change implications on public health in Africa. As argued by Gallup *et al.* (1999), vector-borne diseases, particularly malaria, can have such a large effect on labour productivity which could make many countries in Sub-Saharan Africa to be trapped in a vicious cycle of disease–low productivity–poverty–deficient health care. This has implications on the future welfare of the society. This is further reinforced by the effect of regional warming patterns on Lake Tanganyika. O'Reilly *et al.* (2003) observe that since the beginning of the twentieth century primary productivity of the lake may have decreased by about 20%, implying a roughly 30% decrease in fish yields. They also conclude that the impact of regional effects of global climate change on aquatic ecosystem functions and services can be larger than that of local overfishing.

Evidence from Rabassa *et al.* (2012) reveals that weather shocks exacerbate child morbidity and mortality in Nigeria rural areas and with rainfall shocks having a statistically significant and robust impact on child health in the short run for both weight-for-height and height-for-age, and the incidence of diarrhoea. The intensity is highest in hottest regions.

In summary, climate change has negative impact in most tropical regions' economies both directly and indirectly. This is particularly important because of heavy reliance on rain-fed agriculture which is the main livelihood of the largest segment of the population. To this end, rising trend of temperature could have significant effect on agricultural productivity, farm income and food security as well as indirect effect on labour productivity.

3. Analytical framework for establishing the linkage

This section examines the standard cross-country growth models that can be used to estimate the relationship between economic growth and its key determinants. This is then used to specify a model that reduces the impact of omitted variable bias on parameters of interest.

3.1 The basic cross-country growth regression model

Following the framework in Barro (1991), Levine and Renelt (1992) and Sala-i-Martin (1997), we model y_i, economic growth of country i, as follows:

$$y_i = \gamma_0 + z_i\gamma_k + \beta x_i + \varepsilon_i, \tag{1}$$

where

$$\varepsilon_i \overset{iid}{\sim} N(0, \sigma_\varepsilon^2).$$

In Equation (1), y_i denotes the average growth rate of GDP of country i over a certain year range. In line with Levine and Renelt (1992), z_i denotes a vector of explanatory variables of country i over the same year range that are believed to influence growth and will include a set of variables that are always included in the regression, and then a subset of variables chosen from a pool of variables identified by past studies as potentially important determinants of growth. x_i is (are) the variable(s) of interest that can potentially help explain growth.[3]

The cross-country growth regression model differs in an important way from models that use panel data such as Savvides (1995) and Hoeffler (2002). These models that incorporate panel data tend to address some issues that single cross-country regressions may have. Some of these issues as pointed out in Hoeffler (2002) include reducing the time series to a single (average) observation; omitted variable bias issue and endogeneity of some of the regressors. In addition, these models are used to capture country-specific effects. However, some of these issues may not be as pronounced in the single cross-country regressions. For example, the bias of using a single (average) observation may be small if the variable has not changed much over time as is the case for some of the variables that are included in the economic growth literature.[4] Furthermore, endogeneity problem is usually addressed by using the initial values of the variables that may be endogenous in the model.

Attempts to solve the omitted variable bias have however led to an influx of variables that has been included over time with the norm of looking at variables that are significant to determine the factors that explain differences in growth rates across countries. This has led to the literature addressing uncertainty in the variables to be included in these models.[5] Fernandez *et al.* (2001) used the Bayesian Model Averaging framework that provides opportunity to deal with both model and parameter uncertainties.

Ignoring the issue of using averages, the single cross-section growth regression specification appropriately models differences in growth patterns of countries when there is no correlation between the variable of interest and other explanatory variables. However, when the variable of interest is potentially correlated with unobserved variables, the single cross-section growth regression specification will lead to inconsistent estimate of the variable of interest. In the following section, we describe a Bayesian estimation algorithm, which properly accounts for the

3 Typically, the estimation involves varying the pool of potentially important explanatory variables of growth.

4 It can be argued that variables such as school enrolment, population growth and labour force have not significantly diverged from the norm over a span of the sample period used in many of the growth studies.

5 See Levine and Renelt (1992), Sala-i-Martin (1997) and Fernandez *et al.* (2001) on investigation of model uncertainty.

impact of correlation between unobserved variables and the variable of interest. This specification is important for us to study the impact of climate change on economic growth.

3.2 Linear hierarchical model

Using the Bayesian approach, this article first assumes that climate change variables such as temperature variability will have a different impact on GDP across countries and should be permitted to vary across countries. There is however a degree of commonality across the continent on its impact—higher temperature variability that leads to lower output in South Africa will have an impact on the economy of neighbouring countries even if the temperature variability is not as severe in that country as that of South Africa. On the other hand, climate change variables may also have an impact on many of the explanatory variables that may be included (observed) or not included (unobserved) in the regression equation. Consistent estimate of the parameters of temperature and observed explanatory variables such as initial GDP per capita will require that these variables be uncorrelated with the unobserved variables. This condition is unlikely to hold especially given unavailability of data for many of the variables that can potentially influence economic growth and related to temperature. This is the classic omitted variables bias and inconsistency problem.[6]

We propose a linear hierarchical model that is similar to the classical fixed effects model but exploits the hierarchical prior framework to estimate the parameters of the observed variables that influence economic growth. The proposed model is in the spirit of the normal hierarchical linear model described in Lindley and Smith (1972) and makes an argument similar to Abidoye *et al.* (2012) on controlling for observed and unobserved variables using country-specific constants.[7] In particular, we will introduce a country-specific constant term that captures both the observed and unobserved explanatory variables.

Specifically, the model used in this model is

$$y_{it} = \alpha_i + \beta_i T^{\sigma}_{it-20} + \tau T^{\mu}_{it-20} + \varepsilon_{it} \qquad i = 1, 2, \ldots, N; \quad t = 1, 2, \ldots, T, \tag{2}$$

where

$$\alpha_i = \gamma_0 + \gamma_k z^o_i + z^u_i .$$

T^{σ}_{it-20} and T^{μ}_{it-20} are average temperature anomaly (long-run benchmark) and average long-run temperature over any 20-year interval in time $t-20$ to t, respectively. This specification is similar to Barrios *et al.* (2010) that used a 5-year interval. In contrast to Barrios *et al.* (2010), our interest is in explaining if long-term annual average deviation in temperature influences current GDP growth. The influence of long-run average temperature anomalies on current GDP growth is what we are interested in studying for climate change and these anomalies may not necessarily influence average economic growth over the same period.[8] The focus of our analysis centres on these variables and capture climate change.

6 Abidoye *et al.* (2012) illustrate this problem in a random utility maximization setting but the setting is similar to ours by replacing choice alternatives with time.

7 Detailed description of this model and similar hierarchical models in the Bayesian framework can be found in Koop *et al.* (2007).

8 We argue that using the average economic growth in the interval in time $t-k$ to t and average weather variables for those periods are similar to the cross-country growth regression models where $k = t$. We also estimate this model using 5 year average as presented later.

The model also resolves the omitted variable bias because ε_{it} is no longer correlated with the climate variables of interest (T_{it}^{σ} and T_{it}^{u}) and the unobservable captured in z_i^u. The impact of the observed explanatory variables on economic growth will not be separately identified in the classic fixed effects specification—an advantage of the Bayesian framework.

Equation (2) is estimated using a Bayesian framework and adopts the blocking strategy in Abidoye *et al.* (2012). This approach, working in a manner that is similar to the classical fixed effects model, allows for isolating the impact of the unobservables (capturing them entirely in the country-specific constants) and insulating the climate parameter from their effects.[9]

3.3 Hierarchical priors

As stated in Section 3.2, the country-specific constants capture explanatory variables that are included and excluded in the regression that might explain the differences in economic growth rates across countries.[10] The interactions of all country level variables that are not of interest but typically included in cross-country growth models are solely captured in the country-specific constants. We are also interested in estimating the correlation between the climate variable and the unobserved variables that may not be captured in the regression. This correlation indicates the possible impact an increase in temperature might have on these variables.

