Effects of Temperature and Rainfall Shocks on Economic Growth in Africa

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Paper presented at the 29th Triennial Conference of the ***International Association of Agricultural Economists*** (IAAE) in Milan, Italy from 8 to 14 August, 2015.

Abstract

This paper examines the impact of temperature and rainfall volatility on economic growth in 46 African countries. We employ the Bayesian hierarchical modeling approach which allows us to estimate both country level and Africa-wide impact of climate change and extreme events on economic growth in Africa. Our results show that a 1^0 Celsius increase in temperature leads to 1.58 percentage points decline in economic growth while temperature shock reduces economic growth by 3.22 percentage points. A 1 percent change or shock in rainfall leads to a 6.7 percent change in economic growth. The impact of temperature changes across the 46 countries ranges from -1.24 percent to -1.82 percent in GDP. There are proximity effects on the impact. To maximize the benefits of economies of scale, the paper suggests combined national, cross countries and continental approaches to climate change adaptation in Africa.

Keyword: Climate Change; Economic Growth; Africa; Hierarchical Model; Bayesian framework; Gibbs Sampling.

Classification: C1; C4; C5; O1; Q54, Q56

Introduction

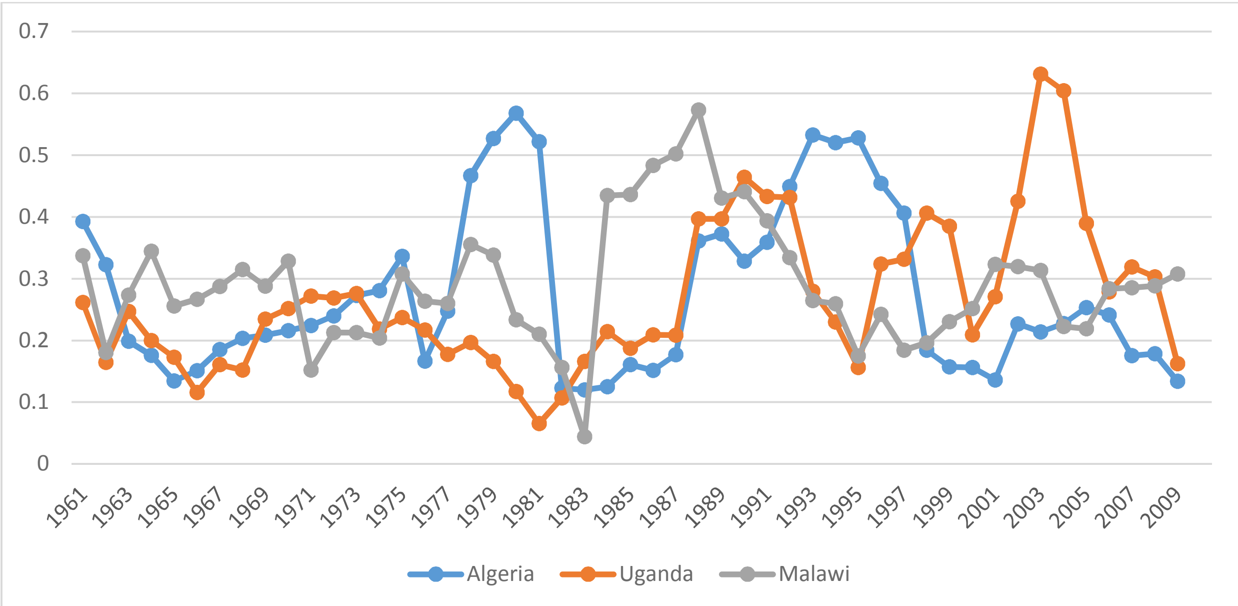
The role climatic conditions play in the agricultural systems in Africa has been well documented. Some studies, though not African specific, have examined the vulnerability of the overall economy and key sectors (e.g. agriculture, forestry, energy, tourism, coastal and water resources) driving economic growth to climate change.[1] The geographical location of most African countries on the lower latitudes has already put the region at a disadvantaged position where about 80 percent of damages from climate change are concentrated with any further warming posing serious threat to productivity and livelihoods (Mendelsohn, 2009; Bansal and Ochoa, 2012).

African countries have experienced temperature and rainfall shocks that are large enough to change agricultural, marine and other sectors productivity since the 1960's.[2] For example, some countries such as Algeria, Uganda and Malawi experienced less temperature anomalies between 1960 and 1977. However since 1977, they have been experiencing larger temperature anomalies (Figure 1). It should be noted that the temperature anomaly of +0.6 degree C in Uganda is one of the highest anomalies in the past 120 years from the global temperature data.[3] Similarly, looking at temperature changes, Sudan, Chad, Uganda and Botswana have experienced substantial rise in temperature – ranging from 1^{o} to over 3^{o} Celsius. Similarly, some other countries such as Mauritania, Niger, Guinea and Sierra Leone have also experienced reduced level of precipitation in the 2000s compared to the 1960s. For example, the average maximum rainfall in the 2000s in Guinea was just 92.6 percent of the average minimum in the 1960s and 93.3 percent for Niger. The Sahel and the Horn of Africa have also experienced substantial and frequent extreme events in the form of droughts which often lead to famine in these regions. The latter decades of the twentieth century in the Sahel were characterized by years in which annual rainfall totals were consistently below the long term mean for the century, and punctuated by years of severe drought (Brooks, 2004). Vizy and Cook (2012) show that the largest rise in heat wave days (ranging from 60 to 120 days) is in the Western Sahel.

A three degree warming for instance will have huge impact on any environment – biodiversity, agriculture and the oceans. The UK Met Office have a map on the impact of global temperature rise of 4 degree C in October 22, 2009.[4] The map shows the impact of forest fire, crops, water availability, sea level rise, marine, drought, tropical cyclones and extreme temperature to name a few. These impacts are based on global models that are based on scientific simulation.

[1] See Dell et al (2012) and Koubi et al (2012) for the economy-wide impact and Boko, et al (2007), and Schlenker and Lobell (2010) for sector specific effects.
[2] Author's computation using gridded data from CRU version 3.0 - Mitchell and Jones, 2005.
[3] http://www.globalissues.org/article/233/climate-change-and-global-warming-introduction#WhatarethemainindicatorsofClimateChange
[4] See http://www.theguardian.com/environment/interactive/2009/oct/22/climate-change-carbon-emissions

Figure 1: 5 Year Mean of Temperature Anomaly – C degrees, 1960 - 2009



The science of the impact of climate change has been relatively conclusive as has been illustrated in the previous paragraphs and various research. However, very minimal studies have been done on the impact on each country in Africa and the continent as a whole. Analysis of countries and regional impact is paramount for proper planning and adaptation strategies. The contribution of this study is to provide estimates of the impact of temperature, precipitation and climate change on 46 African countries' GDP growth.

This paper is unique in several respects. First, the model captures observable and unobservable factors affecting economic growth. Second, the framework of analysis (Bayesian hierarchical model) allows us to pool all countries to obtain regional regression results while at the same time generating specific impact for each country. Third, it is able to disaggregate climate change into its various components (temperature and rainfall shocks), an issue that is rarely addressed in other papers. Finally, the paper adopts current and medium term measures of temperature and rainfall shocks. This paper uses data from 1961 to 2009.

This paper is divided into five parts. Following the introduction is Section 2 which touches on review of empirical evidence on the effects of temperature and rainfall shocks on economic growth. Section 3 presents the model and how our parameters of interest are estimated while Section 4 describes the data and analysis of the findings. Section 5 concludes the paper.

2. Literature Review

Weather conditions (high or low temperature, more or less precipitation and less intense or severe storms) can affect economic activities (agriculture, industrial and services) in many ways. The destruction of ecosystems from erosion, flood and drought, the extinction of endangered species and deaths resulting from extreme weather can have a significant negative impact on economic growth. The channels through which climate variability affects economic activities is varied and diverse. Dell et al (2012) and Koubi et al (2012) show that the transmission channels between weather conditions and economic activities can be clearly identified if the level of GDP is considered, but are ambiguous for the growth rate. For the level of GDP, the short run effect of increase in temperature (or fall in precipitation) could be offset by lower temperature (higher precipitation) in the future thereby leaving the long-run GDP level unaffected. However, the story is different when growth rate is affected because economic growth will be lower even if the level of GDP returns to its normal level. Several factors account for this. The foregone consumption and investment as a result of lower income during the period of higher temperature (lower precipitation) distorts the growth process. Also, heavy investment on adaptation and mitigation programmes will impose some opportunity costs, especially in terms of not investing such resources on science, technology and innovations as well as human and physical capital investment (Pindyck, 2011; Ali, 2012; and Abidoye and Odusola, 2012 and 2015). The resources spent on climate change adaptation and mitigation have the tendency of crowding out investment on other vital drivers of growth and development, especially spending on education, health and infrastructure. The combined effects generate negative impact on economic growth (Frankhauser and Tol, 2005).

The empirical literature has provided some evidence on the effects of temperature and rainfall shocks on economic growth. But the evidence remains inconclusive in terms of results and magnitude of effects. Using historical fluctuations in temperature, Dell et al (2012) find strong linkages between temperature changes and aggregate economic growth. They establish that higher temperatures substantially reduce the level and rate of economic growth in poor countries. Higher temperatures have wide-ranging effects, reducing agricultural and industrial output, and political stability. They conclude that the substantial negative impacts of higher temperatures on poor countries are quite large to explain the cross-sectional temperature-income relationship between rich and poor countries. In poor countries, for instance, a one degree Celsius rise in temperature reduces per-capita income by about 8 percent and leads to a decline in growth rates by about 1.3 percentage points. The paper stresses that annual data on temperature could produce noisy results than medium and long term data. The authors, however, conclude that precipitation has no effect. Their finding on precipitation contrasts Miguel, Satyanath and Sergenti (2004) evidence of strong positive relationship between rainfall and economic growth in Africa. In a similar vein, the finding from Koubi et al (2012) does not produce any evidence to show that climate variability (temperature) affects economic growth.