The introduction of a hierarchical structure into the model allows us to assume that each country shares some degree of 'commonality' in their temperature and economic growth by assuming that the country-specific constant and parameter on temperature are drawn from the same distribution. It also allows for correlation between the impact of temperature and other factors that may influence economic growth. Specifically

$$\theta_i = \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \sim N(\theta_0, \Sigma) \tag{3}$$

where

$$\theta_0 = \begin{bmatrix} \gamma_0 + z_i^o \gamma_k \\ \beta_0 \end{bmatrix} = \begin{bmatrix} z_i \gamma \\ \beta_0 \end{bmatrix}, \tag{4}$$

$$\Sigma = \begin{bmatrix} \sum_{\alpha\alpha} & \sum_{\alpha\beta} \\ \sum_{\alpha\beta} & \sum_{\beta\beta} \end{bmatrix} = \begin{bmatrix} \sigma_\alpha^2 & \rho\sigma_\alpha\sigma_\beta \\ \rho\sigma_\alpha\sigma_\beta & \sigma_\beta^2 \end{bmatrix}. \tag{5}$$

where z_i includes a constant term and the observed/included explanatory variables that influence growth in country i. This also includes variability in extreme events that may destroy infrastructure and affect economic activities in the country. We will describe each of these variables and their sources in the data source section. The correlation between temperature and the intercept is captured by ρ. There are some salient features of the model that is worth mentioning. The specification, as is the case with most cross-country growth model, will not solve the problem of potential correlation between the included explanatory variables and the unobserved variables. It is typically assumed that this assumption holds and the majority of the variables included in z_i are initial parameters. However, if this assumption does not hold, our specification can be

9 As is pointed out in Abidoye *et al.* (2012), this simply echoes standard result that the fixed effects estimator is unbiased even when correlation exists between the fixed effects and other explanatory variables included in the model.

10 Furthermore, the interactions of all country level variables that are of interest but typically included in cross-country growth models are solely captured in the country-specific constants.

extended to make use of the instrumental variables approach to consistently estimate γ. In this article, we are particularly interested in consistently estimating β_i and β_0, and τ. Even when such correlation exists, the inclusion of country-specific constants and our posterior simulator will yield consistent estimates of the parameters of interest.

To complete the model, we specify priors for the remaining parameters. These are enumerated as follows:

$$\left.\begin{array}{r}\gamma \sim N(\mu_\gamma, V_\gamma)\\ \tau \sim N(\mu_\tau, V_\tau)\\ \beta_0 \sim N(\mu_\beta, V_\beta)\\ \sum^{-1} \sim W([\rho_0 R]^{-1}, \rho_0)\\ \sigma_\varepsilon^2 \sim IG(a_\varepsilon, b_\varepsilon)\end{array}\right\} \tag{6}$$

The hyper-parameters (i.e., the priors), such as μ_γ, V_γ, μ_τ, V_τ, ρ_0, a_ε, b_ε, are supplied by researchers and are in general chosen to be relatively vague to allow for dominance of the information from the data. The notation N refers to the normal distribution, whereas $W(.,.)$ represents a Wishart distribution and $IG(.,.)$ represents the inverse gamma distribution. These are parameterised as in Koop *et al.* (2007, pp. 336–9). These particular families of priors are chosen primarily because when combined with the likelihood function yield conditional posterior distributions that are easily recognised and sampled. These proper priors also make model comparison and calculation of the Bayes factor relatively easy.[11] Our prior means μ_γ and μ_β are set to zero vectors with the respective variance V_γ and V_β set to identity matrix and 25, respectively. The priors (hyper-parameters) on the variance term are also selected by choosing $a_\varepsilon = 3$ and $b_\varepsilon = 1/(40)$.[12] ρ_0 is set to be equal to 5 and the prior is chosen to reflect some degree of variability in the temperature and economic growth across countries. Elements of R were also chosen to be relatively diffuse.[13] All these priors are chosen to be reasonably diffuse and non-informative.

3.4 The posterior simulator

We fit the model using the Gibbs sampler and employ a number of blocking steps to mitigate autocorrelations and consistently estimate the parameters of interest. Before describing these, first let $\beth = [\{\theta_i\}_{i=1}^n \quad \tau \quad \gamma \quad \beta_0 \quad \sum^{-1} \quad \sigma_\varepsilon^2\ ]$ and define $\beth_{-\omega}$ as all the elements of $\beth$ other than ω. The joint posterior distribution for all the parameters of this model can be written as follows:

$$p(\beth|y) \propto \left[\prod_{i=1}^{N} p(y_i|M_i, \theta_i, \tau, \ \sigma_\varepsilon^2) p\left(\theta_i|\tau, \gamma, \beta_0, \sum\nolimits^{-1}\right) p\left(\tau|\theta_i, \mu_\tau, V_\tau, \sum\nolimits^{-1}\right)\right] \tag{7}$$
$$p(\gamma|Z, \mu_\gamma, V_\gamma)\ p(\beta_0|X, \mu_\beta, V_\beta) \times \cdots\ p(\sigma_\varepsilon^2|a_\varepsilon, b_\varepsilon)\ p(\sum\nolimits^{-1}|\rho_0, R)$$

11 A potential advantage of the Bayesian approach is its unified treatment of testing hypotheses. We are usually interested in models comparison when we believe the two models we are comparing have equal probability of been the right model. The posterior odds ratio (the ratio of posterior model probabilities) becomes simply the ratio of marginal likelihoods, popularly called the *Bayes factor.* Where *i*s is defined as the posterior probability of model *i*.

12 This chooses the prior mean for σ^2 equal to 20 with standard deviation also equals to 20.

13 This prior assumes has a mean of zero and variance of based on the Wishart distribution.

Step 1. Draw $\{\theta_i\}_{i=1}^{n}|\beth_{-\{\theta_i\}}, y_i$.

This complete posterior conditional is proportional to the joint posterior distribution $p(\beth|y)$. Absorbing all the terms that do not involve θ_i into the normalising constant of this condition gives us the complete posterior conditional for θ_i. We have stacked the observations over time for each country so that

$$\tilde{y}_i = \begin{bmatrix} y_{i1} - \tau T_{i1}^{\mu} \\ y_{i2} - \tau T_{i2}^{\mu} \\ \vdots \\ y_{iT} - \tau T_{iT}^{\mu} \end{bmatrix}, \qquad M_i = \begin{bmatrix} 1 & T_{i1}^{\sigma} \\ 1 & T_{i2}^{\sigma} \\ \vdots & \vdots \\ 1 & T_{iT}^{\sigma} \end{bmatrix}. \tag{8}$$

Thus we obtain

$$p(\theta_i|\beth_{-\theta_i}, \tilde{y})\tilde{N}(D_{\theta_i}d_{\theta_i},\ D_{\theta_i}), \quad i = 1, 2, \ldots,\ N, \tag{9}$$

where

$$D_{\theta_i} = \left(\frac{M'_i M_i}{\sigma_\varepsilon^2} + \sum{}^{-1}\right)^{-1} \quad d_{\theta_i} = \frac{M'_i y_i}{\sigma_\varepsilon^2} + \sum{}^{-1}\theta_0. \tag{10}$$

We sample each of the θ_i by iterating through the corresponding complete conditional.

Step 2. Complete Posterior Conditional for τ.

The complete posterior conditional for τ follows similarly

$$\tau|\beth_{-\tau}, y_i\tilde{N}(D_\tau d_\tau,\ D_\tau), \tag{11}$$

where

$$D_\tau = \left(\sum_{i=1}^{N}\frac{X'_i X_i}{\sigma_\varepsilon^2} + V_\tau{}^{-1}\right)^{-1}, \quad d_\tau = \sum_{i=1}^{N}\frac{X'_i(y_i - M_i\theta_i)}{\sigma_\varepsilon^2} + V_\tau{}^{-1}\mu_\tau, \tag{12}$$

where

$$X_i = \begin{bmatrix} T_{i1}^{\mu} \\ T_{it}^{\mu} \\ \vdots \\ T_{iT}^{\mu} \end{bmatrix} \tag{13}$$

and the other variables are as defined earlier.

Step 2. Complete Posterior Conditional for γ.

The complete posterior conditional for γ is proportional to the joint posterior distribution as follows:

$$p(\gamma|\beth_{-\gamma}; y) \propto \left[\prod_{i=1}^{N} p(\theta_i|\gamma, \beta_0, \sum{}^{-1})\right] p(\gamma|Z, \mu_\gamma, V_\gamma). \tag{14}$$

Once we condition on the θ_is, the mean of γ is simply the linear regression of the country-specific constants on the variables of interest. This is indicated as follows

$$\begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_N \end{bmatrix} = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_N \end{bmatrix} \gamma + \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_N \end{bmatrix}. \tag{15}$$

$$\alpha = z\gamma + u.$$

where the $\mathrm{Var}(u) = \sum_{\alpha\alpha} - \sum_{\alpha\beta} \sum_{\beta\beta}^{-1} \sum_{\alpha\beta}$ because it is a conditional distribution from θ_i.

This can be re-written as follows:

$$\gamma|\beth_{-\gamma}; y\tilde{N}(D_\gamma d_\gamma, D_\gamma), \tag{16}$$

where

$$D_\gamma = \left(\frac{z'z}{\mathrm{Var}(u)} + V_\gamma\right)^{-1} \tag{17}$$

and

$$d_\gamma = \frac{z'\alpha}{\mathrm{Var}(u)} + V_\gamma \mu_\gamma. \tag{18}$$

Step 3. Complete Posterior Conditional for β_0.

The complete posterior conditional for β_0 is similar to that of γ above. Given draws of the θ_i's (β_i's), we can write

$$\begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_N \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \beta_0 + \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_N \end{bmatrix} \tag{19}$$

and

$$\mathrm{Var}(v) = \sum_{\beta\beta} - \sum_{\alpha\beta} \sum_{\alpha\alpha}^{-1} \sum_{\alpha\beta}. \tag{20}$$

In this form, the posterior for β_0 will be

$$\beta_0|\beth_{-\beta_0}; y \sim N(D_{\beta_0} d_{\beta_0}, D_{\beta_0}), \tag{21}$$

where

$$D_{\beta_0} = \left(\frac{N}{\mathrm{Var}(v)} + V_{\beta_0}\right)^{-1} \tag{22}$$

and

$$d_{\beta_0} = \frac{\sum_i^N \beta_i}{N\mathrm{Var}(v)} + V_{\beta_0} \mu_{\beta_0}. \tag{23}$$

Step 4. Complete Posterior Conditional for σ_ε^2.

$$\sigma_\varepsilon^2 | \beth_{-\sigma_\varepsilon^2}; y\,\tilde{I}G\left(N^* \frac{T}{2} + a_\varepsilon, \left[0.5 \sum (y_i - M_i\theta_i)'(y_i - M_i\theta_i) + b_\varepsilon\right]^{-1}\right). \tag{24}$$

Step 5. Complete Posterior Conditional for $\sum^{-1}$.

$$\sum\nolimits^{-1} | \beth_{-\sum^{-1}}; y \sim W\left(\left[\sum (\theta_i - \theta_0)(\theta_i - \theta_0)' + R\rho_0\right]^{-1}, N + \rho_0\right). \tag{25}$$

4. Data, estimation techniques, descriptive statistics and analysis of results

4.1 The data

Temperature data for each African country were obtained through the Climate Research Unit (CRU) at the University of East Anglia, Norwich, UK. The study used observed gridded monthly mean temperature data from the CRU (version 3.0, Mitchell and Jones, 2005) with 0.5 × 0.5 resolution. The CRU dataset is based on station data. The Global Gridded Climatology data are presented at a new high resolution and made available by the Climate Impacts Link Project (Mitchell and Jones, 2005). The CRU data set is composed of monthly 0.50 latitude/longitude gridded series of climatic parameters over the period 1901–2009, which was used to calculate the 20-year moving averages and its standard deviation for each of the countries for the period 1961–2009.[14]

In addition to long-term temperature variables, we also control for extreme events. We focus on extreme events related to climate using data from EM-DAT international disaster database (www.emdat.be).[15] The choice of extreme events is based on clearly defined set of criteria.[16]

For the purpose of studying the impact of climate change on economic growth in Africa, we find it suitable to use data from the 2011 Africa Development Indicators (ADI) (World Bank, 2011). Economic growth is measured as the annual percentage growth rate of GDP at market prices based on constant local currency. Population data were also obtained from ADI. Total population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship—except for refugees not permanently settled in the country of asylum, who are generally considered part of the population of their country of origin. The values shown are midyear estimates.

14 While the cross-section nature of our data over all African countries and our hierarchical model implicitly captures climate change impact and not just year on year temperature changes, we use moving average estimates to be consistent with the literature in this area.

15 While this is one of the best databases on extreme events, we understand the issues in the reporting especially for African countries that may potentially affect the measurement. Reporting of the events may not be captured in all areas and may not necessarily be captured by EM-DAT that started in 1998.

16 For an event to be categorized as a disaster in the EM-DAT database, at least one of the following criteria must be fulfilled: (i) ten (10) or more people reported killed; (ii) hundred (100) or more people reported affected; (iii) declaration of a state of emergency and (iv) call for international assistance.

Human capital investment is proxied for by primary school enrolment rates and life expectancy. Although previous research (e.g., Mankiw *et al.*, 1992; Gemmell, 1996) has reported that using school enrolment to proxy for the level of human capital can be problematic, we still include it in the estimation because it is typically included in studies of economic growth. We also control for technology advancement and spillover by controlling for secondary school enrolment and foreign direct investments (FDI) and their interactions. The theoretical literature on economic growth recognises human capital and FDI as one of the major contributors to economic growth. Some studies, including Borensztein *et al.* (1998), suggest that FDI by itself is not important if the country does not have the capacity to absorb the technologies. We therefore control for the interaction between secondary school enrolment and FDI. The complete data are available for the 34 countries used in this paper.[17]

4.2 Estimation and testing

The algorithm described in Section 3 has been used to run our posterior simulator for 400,000 iterations discarding the first 50,000 of these as the burn-in. The results from these runs suggest that the chain mixes reasonably well and appears to converge within a few hundred iterations.

Although our point estimates are suggestive of good performance, any Makov Chan-Monte Carlo (MCMC)-based inference can be affected by the degree of correlation among the parameter draws over sequential iterations. We present a diagnostics test for our sampler including the *numerical standard errors* (NSE), inefficiency factors and Geweke's (1992) convergence diagnostics. The Monte Carlo standard error (NSE) indicates the variation that can be expected in the moments of the MCMC estimates if the simulations were to be repeated. The mean estimates can be obtained as follows:

$$\mathrm{NSE}(\bar{\vartheta}_m) = \sqrt{\frac{\sigma^2}{m}}\sqrt{1 + 2\sum_{j=1}^{m-1}\left(1 - \frac{j}{m}\right)\rho_j}, \tag{26}$$

where ϑ represents an arbitrary scalar parameter of interest, m denotes the number of post-convergence simulations, $\bar{\vartheta}_m$ represents our estimate of $E(\vartheta|y)$ as the sample average of our post-convergence draws, ρ_j represents the correlation between simulations j periods (iterations) apart and $\sigma^2 \equiv \mathrm{Var}(\vartheta|y)$.

This is related to the effective sample size metric that gives the size of an independent sample giving the same numerical variance as the MCMC sample (Koop *et al.*, 2007). A high degree of correlation will lead to a slow mixing that may prevent exploring all areas of the posterior as needed. These *inefficiency factors* can be calculated by using the definition of the NSE of a Monte Carlo estimate with correlated draws.

4.3 Simple correlation and descriptive analysis

This section examines the main feature of temperature dynamics in the 34 African countries used in this article. Table 1 presents the minimum and maximum temperatures, the difference between the minimum and maximum, the mean (1961 and 2009) and the absolute change

17 The sample consists of Algeria, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Congo Democratic Republic, Congo Republic, Cote d'Ivoire, Egypt, Gabon, Ghana, Kenya, Lesotho, Liberia, Madagascar, Malawi, Morocco, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, Sudan, Swaziland, Tanzania, Togo, Tunisia, Uganda, Zambia and Zimbabwe.