Some other studies have also examined that higher and rising temperature can significantly affect agricultural productivity, farm income and food security. For instance, Schlenker and Lobell (2010) provide evidence on the negative impact of climate change on African agriculture. The mean estimates of aggregate production changes in Sub-Saharan Africa by 2050 to be 22 percent for maize, 17 percent (sorghum), 17 percent (millet), 18 percent (groundnut) and 8 percent (cassava). They find that in all cases, except cassava, the probability that the damages exceed 7 percent of total production is a 95 percent. Others such as Nordhaus and Boyer (2000), Tol (2002), Mendelsohn et al (2006), and Barrios et al (2010) have also provided some evidence on the issue. In addition, Bernauer, *et al*., (2010) find mixed results on the impact of temperature variability on economic growth: the moving average-based measure of temperature for Africa is associated with negative effects but no impact when they used the CRU Miguel dataset. Evidence from Ayinde et al. (2011), reveals that a rise in temperature generates negative effect while an increase in rainfall exerts positive effects on agricultural productivity. Ali (2012) also finds that a fall in rainfall magnitude and changes in variability have a long term drag-effect on growth in Ethiopia. Evidence from Ouraich and Tyner (2014), for instance, shows climate change shocks have altered regional agricultural production pattern in Morocco. Their projections further reveal the impact of climate change on GDP (in the absence of any adaptation) to range from -3.1 per cent (worst-case scenario) to +0.4 per cent (best case scenario).

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^{o} Celsius rise in temperature in mid and high latitudes could increase wheat production by about 10 percent while in low latitude regions, it could reduce by the same amount. Their projection, taking the effect of technology into account, reveals that rising temperature in Russia Federation could increase wheat yield by between 37 and 101 percent by 2050s. Similarly, Waldinger (2013) provides an analysis of the effect of low temperature on economic growth in Europe. Although the effect of temperature varies across climate zones, on average however, further temperature decreases in particularly cold period generate negative effects. The result is strongly negative in cities already experiencing cold climate while cities in relatively warm climate zones benefit from colder temperatures. Cities and small towns depending heavily on agriculture without much access to long distance trade networks are mostly affected.

Bansal and Ochoa (2011) reveal that temperature is an aggregate risk factor that adversely affects equity returns and overall economic growth both at country and global levels. The study shows that the covariance between country equity returns and temperature contains useful information about the cross-country risk premium. For instance, countries closer to the Equator carry a high temperature risk premium which decreases as a country is further away from the Equator. The differences in temperature or temperature shocks mirror exposures to aggregate growth and equity risks. Simply put, portfolios with larger exposure to aggregate growth risks are also exposed to larger temperature shocks. In this study, countries closer to the Equator have larger risk premium while it is negligible in countries with high latitudes. The paper also shows that economies of countries closer to the Equator depend more on climate sensitive sectors, thereby exposing them to higher risk premiums.

Several studies (e.g. Hirvonen, 2014) have also examined the effect of temperature shocks on households' welfare. It examines how fluctuations in temperatures affect household consumption pattern and rural-urban migration in Tanzania. The paper establishes a co-movement between household consumption and temperature. His evidence shows, controlling for rainfall, household fixed effects and various time-varying factors, a one standard deviation increase in the mean monthly growing season temperature decreases household per capita consumption by 4.9 per cent. This is an indication that temperature shocks make rural households more vulnerable in Tanzania. The temperature-induced income shocks are then found to inhibit long-term migration among men. This therefore prevents them from tapping into and benefiting from the opportunities associated with geographical mobility in the country, including consumption and income premiums. Similarly, liquidity constraint associated with rainfall shocks shape aggregate temporary international migration flows from rural Indonesia (Bazzi, 2013), influences men migration in Ethiopia (Gray and Mueller, 2012).

In conclusion, the impact of climate change variability on economic growth in Africa remains inconclusive. The differences in measurement of climate change or climate variability, methodological approach, models employed and scope could account for this inconclusiveness in findings. Addressing the conceptual, methodological, scope and coverage gaps associated with some of the papers on this subjects, our paper brings a different perspective to the effects of temperature and rainfall shocks on economic growth in Africa.

3. Analytical framework

This section examines the standard cross-country growth models that can be used to estimate the relationship between economic growth and its key determinants. In addition to an analytical model to assess how temperature and rainfall shocks affect economic growth, it also proposes a methodology that controls for a specific type 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 (1997b), 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 $\varepsilon_i \overset{iid}{\sim} N(0, \delta_\varepsilon^2)$

In the above, 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. This typically involves sets of variables that are always included in economic growth regression and a subset of variables chosen from a pool of variables identified by past studies as potentially important in explaining growth, which we denote as x_i.

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 former. In the following section, we describe a Bayesian estimation algorithm which properly accounts for the impact of correlation between unobserved variables and temperature and rainfall shocks. This specification is important to study the impact of temperature and rainfall shocks on economic growth.

3.2 Linear Hierarchical Model

Using Bayesian framework, this paper first assumes that the parameter on temperature and rainfall will have a different impact on GDP across countries and should be permitted to vary across countries. However, based on geography and similarity in practices in many African countries especially with regards to contribution of agriculture to GDP, we expect some level of commonality across the continent on its impact. On the other hand, climate variables such as temperature and rainfall may also have some impact on many of the explanatory variables that may be included (observed) or excluded (unobserved) in the model. Consistent estimate of the parameters of temperature or precipitation and observed explanatory variables such as initial GDP per capita or economic growth will require that these variables be uncorrelated with the unobserved variables. This condition is unlikely to hold especially given that we cannot control for all the variables due to unavailability of data on such variables that can potentially influence economic growth and related to temperature and rainfall. This is the classic omitted variables bias and inconsistency problem[5], which are often associated with most of the studies reviewed in section two above.

This paper proposes a linear hierarchical model that is similar to the non-Bayesian fixed effects model but exploits the hierarchical prior framework to estimate the parameters of the observed variables that influence economic growth.[6] We proceed with a model where all the regression coefficients for temperature can vary across countries (random coefficients model), country effects model in which the regression intercepts are allowed to vary across countries combined with a

[5] Abidoye, Herriges, and Tobias (2012) illustrate this problem in a Random Utility Maximization setting.

[6] A hierarchical prior on the parameters in this case makes the parameter vectors with high dimension

pooled model on the impact of temperature and rainfall on Africa. The effect of temperature lags, rainfall and their shocks are also estimated as a pooled model. This model introduces a country-specific constant term that captures both the observed and unobserved explanatory variables that influence economic growth as described in Lindley and Smith (1972) and Abidoye et al (2012).[7]

Rewriting equation (1) to reflect all variables of interest, we have:

$$y_{it} = \alpha_i + x_{it}\beta_i + L_{it}\tau + \varepsilon_{it} \quad i = 1,2,\ldots,N; t = 1,2,\ldots,T. \quad \ldots\ldots\ldots.(2)$$

Where α_i has a hierarchical prior that makes it similar to a cross-country growth regression model. This is specified as:

$$\alpha_i = \gamma_0 + z_i^o\gamma_k + z_i^u \qquad \ldots.. \quad \ldots \quad ..(3)$$

Equation (2) is also called a *mixed* model with the random effects α_i and β_i varying across countries but also imposes a restriction that τ's in equation (3) are constant across countries.

This model resolves the omitted variable bias since ε_{it} is no longer correlated with the variable of interest (x_{it} and L_{it}) and also allows for separately identifying the impact of the observed explanatory variables on economic growth using a hierarchical prior framework.[8]

Equation (3) is estimated using a Bayesian framework and it adopts the blocking strategy used in Abidoye et al (2012) proceeding in a manner that is similar to the classic fixed effects model by isolating the impact of the unobservable (capturing them entirely in the country- specific constants) and to insulate the climate parameters from their effects.[9] The blocking strategy will draw both α_i and β_i and the set of parameters that do not vary across countries - τ in a single block of draws. It also has the added advantage of facilitating the mixing of the chain.

3.3 Hierarchical Priors

High dimensional parameter spaces are usually problematic for nonlinear models because of the high number of parameters to estimate. The model above will require the estimation of 2*N + k (i.e., N intercepts, N country effects, k slope parameters on rainfall and other variables in L and Z plus the pooled effects and error precisions) parameters using N*T data points. Even with large T relative to N, the number of parameters is still large relative to the sample size. The sparseness of data in high-dimensional spaces can result in lower convergence of regression function estimators.

[7] Detailed description of this model and similar hierarchical models in the Bayesian framework can be found in Koop, Poirier, and Tobias (2007).

[8] This is one of the benefits of using the Bayesian framework over the classical fixed effects specification.

[9] As is pointed out in Abidoye, Herriges, and Tobias (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.

Hierarchical priors become highly valuable in cases like this with high dimensional parameter spaces and it is one of the main attractions of the Bayesian framework. One added advantage of the hierarchical prior for estimation purposes is that it places more structure on the distribution by assuming that the random parameters are drawn from the same distribution. This additional structure allows for more accurate estimation, especially if the assumption is consistent with patterns of the data[10].

Starting with the country-specific constants, the expected value of these variables, as is typical of cross-section regressions are the observed variables while the unobserved variables are embedded in the error term. The interactions of all country level variables (excluding temperature and rainfall) typically included in cross-country growth models are solely captured in the country-specific constants. This imposes the extra structure needed for the estimation of the country-specific constants. We are also interested in estimating the relationship between the climate variables (temperature and rainfall) and the unobserved variables that may not be captured in the regression.