Table 1: Descriptive Analysis of Temperature (1961–2009)

Row labels	Minimum	Maximum	Maximum – minimum	Mean temperature	Standard errors	Absolute change in temperature (1961–2009)
Algeria	21.72	24.04	2.32	22.96	0.55	1.01
Benin	26.62	28.61	1.99	27.56	0.46	1.02
Botswana	20.39	23.21	2.82	21.86	0.62	1.46
Burkina Faso	27.54	29.12	1.58	28.32	0.39	1.34
Burundi	19.83	21.73	1.91	20.48	0.46	0.96
Cameroon	24.00	25.51	1.51	24.71	0.33	1.01
Central African Republic	24.28	26.02	1.74	25.10	0.45	1.06
Chad	25.72	28.33	2.61	26.99	0.58	2.61
Congo Democratic Republic	23.79	25.33	1.54	24.62	0.30	0.64
Congo Republic	23.75	25.10	1.35	24.23	0.33	1.01
Cote d'Ivoire	25.58	27.17	1.59	26.41	0.32	0.21
Egypt	21.54	23.74	2.19	22.57	0.56	2.15
Gabon	24.17	25.91	1.75	25.09	0.31	0.46
Ghana	26.45	28.14	1.70	27.29	0.37	0.68
Kenya	23.49	25.55	2.06	24.59	0.43	1.06
Lesotho	11.48	13.40	1.92	12.39	0.49	0.49
Liberia	24.71	26.10	1.39	25.38	0.29	0.42
Madagascar	21.67	22.81	1.14	22.30	0.32	0.05
Malawi	21.20	22.91	1.71	22.01	0.40	0.71
Morocco	16.04	18.47	2.43	17.36	0.53	0.29
Niger	26.20	28.68	2.47	27.45	0.49	2.47
Nigeria	26.19	27.84	1.65	26.93	0.38	1.52
Rwanda	18.32	20.24	1.92	18.99	0.48	1.09
Senegal	27.14	29.06	1.92	28.08	0.46	0.47
Sierra Leone	25.60	26.97	1.37	26.25	0.32	0.60
South Africa	16.96	18.60	1.64	17.85	0.42	0.82
Sudan	25.82	28.86	3.04	27.26	0.73	3.04
Swaziland	19.47	21.16	1.68	20.21	0.44	0.34
Tanzania	21.83	23.38	1.55	22.52	0.42	0.66
Togo	26.24	28.27	2.04	27.19	0.44	0.84
Tunisia	18.40	20.87	2.47	19.71	0.68	1.14
Uganda	22.01	24.58	2.57	23.00	0.67	1.90
Zambia	20.96	23.29	2.33	21.84	0.52	0.92
Zimbabwe	20.29	22.91	2.62	21.28	0.56	1.14

between 1961 and 2009. Based on the mean value, Burkina Faso, Senegal, Benin, Niger and Ghana are among the hottest countries in Africa while Lesotho, Morocco, South Africa, Rwanda and Tunisia appear to be the coldest. Sudan, Botswana and Niger experienced the highest swings between the minimum and the maximum temperature over the period of 49 years. Countries that changed by more than 2°C between 1961 and 2009 are Sudan (3.04), Chad (2.61), Niger (2.47) and Egypt (2.15).

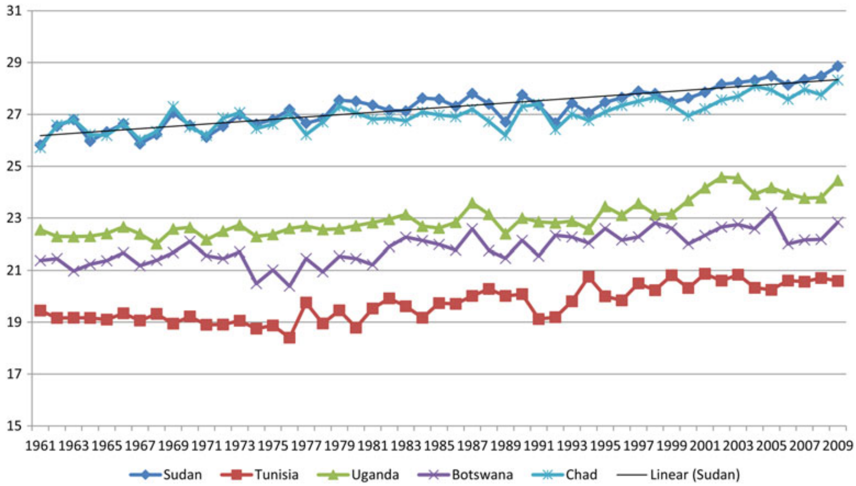

Figure 1: Temperature Trends for Five of the Most Volatile (High Variance) Countries in Africa.

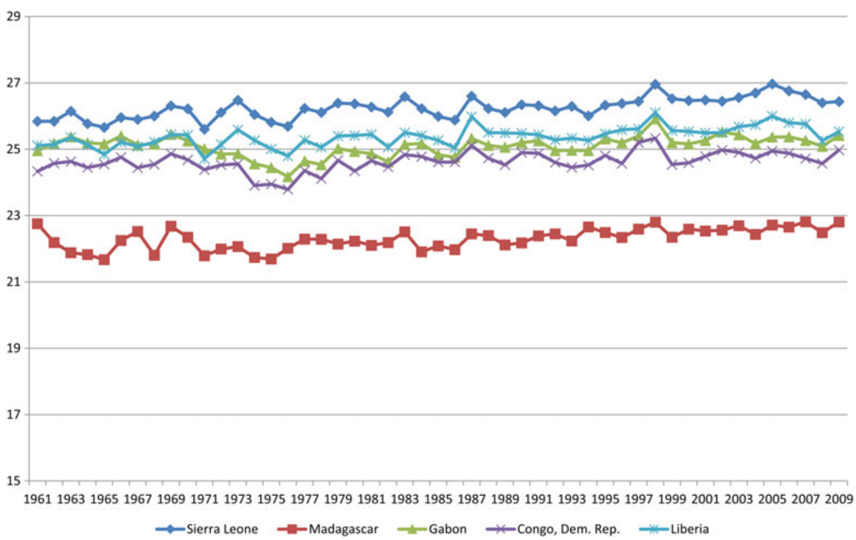

Figure 2: Temperature Trends for Five of the Least Volatile (Lowest Variance) Countries in Africa.

Figure 1 shows the trend of temperature for countries with the highest swings (using variance) over the period. Sudan and Chad have the highest levels and rose consistently between 1961 and 2009. They are followed by Uganda, Botswana and Tunisia. Countries that experienced some relative stability in temperature between 1961 and 2009 include Madagascar, Congo Democratic Republic, Gabon, Liberia and Sierra Leone (see Figure 2).

As shown in Figure 3, lag of temperature change appears to have inverse relationship with the change in current output. This is a clear indication that lag of change in temperature is a good predictor of change in the level of outputs. A similar trend is observed for agriculture

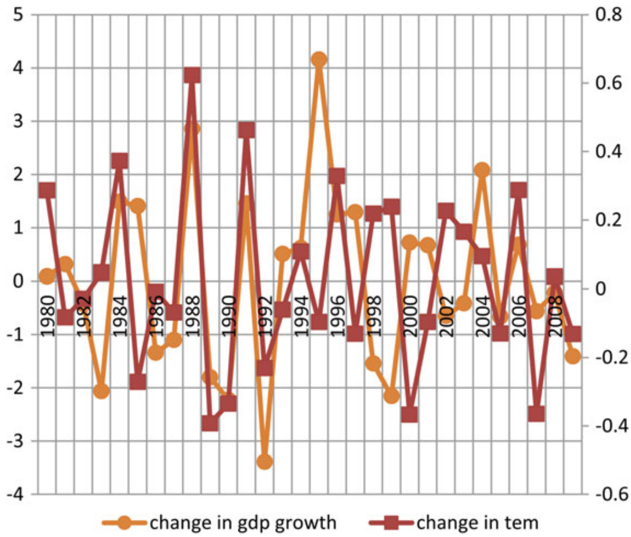

Figure 3: Change in Average GDP Growth and Lag of Temperature Change (1980–2009).