For the estimation of β_i, we assume that each country share some degree of "commonality" in the impact of temperature and or rainfall and economic growth by assuming that the country-specific effect of climate change shocks across Africa are drawn from the same distribution. In addition to this structure, we also allow for correlation between the impact of temperature, rainfall and other factors that may influence economic growth.

Rewriting equation (1) in matrix form gives:

$$\begin{aligned} y_{it} &= [1 \quad x_{it} \quad L_{it}] \begin{pmatrix} \alpha_i \\ \beta_i \\ \tau \end{pmatrix} + \varepsilon_{it} \\ &\equiv M_{it}\theta_i + \varepsilon_{it} \end{aligned} \qquad \ldots\ldots (4)$$

Equation (4) seeks to draw α_i, β_i and τ in a single block. The mean and variance matrix of θ_i will incorporate the hierarchical priors explained earlier.

Specifically:

$$\theta_i = \begin{bmatrix} \alpha_i \\ \beta_i \\ \tau \end{bmatrix} \sim N\left(\begin{bmatrix} z_i\gamma \\ \beta_0 \\ \mu_\tau \end{bmatrix}, \begin{bmatrix} \delta_\alpha^2 & \rho\delta_\alpha\delta_\beta & 0 \\ \rho\delta_\alpha\delta_\beta & \delta_\beta^2 & 0 \\ 0 & 0 & V_\tau \end{bmatrix} \right) \qquad \ldots\ldots\ldots\ldots\ldots (5)$$

The variable z_i includes a constant term and the observed/included explanatory variables that influence growth in country i. The correlation between climate change shocks and the intercept is

[10] See Koop (2003) for more information on this.

captured with ρ and the pooled impact of temperature on Africa is captured with the β_0 parameter and prior for τ defined as $\tau \sim N(\mu_\tau, V_\tau)$. There are some silent features of this model that is worth mentioning – our specification helps controls for the problem of potential correlation between variable of interest and the unobserved variables which may potentially bias β_i and β_0 that we are interested. However, 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 excluded variables. It is typically assumed that this assumption holds. However, if this assumption does not hold, our specification can be extended to make use of instrumental variables approach to consistently estimate γ. Even when such correlation between the observed variables and unobserved variables exists, the inclusion of country-specific constants and our posterior simulator will yield consistent estimates of the parameters of interest.

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

$$\left.\begin{array}{c} \gamma \sim N(\mu_\gamma, V_\gamma) \\ \beta_0 \sim N(\mu_{\beta_0}, V_{\beta_0}) \\ \Sigma^{-1} \equiv \begin{bmatrix} \delta_\alpha^2 & \rho\delta_\alpha\delta_\beta \\ \rho\delta_\alpha\delta_\beta & \delta_\beta^2 \end{bmatrix} \sim W([\rho_0 R]^{-1}, \rho_0) \\ \delta_\varepsilon^2 \sim IG(a_\varepsilon, b_\varepsilon) \end{array}\right\} \dots\dots\dots\dots\dots\dots. (6)$$

The hyper-parameters of the priors above, such as $\mu_\gamma, V_\gamma, \rho_0, a_\varepsilon, b_\varepsilon$ e.t.c., are supplied by the 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 parameterized as in Koop, Poirier, and Tobias (pp. 336-339).[11] These particular families of priors are chosen primarily because when combined with the likelihood function yield conditional posterior distributions that are easily recognized and sampled. These proper priors also make model comparison and calculation of Bayes Factor relatively easy.

Our prior means μ_γ and μ_β are set to zero matrices with the appropriate size and respective variance V_γ and V_β set relatively large to allow vague and proper prior. The priors (hyperparameters) 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. These priors are chosen to be reasonably

[11] Let be an N X N positive definite (symmetric) random matric, A be a fixed (nonrandom) N X N positive definite matric, and v >0 be a scalar degrees-of-freedom parameter. Then H has a Wishart distribution, denoted H ~ W (A,v) with a defined pdf and reduces to the gamma distribution if N=1. The inverted gamma distribution on the other hand has the property that, if Y has an inverted gamma distribution ~ IG (a,b), then 1/Y has a gamma distribution with a mean – E(Y) = $[b(a\text{-}1)]^{-1}$ and Var(Y) = $[b^2(a\text{-}1)^2(a\text{-}2)]^{-1}$for a>2.

[12] This chooses the prior mean for sigma^2 equal to 20 with standard deviation also equal to 20

diffuse and non-informative. Appropriate prior sensitivity analysis carried out shows the results are robust as presented below.

3.4 The Posterior Simulator[13]

Bayesian inference and posterior simulator is a process of updating researchers' prior beliefs of the parameters to be estimated into posterior beliefs based on observed data. The updating - typically termed posterior simulation – involves working in terms of probability densities. The framework involves a joint distribution of all quantities of interest –parameters and data using the principles of probability – Bayes theorem to back out the posterior density of interest. These posterior densities are approximated by a combination of a likelihood function and a prior[14].

The model is fitted using the Gibbs sampler[15] and employing a number of blocking steps to mitigate autocorrelations and consistently estimate our parameters of interest. Specifically, we fit the model via Markov Chain Monte Carlo (MCMC) methods that utilizes the Gibbs sampler. The idea is to draw from the posterior conditional distributions rather than the joint posterior distributions themselves that are usually difficult to draw from.

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

4.1 The Data

This section describes the data used to run the models specified above. Temperature and rainfall data for each African country is deduced from the database of Climate Research Unit (CRU) using observed gridded monthly mean temperature and rainfall data (CRU, version 3.0 as outlined in Mitchell and Jones, 2005).[16] The CRU dataset is based on station data and composed of monthly 0.50 latitude/longitude gridded series of climatic parameters over the period 1901-2009. However the data used for this paper runs from 1961-2009.[17]

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[13] For readers interested in detailed model specification see Appendix 1.
[14] See Koop et al (2007) and other Bayesian econometrics texts for further reading on this.
[15] The Gibbs sampler is an iterative algorithm that has become an indispensable tool to Bayesians and researchers undertaking simulation based inference. For more information see Koop, et al (2007).
[16] According to the Climatic Research Unit (CRU) project team, the reference for CRU version 3.0 is Mitchell and Jones, 2005.
[17] The Global Gridded Climatology data is presented at a new high resolution and made available by the Climate Impacts LINK project, Climate Research Unit, University of East Anglia, Norwich, UK (Mitchell and Jones, 2005).

Data for other explanatory variables are obtained from the Africa Development Indicators (ADI) (2011). Economic growth is measured as the annual percentage growth rate of GDP at market prices based on constant local currency. The population values are midyear estimates.

The primary and secondary school enrolment rates, and life expectancy are used as proxies for human capital investment. Although previous research (e.g. Mankiw *et al* (1992) and Gemmell (1996)) has argued that using school enrolment as a proxy for the level of human capital can be problematic. Because it has been used in many other studies, we therefore allow the model likelihood to dictate if it should be included or not.

The model also controls for availability of port, language spoken, and initial private savings as a ratio of GDP. Availability of a port is used to proxy for geography and savings and language are typically controlled for in the growth literature. Savings is an increasing function of economic growth but is also endogenous because higher economic growth can lead to higher savings. As with other variables, we avoid the endogeneity problem by using initial savings. Language can capture trade opportunities and heterogeneity in growth patterns with francophone African countries typically with high similarity which can be observed in the growth patterns.

The data is available for 46 countries[18]. The choice of the countries is based on data availability on the economic growth variables. However, the panel was unbalanced because of gaps in data for some countries.

4.3 Estimation and Testing

The algorithm described in Section 3 has been used to run our posterior simulator for 500 000 iterations discarding the first 50 000 of these as the burn-in.[19] Results from these runs suggest that the Markov Chan - Monte Carlo (MCMC) simulation chain from the posterior mixed reasonably well and appears to converge within a few hundred iterations.

Although our point estimates are suggestive of good performance, any MCMC-based inference can be affected by the degree of correlation among the parameter draws over sequential iterations. The mixing of the posterior simulations has been used to determine how many draws are needed to achieve the same level of numerical precision that would be obtained under an independent and identically distributed (*iid)* sampling. When the degree of correlation is high it leads to a slow mixing that may limit the simulator from exploring all areas of the posterior as may be needed.

[18] The countries are: Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Congo, Democratic Republic of Congo, Cote d'Ivoire, Egypt, Equatorial Guinea, Eritrea, Ethiopia, Gabon, The Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, Sudan, Swaziland, Tanzania, Togo, Tunisia, Uganda, Zambia, Zimbabwe.

[19] ``Burn-in'' is a colloquial term that describes the practice of throwing away some iterations at the beginning of an MCMC run to discard the iterations before convergence is reached.

These *inefficiency factors*, can be calculated by using the definition of the *numerical standard errors* (NSE) of a Monte Carlo estimate with correlated draws. The mean estimates can be obtained as:

$$NSE(\bar{\vartheta}_m) = \sqrt{\frac{\sigma^2}{m}}\sqrt{1+2\sum_{j=1}^{m-1}\left(1-\frac{j}{m}\right)\rho_j}, \qquad \ldots.. \quad \ldots. \quad \ldots.. (6)$$

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 $\sigma^2 \equiv Var(\vartheta|y)$.

The NSEs for our models are small relative to the mean estimates which indicate our simulation estimates accurately approximate the posterior means of the selection parameters. This, again, suggests that our algorithm mixes quite well. The values for the NSEs for the country effect parameters are presented in Appendix 2.