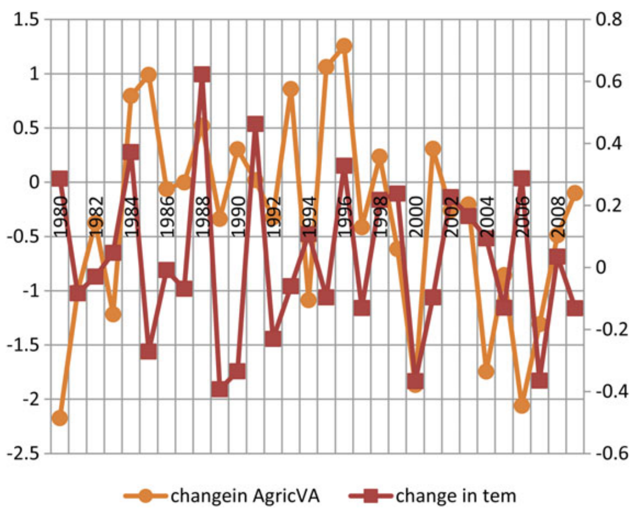

Figure 4: Change in Average Change in Agriculture Value Added and Lag of Temperature Change (1980–2009).

(Figure 4). The pattern for most countries follows the regional trend as shown for Sudan in Figure 5. The correlation index between temperature and agriculture value added is –0.61.[18]

18 The fact that the agricultural value added is negatively correlated with economic growth is interesting but not very informative. It would be interesting to see if the impacts on sectoral GDP or sectoral growth mirror that of the aggregate economic growth.

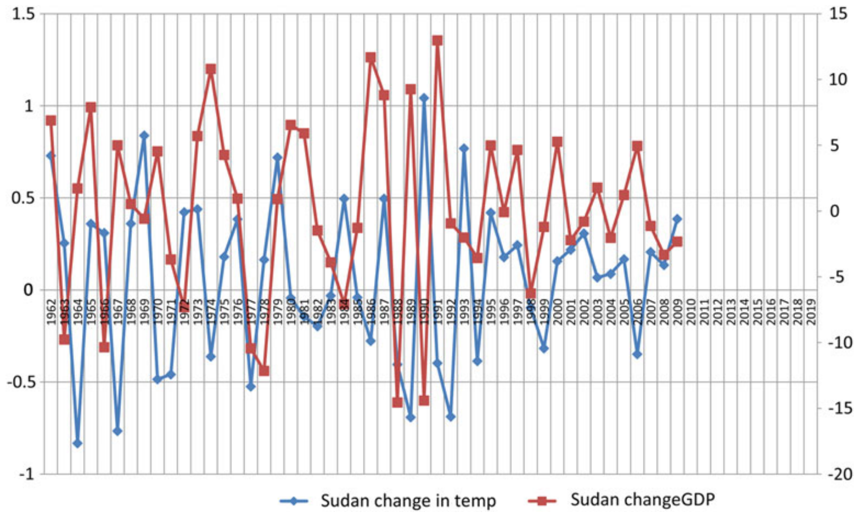

Figure 5: Change in Temperature and Change in GDP (Sudan).

4.4 Empirical results

The analysis of the link between climate change and economic growth is based on the common intercept α_0, common slope β_0 and τ, variance parameters of the second-stage covariance $\sum$ (denoted by $\sigma^2{}_\alpha$ and $\sigma^2{}_\beta$), the correlation between the intercept and slope, denoted $\rho_{\alpha,\beta}$, for the 34 African countries based on data availability. In addition to the pooled result, we analyse the slope and intercept results for the 34 countries. We report parameter posterior means and posterior probabilities of the effect of temperature change being negative on economic growth [denoted as $P(.\langle 0|y)$]. The results with simulation diagnostics are reported in 'Appendix: Country Estimates with Model Diagnostics for the Full Sample'.

Table 2 presents the result of common parameter estimates. The results of the multivariate regression are generally consistent with previous studies and will not be discussed at length. The evidence is not strong that population growth, initial investment (FDI), initial net primary school enrolment and initial secondary school enrolment are individually important for economic growth.[19] The initial values of FDI, net primary school enrolment and secondary school enrolment are too small to substantially drive the growth process in Africa.[20] Our findings on the FDI tend to support Borensztein *et al.* (1998) argument that FDI by itself is not important if the country does not have the capacity to absorb the technologies as evident in the weak results when the interactions between FDI and secondary school enrolment are controlled for. The results show the importance of the initial condition (the log of initial GDP per capita) in the continent growth process. However, it does not provide evidence in

19 The model fit tests for the joint importance of these variables.

20 See Barro (1996) for detailed analysis. They stated that growth rates are enhanced mostly by high initial schooling and life expectancy, and lower fertility rate.

Table 2: Dependent Variable is GDP Growth Rate, Using Data from 1961 to 2009

Explanatory variables	M1	M2	M3	M4	M5
Climate change (deviation from 20-year temperature average) ('pooled' impact on Africa)	−0.7869 (0.9228)	−1.1313 (0.9282)	−0.7433 (0.9303)	−0.6498 (0.9244)	−0.6669 (0.9271)
Climate change (20-year temperature moving average) ('pooled' impact on Africa)	−0.0624 (0.8254)	−0.0555 (0.7657)	−0.0055 (0.5514)	−0.0126 (0.4378)	−0.0302 (0.3330)
Constant	5.3999 (0.0000)	5.8407 (0.0215)	−11.24 (0.9441)	−6.0895 (0.8040)	−5.2055 (0.7627)
Initial GDP per capita (log)		0.0342 (0.4647)	−0.3618 (0.8296)	−0.1817 (0.6808)	−0.1527 (0.6541)
Population growth		−0.28 (0.6777)	−0.4943 (0.8159)	−0.399 (0.7777)	−0.3421 (0.7376)
Initial primary school enrolment (log)			−0.0261 (0.5201)		−0.2787 (0.6816)
Initial life expectancy (log)			5.014 (0.0069)	3.2631 (0.0484)	3.2753 (0.0499)
Initial foreign direct investment–GDP ratio				−0.1582 (0.9950)	−0.2182 (0.5141)
Initial secondary school enrolment (log)				0.211 (0.2349)	0.2606 (0.4811)
Initial FDI X secondary school enrolment					0.0607 (0.4966)
Extreme events (standard deviation)				−0.0509 (0.6903)	−0.0514 (0.6900)
Sigma square alpha	0.7804 (0.0000)	2.7567 (0.0000)	0.6214 (0.0000)	0.4391 (0.0000)	0.4592 (0.0000)
Sigma beta	1.1518 (0.0000)	1.1139 (0.0000)	0.7851 (0.0000)	0.5133 (0.0000)	0.5259 (0.0000)
Pooled sample size, *N*	1605	1605	1605	1605	1605

Note: The numbers in parenthesis are $P\ (. < 0|y)$.

favour of unconditional convergence.[21] Our finding tends to confirm the findings from Barro (1996) that for given values of human capital (e.g., primary education and secondary education), investment and other variables, growth is negatively related to the initial level of real per capita GDP. The initial value of life expectancy is largely positive and significant at about 95% confidence level. This could be suggesting that life expectancy does not only serve as a proxy for health status but also for the quality of human capital.

The result shows that the relationship between proxies of climate change and other factors that influence economic growth is mostly negative. This suggests that there is some evidence that countries with lower temperature increases will tend to have higher growth rates. From our results, long-run climate change as measured by temperature anomaly (20 years average) captures the impact on economic growth better than just the 20-year moving average of temperature. They are both negative but evidence is stronger for temperature anomaly (92% of probability that it is negative) while evidence for the latter is not as strong (ranges between 33 and 82%).

Table 3 presents the results using average temperature anomaly over a 5-year period. The difference between the first and second column is the dependent variable. The first column is similar to Table 2 but using 5 year average for temperature instead of 20 year average. The impacts of temperature anomalies are larger than those of Table 2. Changing the dependent variable to 5-year average GDP growth interval, the results differ. We do not find evidence that

Table 3: Results Using 5 Year Intervals

Explanatory variables	Using T – 5-year average for temperature	Using T – 5-year average for temperature and GDP growth
Climate change: 5 year anomaly ('pooled' impact on Africa)	−3.4562 (0.9881)	0.2664 (0.4300)
Climate change (5-year temperature moving average) ('pooled' impact on Africa)	−0.0173 (0.5932)	0.0039 (0.4740)
Constant	−6.1454 (0.7974)	−11.9153 (0.9478)
Initial GDP per capita (log)	−0.2159 (0.7091)	−0.1638 (0.6848)
Population growth	−0.4005 (0.7722)	−1.0334 (0.9785)
Initial primary school enrolment (log)	−0.2952 (0.6907)	−0.2725 (0.3106
Initial life expectancy (log)	3.8020 (0.0304)	4.9952 (0.0057)
Initial foreign direct investment–GDP ratio	−0.1874 (0.5124)	−0.0471 (0.5026)
Initial secondary school enrolment (log)	0.2340 (0.4833)	−0.0619 (0.5039)
Initial FDI X secondary school enrolment	0.0388 (0.4979)	−0.1166 (0.5087)
Extreme events (standard deviation)	−0.0377 (0.6522)	−0.0998 (0.8833)
Sigma square alpha	0.4721 (0.0000)	0.4740 (0.0000)
Sigma beta	1.1267 (0.0000)	48.71 (0.0000)
Pooled sample size, N	1605	1530

Note: The numbers in parenthesis are $P(. < 0|y)$.

21 This is not really new given that studies such as Barro and Sala-i-Martin (1992) and Mankiw *et al.* (1992) have also reported failure of unconditional convergence when tested for the heterogeneous group of countries.

climate change proxies influence long-run economic growth as measured by 5 year interval average.

Table 4 presents the results for the pooled and individual countries. For all countries, the relationship between climate change[22] and economic growth is largely negative. Evidence from the larger sample (1961–2009) tends to show higher level of damages to economic

Table 4: Country Level Result—Dependent Variable Is GDP Growth Rate

Row labels	All sample period (1961–2009)		1961–2000	
	Beta i_s	P (. <0|y)	Beta i_s	P (. <0|y)
‘Pooled’ impact	**−0.6669**	**0.93**	**−0.4494**	**0.83**
Algeria	−0.6701	0.81	−0.4735	0.73
Benin	−0.5919	0.79	−0.3881	0.70
Botswana	−0.1626	0.61	−0.0875	0.56
Burkina Faso	−0.5149	0.76	−0.3153	0.66
Burundi	−0.8054	0.83	−0.4928	0.72
Cameroon	−0.6801	0.81	−0.4458	0.72
Central African Republic	−0.9609	0.86	−0.6025	0.76
Chad	−0.7822	0.85	−0.5429	0.75
Congo, Dem. Rep.	−1.1120	0.88	−0.7324	0.78
Congo, Rep.	−0.6781	0.81	−0.4806	0.73
Cote d’Ivoire	−0.6228	0.79	−0.4109	0.70
Egypt, Arab Rep.	−0.4388	0.73	−0.2527	0.64
Gabon	−0.5730	0.78	−0.3944	0.69
Ghana	−0.8205	0.84	−0.5709	0.75
Kenya	−0.5194	0.76	−0.3229	0.67
Lesotho	−0.7006	0.82	−0.5203	0.74
Liberia	−0.8095	0.84	−0.5633	0.75
Madagascar	−0.9442	0.87	−0.6587	0.78
Malawi	−0.4608	0.74	−0.3073	0.66
Morocco	−0.5281	0.86	−0.4515	0.81
Niger	−0.7939	0.84	−0.5272	0.74
Nigeria	−0.1261	0.61	0.1344	0.40
Rwanda	−0.4981	0.92	−0.4184	0.84
Senegal	−0.7767	0.85	−0.5448	0.76
Sierra Leone	−0.7469	0.83	−0.5711	0.75
South Africa	−0.7958	0.83	−0.4983	0.73
Sudan	−0.6359	0.80	−0.5052	0.74
Swaziland	−0.2906	0.67	−0.2344	0.63
Tanzania	−0.6331	0.81	−0.4631	0.72
Togo	−0.9081	0.93	−0.7665	0.89
Tunisia	−0.4200	0.77	−0.2914	0.69
Uganda	−0.6978	0.82	−0.3788	0.69
Zambia	−0.8891	0.85	−0.6747	0.77
Zimbabwe	−1.0893	0.91	−0.5265	0.75

Note: ‘***Pooled impact***’ represents the combined impact for the 34 countries.

22 This is proxied by the long run temperature average anomaly.

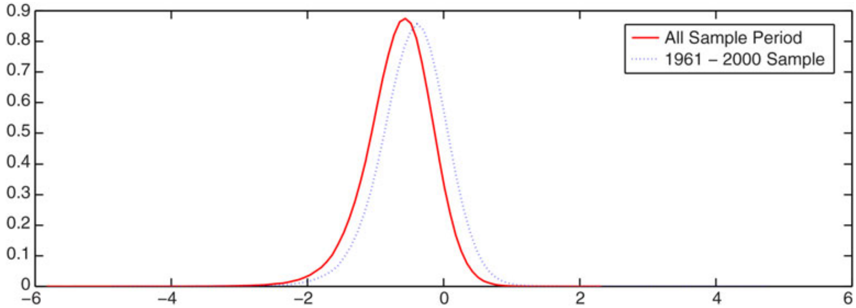

Figure 6: Distribution of the 'Pooled' Mean Effect of Temperature Deviation on GDP Growth in Africa.

growth than the shorter sample. A 1.00 unit change in climate change anomaly slows down economic growth by 0.67% for the larger sample. The value of $P\ (. <0|y)$ implies that there is strong evidence to support that the effect of climate change on economic growth in Africa is negative—93% at all times. For the smaller sample, a 1.00-unit increase in temperature anomaly reduces GDP growth by 0.45%. This is better illustrated in Figure 6 that shows the distribution of the 'pooled' effect of climate change on GDP growth in Africa. The majority of the posterior distribution for the shorter and large samples are clearly massed away from zero with the smaller sample massed closer to zero. As could be observed from Figure 6, the extended sample size has a higher mean effect of climate change on economic growth from about −0.67 for the 1961–2009 sample to −0.45 for the 1961–2000 sample. This tends to show the impact of climate change is becoming more intense in recent times.[23] The emerging reality calls for stronger efforts to adapt to climate change in the continent.