The posterior mean is commonly used to interpret a moment of the posterior distribution. The posterior probabilities, while similar to the classical p-value, provide information on the degree of posterior certainty that the impact of the parameter is negative. The algorithm described above is used to run the growth models.

4.3 Descriptive Analysis

This section presents the main feature of temperature and dynamics in the 46 African countries used in this paper. The focus is on yearly temperature and five-year average rainfall including their deviations from that average. This is because gross domestic product (GDP) growth data is mainly available on yearly basis for the African countries.[20] Table 1 shows the minimum and maximum, the difference between the minimum and maximum, the mean (1961 and 2009) and the absolute change between 1961 and 2009 of the yearly average temperature.[21] Based on the mean value for the sample period, Mali, Burkina Faso, Senegal, and Mauritania are among the hottest countries in Africa on average while Lesotho, Morocco, South Africa, Rwanda and Tunisia appear to be the coldest. Sudan, Botswana and Zimbabwe experienced the highest change over the period of 49 years when we take the difference between the maximum and minimum yearly average temperature as in column 3 of Table 1. Countries that changed by more than 2^{o} Celsius between 1961 and 2009 are Sudan (3.04), Chad (2.61), Niger (2.47) and Egypt (2.15).

[20] Apart from data availability, average temperature nets out the effect of seasonality and climate change by definition focuses on average temperature differential and deviation. Thus, while we recognize that yearly temperature and rainfall may not accurately capture daily or growing season temperature fluctuation, we argue that they adequately reflect the influence of temperature and rainfall averages on economic growth.
[21] This does not imply that the temperature for that country within a year does not go below or above the minimum or maximum but the mean of the yearly average in that period is reported.

Figure 1 shows the series of temperature for countries with the top 5 countries with the highest change between the maximum and minimum yearly average temperature as in column 3 of Table 1. Sudan and Chad have the highest levels and the yearly average have been rising consistently during the period. They are followed by Niger, Egypt, Uganda and Libya. Countries that experienced some relative stability in temperature during the period of analysis include Madagascar, Congo Democratic Republic, Gabon, Liberia and Sierra Leone (see Figure).

As shown in Table 3, the unconditional effect of temperature change lag appears to have an inverse relationship with the change in current output. We include temperature lags in the regression to aid our understanding of the impact of temperature dynamics and economic growth.

Figure 3 presents a simple summary statistics for rainfall. Liberia has the highest average yearly rainfall of all the African countries but also experienced the highest fluctuation (as captured by the standard deviation) for the period. Guinea Bissau and Equatorial Guinea, The Gambia are among the countries with the highest rainfall and variation in rainfall during the period of analysis. In the next section we used a five-year moving average and 5-year average deviation of rainfall to capture the long run impact of rainfall on economic growth.

4.4 Analysis of the results

This paper answers the following questions: (1) what is the impact of temperature and rainfall on economic activities in Africa? (2) What is the impact of climate shock as measured by long run deviation from the mean on economic growth in Africa? (3) What is the residual/lag impact of temperature on economic growth in Africa? (4) Given recent interventions and adaptation strategies, is there any difference in the impact of temperature shocks between 1960's to 2000 compared to the whole sample period?

The analysis below is based on parameter posterior means and posterior probabilities of the parameter being negative [denoted $P(. <0|y)$]. It provides the link between temperature, rainfall, and their long run deviations on the one hand and economic growth on the other based on the pooled regression parameters, the slope and intercept results for 46 African countries.

Table 2 presents the result of common parameter estimates. The presentation of different variants of the model provides some robustness checks to test our different hypothesis, as is typical of cross-section economic growth models. In the first three columns of Table 2, we control for initial GDP per capita, population, primary school enrolment and life expectancy. Although evidence is not strong, the initial conditions of human capital (proxied by initial primary school enrolment and life expectancy) contribute positively to economic growth. The evidence is strongest for life expectancy with the probability of it being positive at about 70 percent. This evidence may be suggesting that life expectancy may not only serve as a proxy for human capital but also an indicator of quality of life. There is little or no evidence in support of the initial condition of net primary school enrolment and population growth influencing economic growth in Africa. The results show the importance of initial condition (the log of initial GDP per capita) in the continent growth process. These results are generally consistent with previous studies on determinants of growth in Africa.

In addition to these variables, we also control for geography as measured by port, language, initial private savings as a ratio of GDP and technology transfer as measured by foreign direct investment, secondary school enrolment and their interaction. While there is little evidence that port, language and savings have a significant impact on economic growth, technology transfer measures provide interesting results. The initial conditions of foreign direct investment show a negative impact on growth with the probability of this being negative ranging between 70 per cent and 90 percent across the various models. This is in line with the literature on foreign direct investments (FDIs). FDI without adequate human capital for the transfer to take place will potentially stunt economic growth. As reported in the results, there is strong evidence that FDI reduces economic growth when its interaction with secondary school enrolment is not controlled for. When the interaction is controlled for, the negative impact on growth fell. The inclusion of this interactive variable reduces the negative impact of temperature on economic growth (see models 5 and 7). It shows the variable has both direct and indirect effects on economic growth. This clearly suggests that countries with high quality of secondary school education are likely to reap the benefits of enhanced economic growth. Even if the right human capital is in place, strong national institutions are needed to avoid expropriation through clandestine capital outflows. There is also evidence that high secondary school enrolment increases growth.

The role temperature, rainfall, and their respective shocks play in explaining economic growth in Africa is pivotal. In column 1, when only temperature and rainfall are the included variables, a 1^0 Celsius in temperature tends to reduce economic growth by 1.28 percentage points and the relationship is always established at a probability level of 92.3 percent. The relationship is even more pronounced across most of the seven models, the impact of a 1^0 Celsius ranges between -1.25 percentage points and -1.59 percentage points on economic growth in Africa. The results from models 3, 5 and 7 reveal that the serious negative impact of a rise in temperature is certain, with probability levels of 100.00 percent.

To capture the residual impact of temperature, we introduce five-year temperature lags. However, the relationship of the lag temperature on economic growth is non-linear – becoming positive in the first year lag, turning negative in the second year lag and changing to positive trend in the third to the fifth year lags. The probability level becomes relatively weaker after the second year lag (Table 3). Based on the foregoing and using the current temperature and the first two-year lags, the cumulative net impact of temperature on economic growth can be crudely calculated as -0.6141 (-1.586 + 1.2616 – 0.2897), which still remain quite high for the continent.

The impact of rainfall is positive across all the seven models. A one percentage change in the rainfall medium term (5-year moving average) mean volume appears to increase economic growth by 2.8 percent in Model 1. This positive relationship is established at a probability level of 93.60 percent. For all the models the impact ranges between 2.74 percent and 6.73 percent with the relationship being established at 92.7 per cent and 95.8 percent probabilities. This result tends to underscore what African economy is losing from absence of irrigated farming and the frequent extreme droughts in the Sahel and the Horn of Africa.

In order to estimate the impact of climate change shocks on economic growth, we control for the temperature and rainfall deviations from their respective 5-year moving averages. Unexpected change in temperature and rainfall (rise or fall) produce significant impact on economic growth in Africa. An unexpected rise of one standard deviation from the average temperature reduces economic growth by 3.22 percentage points with 99 percent of the mass in the positive region. This implies that an unexpected reduction in temperature by at least one standard deviation from the mean will raise GDP by 3.22 percentage points. Any shock (rise or fall) in rainfall (deviation) of at least a magnitude of one percent from its 5-year mean value may lead to a rise or fall in economic growth by 6.76 percent (Table 3). The effect of any unfavorable deviations from temperature or rainfall is quite damaging to the African economy. In addition, to be fully engaged in efforts that will lead to enhanced climate change adaptation, heavy investment in meteorological services and weather indexed insurance to farmers will help to ameliorate the excruciating effect of weather shocks to the economy.

The impact of climate change is not only on economic growth. It also affects other determinants of economic growth. The correlation between temperature and other factors that influence economic growth is mostly negative but with weak probability. The probability that the relationship is negative is established at about 60 percent across all the models (Table 2). This implies that African countries with lower temperature increases tend to have higher growth rates compared to those with a high rise in temperature. This suggests the combined direct and indirect effects of climate change could be more serious than envisaged especially if the impact of temperature increase on growth fundamentals – particularly those with irreversible consequences – is negative (especially life expectancy). Finally, there is evidence of individual heterogeneity across countries as shown by the estimates of δ^2_α and δ^2_β with $\delta^2_\alpha = 0.17$ and $\delta^2_\beta = 0.13$ on average.

The country level impact of temperature on economic growth and their probabilities of being negative (Pr (: < 0ly)) is overwhelmingly negative (Table 4). It shows the continental average blurs the individual countries performance which most other studies have not been able to unravel. The results shows that the largest impact of temperature on economic growth is in the Democratic Republic of Congo followed by Sierra Leone, Madagascar and Central African Republic. Evidence from the 46 countries is largely negative with β_i ranging from -1.822 for Democratic Republic of Congo and -1.244 for Equatorial Guinea. The worst hit five countries are Congo Democratic Republic, Sierra Leone, Tanzania, Madagascar, and Central African Republic. A 1^0 Celsius rise in temperature reduces economic growth by between 1.75 percent and 1.82 percent for these five countries. The negative impact is more severe than the continental average of 1.58 percent in 19 countries (see Table 4). Five countries with the least impacts are Equatorial Guinea, Egypt, Eritrea, Angola, and Algeria. Egypt and Algeria have one of the largest irrigation schemes in Africa while

Equatorial Guinea and Angola, apart being blessed with swampy forests also rely on oil money, when to suggest a better capacity to cope with the effect of weather shocks.

The intensity of temperature change varies from country to country. Yet, it has no respect for boundaries. Similarity in impact on economic growth, based on geographic proximity, provides a strong basis for grouping countries into at least nine sub-groups (Figure 4): (i) Mali and Mauritania; (ii) Niger and Libya; (iii) Algeria and Morocco; (iv) Cameroon and CAR; (v) Senegal, Guinea, Cote d'Ivoire and Ghana; (vi) Nigeria, Benin and Togo; (vii) Ethiopia, Somalia, Kenya and Uganda; (viii) Zimbabwe, Zambia, Rwanda and Burundi; and (ix) Namibia, Botswana, South Africa, Lesotho, Swaziland, Mozambique and Malawi. Similar multi-countries impact calls for economies of scale in climate change adaptation. Combined national, regional and continental adaptation strategies are more appealing to reap the synergy associated with economies of scale. The regional approach also helps to mitigate the risks of asymmetric capacity to adapt to climate change in Africa.

To determine if the impact of climate change on economic growth has been improving or worsening over the past five decades, we divided the period into two: one smaller sample (1961-2000) and a full sample (1961 and 2009). We then compare the results from these two samples (see Table 4 and Figure 5). The impact of temperature on economic growth in Africa was found to be higher in the full sample than the small sample. Evidence from the small sample (1961-2000) tends to show lower level of damages to economic growth than the larger sample. A 1^{o} Celsius rise in temperature slows down economic growth by 1.42 percentage point for the small sample with a probability value of 0.99 compared with 1.59 for the full sample period for Africa. Despite the substantial drag on growth emanating from change in temperature, agricultural productivity in Africa has increased since 2000 (Block, 2010). It shows that without the damaging effects of climate change on agriculture, agricultural productivity and production would have been quite substantial. However, there is a relatively stronger evidence that the net effect of a change in temperature incorporating the 5-year lags is higher in the small sample (-0.121) than in the full sample (-0.041).[22] This tends to suggest adaptation to extreme weather changes is improving. Finally, across the two samples, there is no significant difference in terms of the long run temperature shock impact as measured by a 5-year deviation from the mean.

[22] This ignores the fact that there is weak evidence that the probability that the parameters of the 3rd, 4th and 5th lags in the full sample are positive. We report the estimates for the lags and rainfall for the sub-sample in the appendix.

5. Conclusions

Africa is at the centerpiece of climate change and it exhibits a good case for climate change paradox – contributes marginally to greenhouse gas emission but bears excruciating impacts with limited capacity to manage them. 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 is substantial. Yet, in the past five decades, many countries in Africa such as Sudan, Chad, Uganda and Botswana have experienced high rise in temperature – ranging from 1^o Celsius to over 3^o Celsius. During the same period, countries such as Mauritania, Niger, Guinea and Sierra Leone also experienced substantial decline in rainfall - average annual maximum rainfall in the 2000s in Guinea and Niger fell short of their average annual minimum in the 1960s. The impact of changes in temperature and rainfall on Africa's economy is considerably large. A 1^0 Celsius increase in temperature leads to 1.58 percentage points decline in economic growth while an unexpected one degree standard deviation from the average shock tends to generate 3.22 percentage points decline in GDP. On the other hand a one percent change (rise/fall) in rainfall leads to a 6.7 percent (increase/decline) in economic growth. Any rainfall shock also generates a similar effect. The impact of temperature changes is even more excruciating at the country level – ranging from -1.24 (Equatorial Guinea) and -1.82 (Democratic Republic of Congo). These developments make proactive management of climate change adaptation and the impact of climate change imperative in Africa.

Given that very few African countries have the capacity to deal with climate change adaptation, the possibility of using economies of scale to deal with this challenge offers some bilateral, multi-countries or regional oriented strategies. The regional approach helps to mitigate the risks of asymmetric capacity to adapt to climate change in Africa.

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Table 1: Descriptive analysis using average yearly temperature between 1961 and 2009 in Africa

Countries	Min	Max	Max - Min	Mean	Standard Deviation	Absolute change (1961 – 2009)
Algeria	21.7183	24.0408	2.3225	22.9593	0.5498	1.0092
Angola	21.1717	22.4442	1.2725	21.6619	0.2948	0.6150
Benin	26.6167	28.6092	1.9925	27.5625	0.4599	1.0200
Botswana	20.3900	23.2067	2.8167	21.8570	0.6175	1.4567
Burkina Faso	27.5367	29.1192	1.5825	28.3158	0.3950	1.3367
Burundi	19.8467	21.7325	1.8858	20.4821	0.4582	0.9625
Cameroon	23.9950	25.5050	1.5100	24.7096	0.3263	1.0117
Central African Republic	24.2825	26.0192	1.7367	25.0949	0.4455	1.0608
Chad	25.7200	28.3292	2.6092	26.9862	0.5752	2.6092
Congo, Dem. Rep.	23.7883	25.3300	1.5417	24.6242	0.3007	0.6442
Congo, Rep.	23.7483	25.0975	1.3492	24.2292	0.3327	1.0075
Cote d'Ivoire	25.5775	27.1658	1.5883	26.4062	0.3228	0.2133
Egypt, Arab Rep.	21.5442	23.7383	2.1942	22.5724	0.5603	2.1450
Equatorial Guinea	23.7967	25.3725	1.5758	24.5874	0.2805	0.6792
Eritrea	25.3542	27.4750	2.1208	26.5285	0.5428	1.8333
Ethiopia	21.8142	23.5233	1.7092	22.6137	0.3842	1.4750
Gabon	24.1667	25.9117	1.7450	25.0922	0.3118	0.4558
Gambia, The	26.5900	28.4700	1.8800	27.4524	0.4575	0.4725
Ghana	26.4450	28.1433	1.6983	27.2854	0.3723	0.6758
Guinea	25.0483	26.5592	1.5108	25.7261	0.3405	0.6742
Guinea-Bissau	26.1575	27.8758	1.7183	26.9548	0.4151	0.3925

Kenya	23.4600	25.5508	2.0908	24.5894	0.4281	1.0558
Lesotho	11.4783	13.3975	1.9192	12.3937	0.4861	0.4900
Liberia	24.7108	26.1017	1.3908	25.3811	0.2940	0.4175
Libya	21.2167	23.0992	1.8825	22.2126	0.4904	1.8825
Madagascar	21.6717	22.8117	1.1400	22.2972	0.3214	0.0533
Malawi	21.1992	22.9067	1.7075	22.0151	0.4000	0.7092
Mali	27.4425	29.3650	1.9225	28.5028	0.4787	1.2508
Mauritania	26.7217	29.0292	2.3075	27.9403	0.5555	0.7558
Morocco	16.0350	18.4650	2.4300	17.3518	0.5302	0.2858
Mozambique	23.1583	24.8175	1.6592	23.8753	0.3713	0.2883
Namibia	19.1475	20.9667	1.8192	20.2395	0.3716	0.9458
Niger	26.2017	28.6750	2.4733	27.4515	0.4876	2.4733
Nigeria	26.1875	27.8358	1.6483	26.9258	0.3789	1.5208
Rwanda	18.3283	20.2417	1.9133	18.9906	0.4815	1.0875
Senegal	27.1425	29.0617	1.9192	28.0759	0.4617	0.4650
Sierra Leone	25.6000	26.9650	1.3650	26.2442	0.3212	0.5967
Somalia	26.2883	27.5167	1.2283	26.9508	0.2649	0.6600
South Africa	16.9583	18.5950	1.6367	17.8460	0.4205	0.8250
Sudan	25.8158	28.8592	3.0433	27.2606	0.7315	3.0433
Swaziland	19.3950	21.1558	1.7608	20.2124	0.4443	0.3408
Tanzania	21.8308	23.3808	1.5500	22.5235	0.4159	0.6550
Togo	26.2367	28.2742	2.0375	27.1916	0.4424	0.8367
Uganda	22.0092	24.5800	2.5708	23.0009	0.6691	1.9025
Zambia	20.9608	23.2917	2.3308	21.8409	0.5243	0.9167
Zimbabwe	20.2942	22.9133	2.6192	21.2825	0.5556	1.1375

Table 2: Dependent Variable is GDP growth rate using data from 1961-2009 (P (. <0|y) in parentheses)

Explanatory Variables	M1	M2	M3	M4	M5	M6	M7
Temperature ("Pooled" impact on Africa)	-1.2845 (0.9228)	-1.3987 (0.9992)	-1.2781 (1.0000)	-1.3180 (0.9768)	-1.4206 (1.0000)	-1.2544 (0.9846)	-1.5861 (1.0000)
Rainfall 5-year moving average ("Pooled" impact on Africa)	0.0283 (0.0639)	0.02818 (0.0659)	0.02738 (0.0728)	0.0331 (0.0438)	0.0334 (0.0452)	0.0673 (0.0440)	0.0338 (0.0424)
Constant	0.1545 (0.4268)	0.0966 (0.4606)	0.05184 (0.4792)	0.0158 (0.4939)	0.0366 (0.4849)	0.0377 (0.4848)	0.0230 (0.4909)
Log Initial GDP per capita		0.5245 (0.2142)	0.33811 (0.3186)	0.3196 (0.3390)	0.4066 (0.2940)	0.3575 (0.3197)	0.3628 (0.3214)
Population Growth		0.0615 (0.4716)	0.02718 (0.4900)	-0.0548 (0.5240)	-0.0316 (0.5131)	-0.0291 (0.5156)	-0.0675 (0.5286)
Primary School Enrolment (log)			0.14404 (0.4349)	0.0338 (0.0484)	0.0788 (0.4625)	0.0490 (0.4736)	0.0677 (0.4697)
Life expectancy (log)			0.29136 (0.3704)	0.1259 (0.4457)	0.1971 (0.4133)	0.1981 (0.4137)	0.1455 (0.4340)
Port				-0.0388 (0.5153)			-0.0163 (0.5069)
Foreign Direct Investment GDP ratio				-0.4493	-0.3835	-0.4471	-0.3899

				(0.8923)	(0.7096)	(0.9044)	(0.7119)
				0.0622			0.0752
Language				(0.4742)			(0.4651)
				-0.0002			-0.0023
Savings				(0.5042)			(0.5046)
				0.2840	0.2915	0.2434	0.3072
Secondary School Enrolment (log)				(0.3711)	(0.3673)	(0.3908)	(0.3621)
					-0.0923		-0.0807
FDI X Secondary School Enrolment					(0.5534)		(0.5478)
	0.1680	0.1696	0.17271	0.1702	0.1684	0.1695	0.1699
Sigma square alpha	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	0.1240	0.1240	0.1243	0.1298	0.1272	0.1267	0.1308
Sigma beta	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	-0.0395	-0.0406	-0.0405	-0.0397	-0.0402	-0.0406	-0.0397
correlation (rho)	(0.6025)	(0.6047)	(0.6047)	(0.5999)	(0.6026)	(0.6036)	(0.6002)

Table 4: Estimation results used for robustness – using Model 7.