The inclusion of extreme events does not add much to the model, although its impact is largely negative but does not show any strong evidence in Africa once we condition for deviation from long-run deviation and average. Other explanation may be as a result of the measure of extreme events in Africa or based on recent activities that can help reduce extreme event impacts in Africa—although we would have noticed that in the parameter estimate between the small and large samples. One of these initiatives is the World Meteorological Organization's 'Severe Weather Forecasting Demonstration Project' (SWFDP). The project, which was piloted in Southern African countries in 2007—now covering 16 countries in the region—but later extended to six Eastern African countries, is successfully strengthening capacity in National Meteorological and Hydrological Services (NMHSs) to deliver improved forecasts and warnings of severe weather to save lives, livelihoods and property. The project has improved the lead-time and reliability for alerts about high-impact events such as heavy precipitation, severe winds and high waves. It has strengthened interaction with disaster management and civil protection agencies, local communities and media.[24]

To gauge the impact of the four largest economies (South Africa, Egypt, Nigeria and Algeria) on the overall impact on the pooled data, a with-or-without analysis reveals the strength of these countries on the overall performance. When Nigeria and South Africa

23 No formal test is presented to test for significant difference in these impacts.

24 For more information, see https://www.wmo.int/pages/prog/www/swfdp/index_en.html.

Table 5: Estimation Results Removing At Least One of the Largest Economies in Africa (1961–2009)

Countries	'Pooled' mean	P (:|y < 0)
Removing Algeria and Egypt	−0.6244	0.9148
Removing Nigeria and South Africa	−0.8725	0.9575

were removed, the severity of the impact is higher than when it was not (Table 5). A one unit increase in climate change (when Nigeria and South Africa are not controlled for) raises the severity of the impact of economic growth from 0.67 percentage point (for all countries) to 0.87 percentage point and positive with a probability of 96% (Table 5). Several factors could account for this significant influence on the continent. The most obvious is the level of economic integration of these countries—especially Nigeria in ECOWAS and South Africa in SADC and COMESA. All the neighbouring countries to these large economies always benefit from their relaxed trade relations. The opposite holds for Egypt and Algeria. The exclusion of the two countries from the model reduces the severity of the impact of climate change on economic growth from 0.67% (for all countries) to 0.62%. The urgent need to ameliorate the impact of climate change explains why countries like Egypt have been involved in acquisition of large-scale agricultural land in sub-Saharan Africa. For instance, out of the 20 top land acquirers in Sub-Saharan Africa, 12 countries show that the intensity of water use implied by the land deals is greater than the current average domestic rate of water use; it is more than double for countries such as Egypt and the United Arab Emirates (Odusola, 2014). The fact that agricultural products from land acquisition in sub-Saharan Africa is largely exported to countries of origin of acquirers further weakens the capacity of most African countries to meet their national food security and industrial requirements as well as cope with the threat of climate change.

Analysis of the individual country provides more illuminating results. It shows that countries in Africa share some degree of 'commonality' on the effect of climate change on GDP growth rate. The intercept and slope parameters are drawn from the same normal population with climate change having a negative impact on GDP growth rate in Africa. Across the 34 countries, the effect of temperature on economic growth is largely negative with β_i ranging between −0.163 for Botswana and −1.112 for Congo Democratic Republic (for the large sample) and 0.088 for Botswana and 0.766 for Togo (for the small sample). As indicated in Table 4 and using the large sample size (1961–2009), climatic change will have the highest impact on countries such as Democratic Republic of Congo, Zimbabwe, Central African Republic, Madagascar, Togo, Zambia, Ghana, Burundi and Liberia. The least effect is noted among countries such as Nigeria, Botswana, Swaziland and Tunisia.

There is also the proximity effect on a few countries in terms of the similarity of the effects of climate change on economic growth. Chad and Niger; Benin and Burkina Faso; Cameroon and Congo; Sudan, Tanzania and Uganda; and South Africa and Lesotho are good examples. An important policy implication of this is that there could be economies of scale in dealing with the effect of climate change both in terms of mitigation and adaptation through cross border or regional efforts.

5. Conclusions

The vulnerability of the African economy and key sectors driving economic performance (such as agriculture, forestry, energy, tourism, coastal and water resources) to climate change has been acknowledged to be substantial. The inability of most African countries to create jobs in the formal sectors of the economy could further strengthen the dependence of majority of the population on these sensitive sectors. Yet, in the past five decades, many countries in Africa such as Sudan, Chad, Uganda, Botswana and Tunisia have experienced substantial rise in temperature—ranging from 1 to over 3°C. Managing the impact of climate change on Africa's economy has therefore become an important development challenge.

Sudan, Botswana and Niger experienced the highest swings—temperature variability. Their temperature changed by more than 2°C between 1961 and 2009 while countries such as Madagascar, Congo Democratic Republic, Gabon, Liberia and Sierra Leone experienced some relative stability. This study, using descriptive statistics, finds some unconditional evidence to support that lag of temperature change has inverse relationship with the change in current output and appears to be a good predictor of change in the level of outputs.

Based on data from 1961 and 2009, a one unit rise in climate change proxy reduces GDP growth by 0.667 percentage point. The impact is not homogenous across countries. The highest impact is on countries such as Democratic Republic of Congo, Zimbabwe, Central African Republic and Madagascar while the least impact tends to be on Nigeria, Botswana and Swaziland. These estimates are valuable for policy makers and provide input to cost–benefit analysis of adaptation projects in Africa.

Given the critical role of agriculture in Africa's economic growth and development, heavy investment in research and development on the most appropriate adaptation interventions such as development of drought resistant crops and promoting the development of water resources management infrastructure (e.g., dams) would be vital in moving forward. These will however be weighed with the benefits of GDP growth loss averted. To ensure a proactive engagement in addressing this challenge, climate change adaptation should be integrated into national development agenda and also reflected into budget implementation. The proximity effect exhibited by the findings raises the need for economies of scale in dealing with the effect of climate change. Sub-regional or cross-border climate change mitigation and adaptation initiatives may be more effective in the continent.

Using the four largest economies as the controlling factor for the impact of temperature changes on economic growth provides some illuminating results with policy relevance. There is evidence that Nigeria and South Africa serve as important stabilisers to the impact of climate change in the continent. One possible link for this stabilising role could be economic integration—especially Nigeria in ECOWAS and South Africa in SADC and COMESA. During the period of serious economic downturns in most neighbouring countries to South Africa and Nigeria, cross-border trade with them tends to douse such pressure. Efforts to strengthen regional trade and integration may be an important strategy to indirectly ameliorate effects of climate change in the continent.

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References

Abidoye B. O., Herriges J. A., Tobias J. L. (2012) ‘Controlling for Observed and Unobserved Site Characteristics in RUM Models of Recreation Demand’, *American Journal of Agricultural Economics*, 94 (5): 1070–93.

Ali S. N. (2012) ‘Climate Change and Economic Growth in a Rain-Fed Economy: How Much Does Rainfall Variability Cost Ethiopia?’ (8 February 2012). Available at SSRN: http://ssrn.com/abstract=2018233 or http://dx.doi.org/10.2139/ssrn.2018233.

Ayinde O. E., Muchie M., Olatunji G. B. (2011) ‘Effect of Climate Change on Agricultural Productivity in Nigeria: A Co-integration Model Approach’, *Journal of Human Ecology*, 35 (3): 189–94.

Barrios S., Bertinelli L., Strobl E. (2010) ‘Trends in Rainfall and Economic Growth in Africa: A Neglected Cause of the African Growth Tragedy’, *The Review of Economics and Statistics*, 92 (2): 287–298.

Barrios S., Ouattara O., Strobl E. (2008) ‘Impact of Climatic Change on Agricultural Production: Is It different for Africa?’, *Food Policy*, 33 (4).

Barro R. J. (1991) ‘Economic Growth in a Cross Section of Countries’, *The Quarterly Journal of Economics*, 106 (2): 407–43.

Barro R. J. (1996) ‘Determinants of Economic Growth: A Cross-Country Empirical Study’, NBER Working Paper 5698.

Barro R. J., Sala-i-Martin X. (1992) ‘Convergence’, *Journal of Political Economy*, 100 (2): 223–51.

Boko M., Niang I., Nyong A., Vogel C., Githeko A., Medany M., Osman-Elasha B., Tabo R., Yanda P. (2007) ‘Africa’, in Parry M. L., Canziani O. F., Palutikof J. P., van der Linden P. J., Hanson C. E. (eds), *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge, UK: Cambridge University Press, pp. 433–67.

Borensztein E., De Gregorio J., Lee J. W. (1998) ‘How Does Foreign Investment Affect Growth?’, *Journal of International Economics*, 45 (1): 115–35.

Dell M., Jones B. F., Olken B. A. (2012) ‘Temperature Shocks and Economic Growth: Evidence from the Last Half Century’, *American Economic Journal: Macroeconomics*, 4 (3): 66–95. http://www.kellogg.northwestern.edu/faculty/jones-ben/htm/climatechange.pdf.