	Full Sample (1961 -2009)		Sub-sample (1961 - 2000)	
Variables	Posterior Mean	Pr(:<0ly)	Posterior Mean	Pr(:<0ly)
Temperature Lag 1	1.2616	0.0058	1.1376	0.0223
Temperature Lag2	-0.2897	0.7179	-0.4487	0.7868
Temperature Lag 3	0.0926	0.4264	-0.2014	0.6381
Temperature Lag 4	0.2336	0.3209	0.3724	0.2592
Temperature Lag 5	0.2473	0.3026	0.4394	0.2076
Rainfall 5- year MA*	0.0338	0.0424	0.0406	0.0278
Rainfall shocks**	0.0676	0.0595	0.0829	0.0514
Temperature shocks	-3.2186	0.9898	-3.2621	0.9795

Note: * MA is moving average

- **Shocks for both temperature and rainfall are measured based on standard deviation from their respective five-year moving averages.**

Table 4: Country Level result - Dependent Variable is GDP Growth Rate

	All sample (1961 – 2009)		1961 – 2000	
Countries / Variable	Posterior Mean	Pr(:<0ly)	Posterior Mean	Pr(:<0ly)
Pooled Mean Temperature Effect	-1.586	1.000	-1.420	1.000
Algeria	-1.482	1.000	-1.277	0.998
Angola	-1.464	1.000	-1.452	1.000
Benin	-1.590	1.000	-1.414	1.000
Botswana	-1.533	1.000	-1.298	0.997
Burkina Faso	-1.539	1.000	-1.359	1.000
Burundi	-1.684	1.000	-1.528	1.000
Cameroon	-1.703	1.000	-1.538	1.000
Central African Republic	-1.749	1.000	-1.571	1.000
Chad	-1.484	1.000	-1.337	0.999
Congo, Dem. Rep.	-1.822	1.000	-1.697	1.000
Congo, Rep.	-1.670	1.000	-1.516	1.000
Cote d'Ivoire	-1.639	1.000	-1.442	1.000
Egypt, Arab Rep.	-1.409	1.000	-1.197	0.996
Equatorial Guinea	-1.244	0.999	-1.145	0.992
Eritrea	-1.450	1.000	-1.170	0.990

Ethiopia	-1.537	1.000	-1.430	1.000
Gabon	-1.691	1.000	-1.497	1.000
Gambia, The	-1.574	1.000	-1.405	1.000
Ghana	-1.637	1.000	-1.475	1.000
Guinea	-1.681	1.000	-1.483	1.000
Guinea-Bissau	-1.727	1.000	-1.535	1.000
Kenya	-1.544	1.000	-1.348	1.000
Lesotho	-1.542	1.000	-1.415	0.996
Liberia	-1.582	1.000	-1.442	0.997
Libya	-1.514	1.000	-1.390	0.996
Madagascar	-1.771	1.000	-1.633	1.000
Malawi	-1.549	1.000	-1.388	1.000
Mali	-1.516	1.000	-1.325	0.999
Mauritania	-1.507	1.000	-1.295	0.997
Morocco	-1.492	1.000	-1.327	0.999
Mozambique	-1.572	1.000	-1.465	1.000
Namibia	-1.595	1.000	-1.419	0.999
Niger	-1.534	1.000	-1.351	0.999
Nigeria	-1.581	1.000	-1.410	1.000
Rwanda	-1.628	1.000	-1.517	1.000
Senegal	-1.612	1.000	-1.432	1.000
Sierra Leone	-1.800	1.000	-1.712	1.000
Somalia	-1.570	1.000	-1.377	1.000
South Africa	-1.517	1.000	-1.372	0.999
Sudan	-1.489	1.000	-1.253	0.998
Swaziland	-1.543	1.000	-1.421	0.999
Tanzania	-1.790	1.000	-1.605	1.000
Togo	-1.563	1.000	-1.376	1.000
Uganda	-1.508	1.000	-1.369	0.999
Zambia	-1.685	1.000	-1.533	1.000
Zimbabwe	-1.644	1.000	-1.380	0.999

Figure 1: Temperature Series for five of the Most Volatile (High variance) Countries in Africa

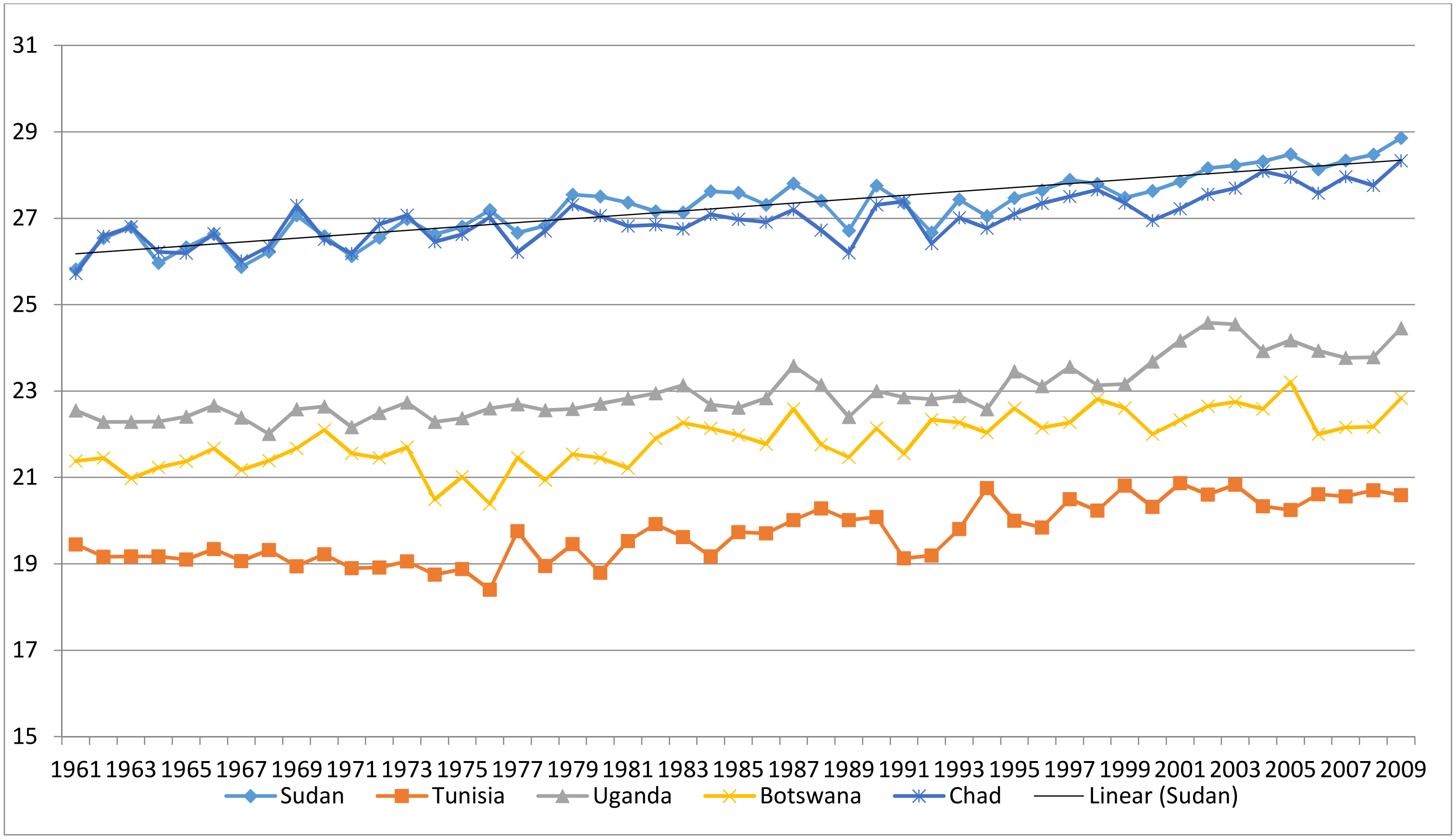


Figure 2: Temperature Series for five of the Least Volatile (Lowest variance) Countries in Africa