Fankhauser S., Tol R. S. J. (2005) ‘On Climate Change and Economic Growth’, *Resource and Energy Economics*, 27 (1): 1–17.

Fernandez C., Ley E., Steel M. F. J. (2001) ‘Model Uncertainty in Cross-country Growth Regressions’, *Journal of Applied Econometrics*, 16 (5): 563–76.

Gallup J. L., Sachs J. D., Mellinger A. D. (1999) ‘Geography and Economic Development’, *International Regional Science Review*, 22 (2): 179–232.

Gemmell N. (1996) ‘Evaluating the Impacts of Human Capital Stocks and Accumulation on Economic Growth: Some New Evidence’, *Oxford Bulletin of Economics and Statistics*, 58 (1): 9–28.

Gornall J., Betts R., Burke E., Clark R., Camp J., Willett K., Wiltshire A. (2010) ‘Implications of Climate Change for Agricultural Productivity in the Early Twenty-First Century’, *Philosophical Transactions of the Royal Society of Biological Sciences*, 365 (1554): 2973–89.

Hoeffler A. (2002) ‘The Augmented Solow Model and the African Growth Debate’, *Oxford Bulletin of Economics and Statistics*, 64 (2): 135–58.

Intergovernmental Panel on Climate Change (IPCC) (2007a) ‘Climate Change 2007: Impacts, Adaptation and Vulnerability’, in Parry M.L., Canziani O.F., Palutikof J.P., van der Linden P. J., Hasen C.E. (eds), *Contribution of Working Group II to the Fourth Assessment Report of the IPCC*. Cambridge: UK and New York: Cambridge University Press.

IPCC. (2007b, November) 'Climate Change 2007: Synthesis Report', in Pachauri R. K., Reisinger A. (eds), *Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Vol. 446. Switzerland: IPCC Geneva.

Koop G., Poirier Dale J., Tobias Justin L. (2007) *Bayesian Econometric Methods*. Cambridge: Cambridge University Press.

Levine R., Renelt D. (1992) 'A Sensitivity Analysis of Cross-country Growth Regressions', *The American Economic Review*, 942–63.

Lindley D. V., Smith A. F. M. (1972) 'Bayes Estimates for the Linear Model', *Journal of the Royal Statistical Society. Series B (Methodological)*, 1–41.

Mankiw N. G., Romer D., Weil D. N. (1992) 'A Contribution to the Empirics of Economic Growth', *The Quarterly Journal of Economics*, 107 (2): 407–37.

Mendelsohn R. (2008) 'The Impact of Climate Change on Agriculture in Developing Countries', *Journal of Natural Resources Policy Research*, 1: 5–19.

Mitchell T. D., Jones P. D. (2005) 'An Improved Method of Constructing a Database of Monthly Climate Observations and Associated High-resolution Grids', *International Journal of Climatology*, 25 (6): 693–712.

Odusola A. F. (2014, April) 'Land Grab in Africa: A Review of Emerging Issues and Implications for Policy Options', Working Paper Number 124, International Centre for Inclusive Growth.

O'Reilly C. M., Alin S. R., Plisnier P., Cohen A. S., Mckee B. A. (2003, 14 August) 'Climate Change Decreases Aquatic Ecosyst Productivity of Lake Tanganyika, Africa', *Nature*, 424: 766–8.

Pindyck R. S. (2011) 'Fat Tails, Thin Tails, and Climate Change Policy', *Review of Environmental Economics and Policy*, 5 (2): 258–74.

Rabassa M., Skoufias E., Jacoby H. G. (2012) 'Weather and Child Health in Rural Nigeria', World Bank Policy Research Working Paper 6214, http://www-wds.worldbank.org/servlet/WDSContentServer/WDSP/IB/2012/10/02/000158349_20121002133547/Rendered/PDF/wps6214.pdf.

Sala-i-Martin X. X. (1997) 'I Just Ran Two Million Regressions', *The American Economic Review*, 178–83. http://www.nber.org/papers/w6252.

Savvides A. (1995) 'Economic Growth in Africa', *World Development*, 23 (3): 449–58.

Science Daily (2010, March) 'Climate Change One Factor in Malaria Spread', http://www.sciencedaily.com/releases/2010/03/100303162906.htm.

Tanser F. C., Sharp B., Le Sueur D. (2003) 'Potential Effect of Climate Change on Malaria Transmission in Africa', *The Lancet*, 362 (9398): 1792–8.

UNDP (2006) 'Fighting Climate Change: Human Solidarity in a divided World', Human Development Report 2007/2008. New York: United Nations Development Programme.

World Bank Group. (2011) *Africa Development Indicators 2011*. Washington, DC: World Bank.

Appendix: Country Estimates with Model Diagnostics for the Full Sample

Country	Beta i_s	P (. <0|y)	Standard deviation	NSE	IEF	Geweke's CD
Algeria	−0.6701	0.81	0.8203	0.0058	19.8326	−0.7759
Benin	−0.5919	0.79	0.7945	0.0047	13.9749	−1.3728
Botswana	−0.1626	0.61	0.8738	0.0047	11.6482	−1.5544
Burkina Faso	−0.5149	0.76	0.8010	0.0043	11.4901	−1.4329
Burundi	−0.8054	0.83	0.9536	0.0080	27.4570	−0.4963
Cameroon	−0.6801	0.81	0.8377	0.0057	18.6054	−0.7641
Central African Republic	−0.9609	0.86	0.9997	0.0087	30.1565	−0.3431
Chad	−0.7822	0.85	0.8437	0.0059	19.1518	−0.9592
Congo, Dem. Rep.	−1.1120	0.88	1.1275	0.0107	35.7753	−0.1392
Congo, Rep.	−0.6781	0.81	0.8348	0.0057	18.1138	−0.6844
Cote d'Ivoire	−0.6228	0.79	0.8293	0.0053	15.9314	−0.7128
Egypt, Arab Rep.	−0.4388	0.73	0.7718	0.0042	11.4276	−1.2145
Gabon	−0.5730	0.78	0.8276	0.0047	12.6271	−1.0792
Ghana	−0.8205	0.84	0.9103	0.0071	24.1732	−0.3753
Kenya	−0.5194	0.76	0.8090	0.0046	12.9045	−1.4111
Lesotho	−0.7006	0.82	0.8334	0.0089	45.2399	−0.5094
Liberia	−0.8095	0.84	0.9200	0.0068	21.8646	−0.4048
Madagascar	−0.9442	0.87	0.9659	0.0089	33.1638	−0.3062
Malawi	−0.4608	0.74	0.8110	0.0043	11.0852	−1.4441
Morocco	−0.5281	0.86	0.4887	0.0029	14.1641	−0.6736
Niger	−0.7939	0.84	0.8905	0.0070	24.2547	−0.4335
Nigeria	−0.1261	0.61	0.4643	0.0024	10.2432	−1.8598
Rwanda	−0.4981	0.92	0.3845	0.0018	8.2086	−1.7803
Senegal	−0.7767	0.85	0.8018	0.0061	23.2067	−0.4978
Sierra Leone	−0.7469	0.83	0.8715	0.0061	19.3176	−1.2015
South Africa	−0.7958	0.83	0.9127	0.0072	24.4004	−0.3658
Sudan	−0.6359	0.8	0.8030	0.0064	25.2917	−0.7962
Swaziland	−0.2906	0.67	0.8083	0.0040	9.4906	−1.7049
Tanzania	−0.6331	0.81	0.7905	0.0054	18.6739	−0.7424
Togo	−0.9081	0.93	0.6277	0.0043	18.6852	−1.3779
Tunisia	−0.4200	0.77	0.5862	0.0030	10.3243	−0.7890
Uganda	−0.6978	0.82	0.8382	0.0058	18.7774	−0.9634
Zambia	−0.8891	0.85	0.9498	0.0087	32.8960	−0.2728
Zimbabwe	−1.0893	0.91	1.0042	0.0093	34.1980	−0.0897

CD, Geweke's (1992) CD diagnostics based on AC-adjusted numerical standard errors; IEF, inefficiency factors; NSE, numerical standard errors.