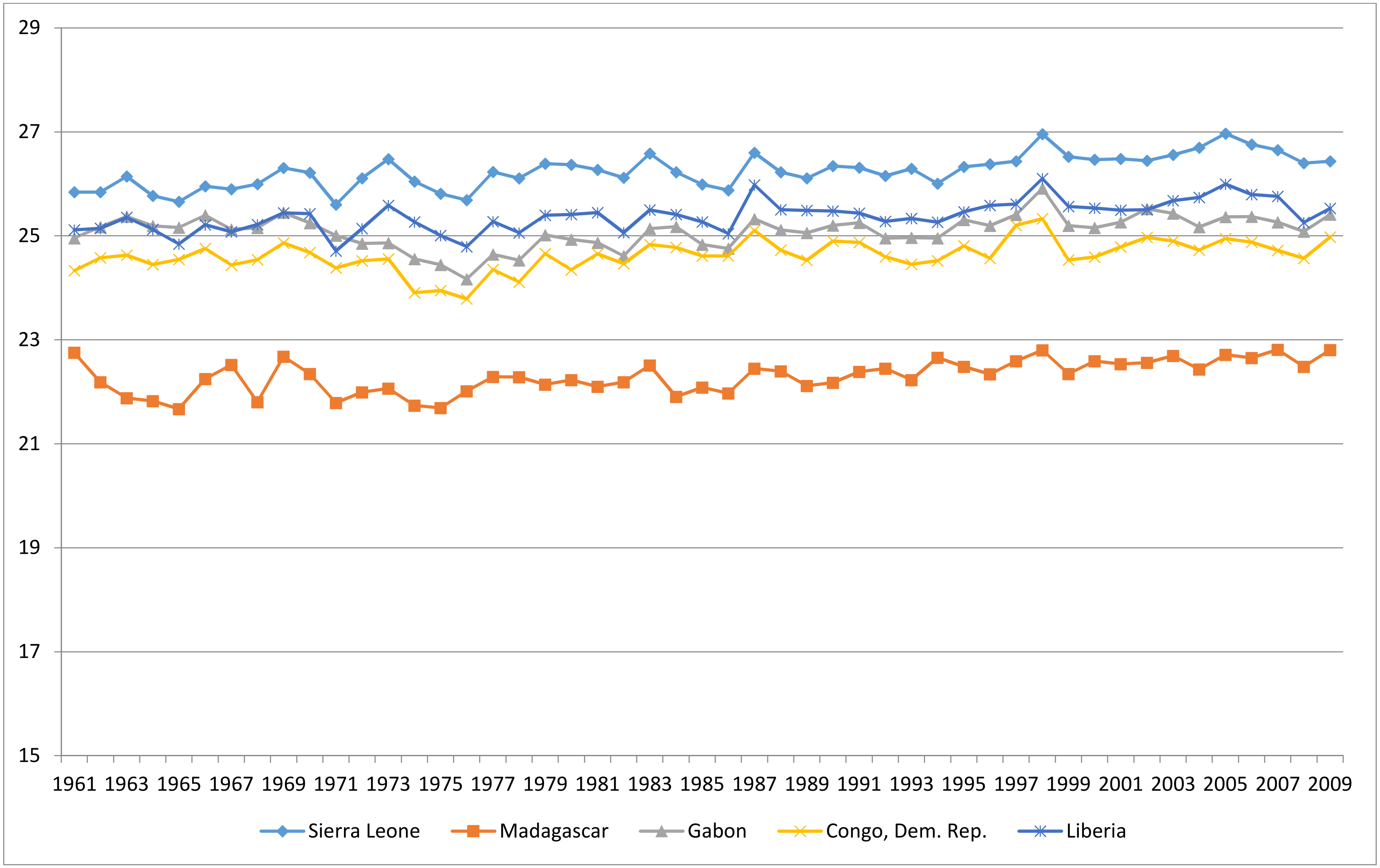


Figure 3: Minimum, Maximum and Standard Deviation of yearly rainfall average (1961-2009)

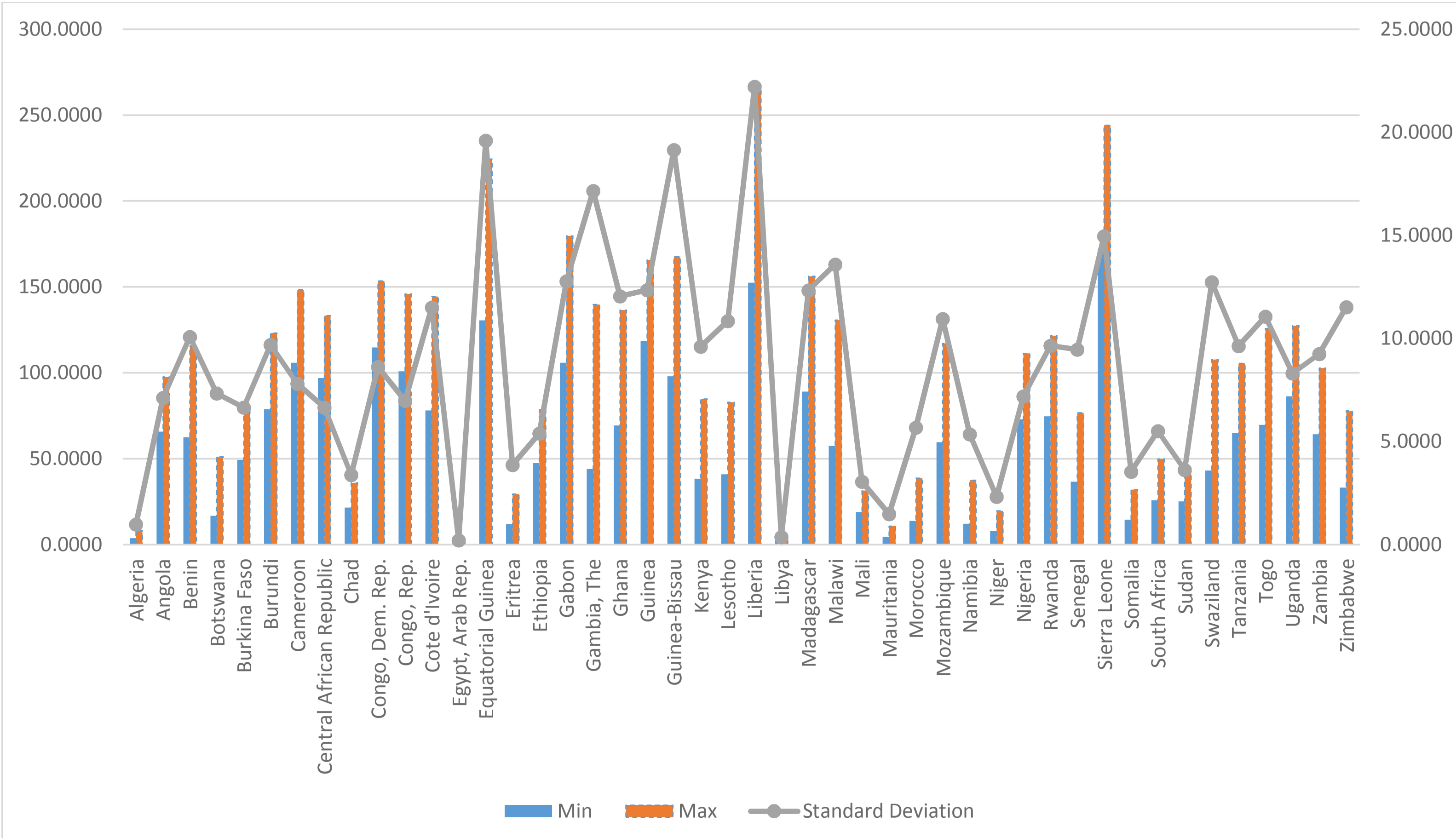


Figure 4: The intensity of Temperature Impact on Economic Growth in Africa

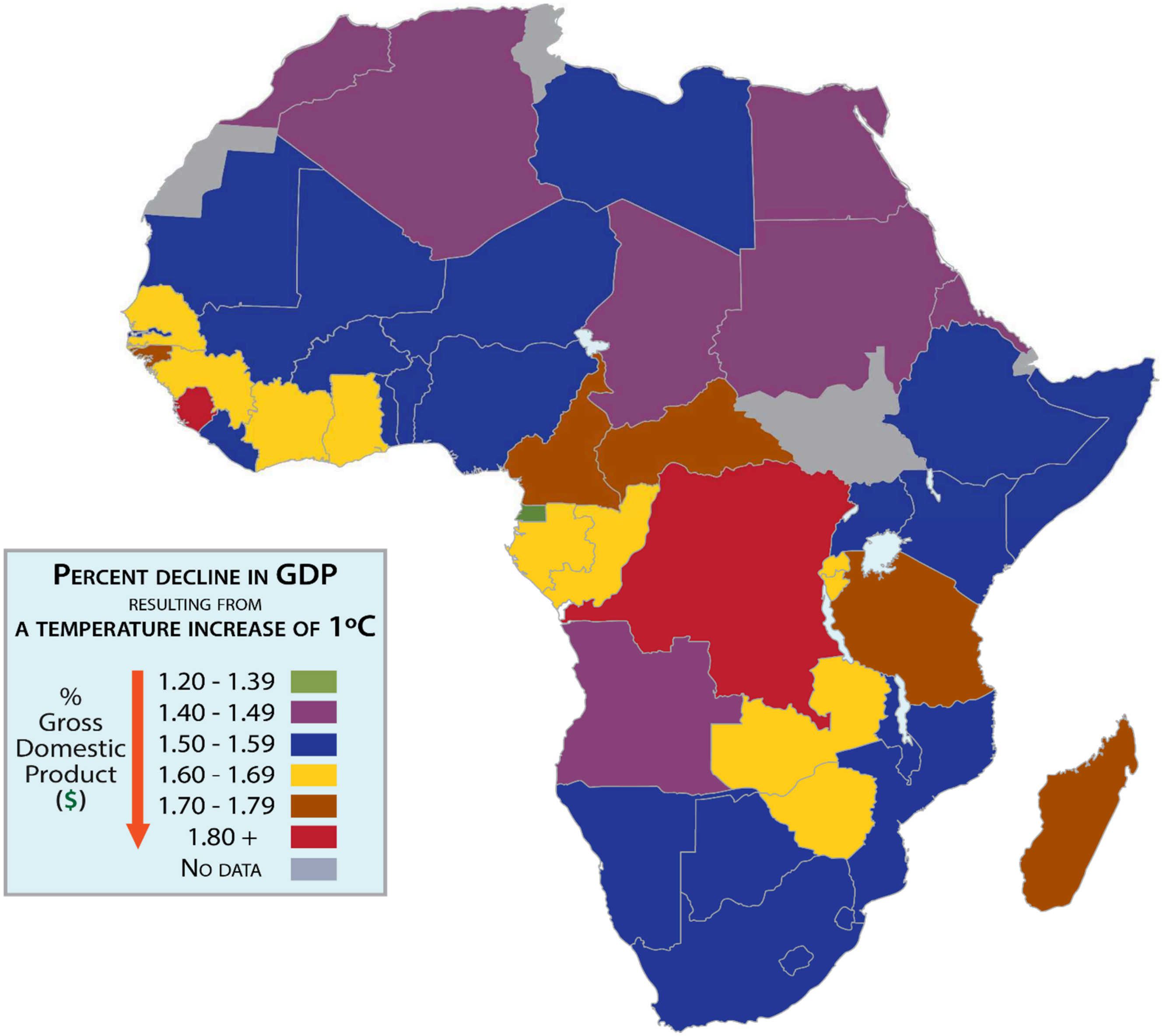
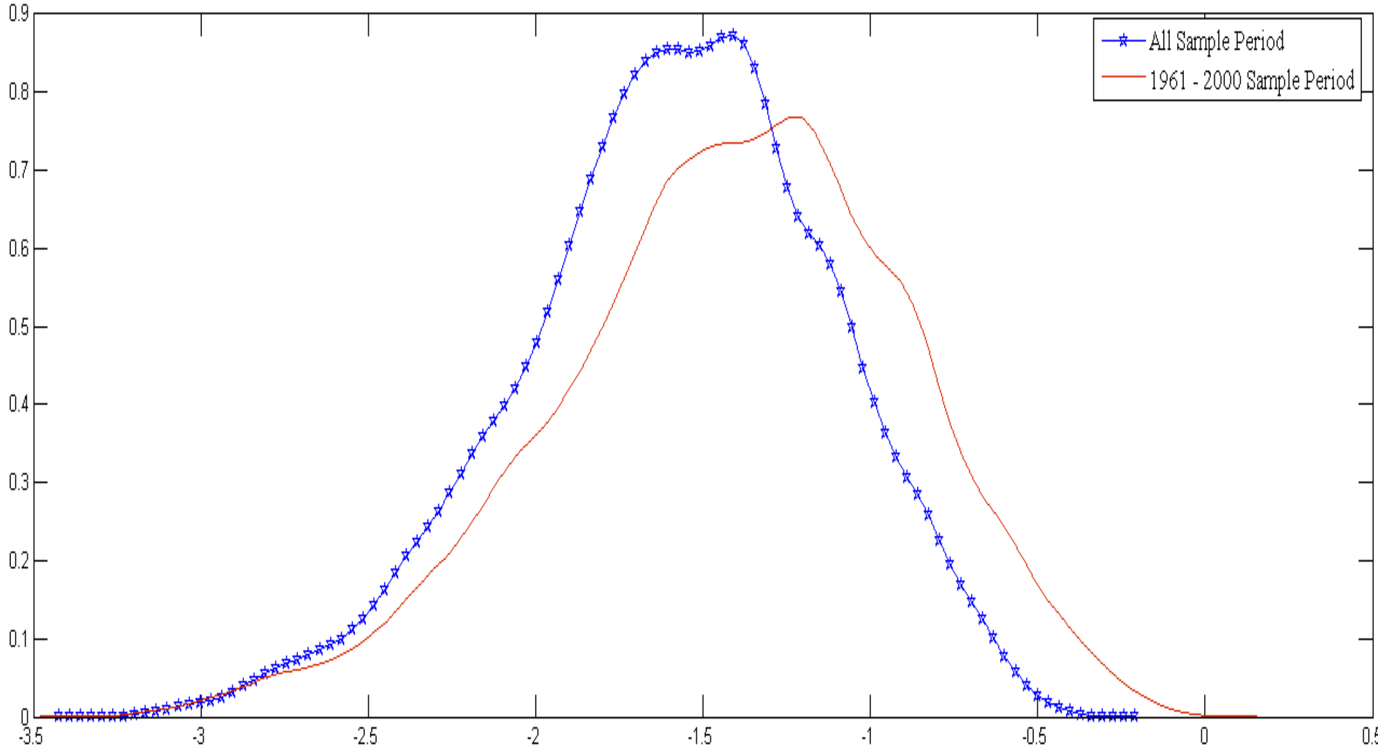


Figure 5: Distribution of the "Pooled" Mean Effect of Temperature on GDP Growth in Africa



Appendix

Appendix 1: Additional information on the model specification

For estimation purposes, we rewrite equation (1) in matrix form as:

$$\begin{aligned} y_{it} &= [1 \quad x_{it} \quad L_{it}] \begin{pmatrix} \alpha_i \\ \beta_i \\ \tau \end{pmatrix} + \varepsilon_{it} \\ &\equiv M_{it}\theta_i + \varepsilon_{it} \end{aligned} \qquad \ldots\ldots \text{(A1)}$$

The above equation (A1) will seek to draw α_i, β_i and τ in a single block. The mean and variance matrix of θ_i will incorporate the hierarchical priors explained earlier.

Specifically:

$$\theta_i = \begin{bmatrix} \alpha_i \\ \beta_i \\ \tau \end{bmatrix} \sim N\left(\theta \equiv \begin{bmatrix} z_i\gamma \\ \beta_0 \\ \mu_\tau \end{bmatrix}, \widetilde{\Sigma} \equiv \begin{bmatrix} \delta_\alpha^2 & \rho\delta_\alpha\delta_\beta & 0 \\ \rho\delta_\alpha\delta_\beta & \delta_\beta^2 & 0 \\ 0 & 0 & V_\tau \end{bmatrix} \right) \qquad \ldots\ldots\ldots\ldots\ldots.(A2)$$

Posterior Simulator

Before describing the posterior simulator, first let $\beth = [\{\theta_i\}_{i=1}^{n} \quad \gamma \quad \beta_0 \quad \widetilde{\Sigma}^{-1} \quad \sigma_\varepsilon^2]$ 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:

$$p(\beth|y) \propto \left[\prod_{i=1}^{N} p(y_i|M_i, \theta_i, \sigma_\varepsilon^2) p\left(\theta_i \middle| \gamma, \beta_0, \mu_\tau, V_\tau, \widetilde{\Sigma}^{-1}, z_i\right)\right] p\left(\gamma \middle| \mu_\gamma, V_\gamma, \delta_\alpha^2\right) p\left(\beta_0 \middle| \mu_{\beta_0}, V_{\beta_0}, \delta_\beta^2\right) p\left(\gamma \middle| \mu_\gamma, V_\gamma, \delta_\alpha^2\right)$$

$$p(\sigma_\varepsilon^2|a_\varepsilon, b_\varepsilon)\; p(\Sigma^{-1}|\rho_0, R) \qquad \ldots\ldots\ldots\ldots\ldots\ldots.(A3)$$

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

This complete conditional is proportional to the joint posterior distribution $p(\beth|y)$. Absorbing all the terms that do not involve θ_i into the normalizing 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:

$$y_i = \begin{bmatrix} y_{i1} \\ y_{i2} \\ \vdots \\ y_{it} \end{bmatrix}, \qquad M_i = \begin{bmatrix} 1 & x_{i1} & L_{i1} \\ 1 & x_{i2} & L_{i2} \\ \vdots & \vdots & \vdots \\ 1 & x_{iT} & L_{iT} \end{bmatrix}.$$

Thus, using the result of Lindley and Smith (1972) we obtain:

$$p(\theta_i | ב_{-\theta_i}, y) \sim N(D_{\theta_i} d_{\theta_i}, D_{\theta_i}), \;\; i = 1,2,\dots,N \qquad \dots\dots\dots\dots\dots\dots(A4)$$

Where

$$D_{\theta_i} = \left(\frac{M_i' M_i}{\sigma_\varepsilon^2} + \tilde{\Sigma}^{-1} \right)^{-1} \quad d_{\theta_i} = \frac{M_i' y_i}{\sigma_\varepsilon^2} + \tilde{\Sigma}^{-1}\theta$$

We sample each of the θ_i by drawing from the corresponding complete conditional.

Step 2: Complete Posterior Conditional for γ and β_0 will follow by conditioning on α_i and β_i respectively.

The complete conditionals for γ:

$$\gamma | ב_{-\gamma} \sim N(Rr, R)$$

Where

$$R = \left(\frac{z'z}{\sigma_\alpha^2} + V_\gamma^{-1} \right)^{-1} \quad r = \frac{z'\bar{\alpha}}{\sigma_\alpha^2} + V_\gamma^{-1}\mu_\gamma$$

And $\bar{\alpha}$ is all the country specific constants stacked.

Step 3: Complete Posterior Conditional for σ_ε^2

$$\sigma_\varepsilon^2 | ב_{-\sigma_\varepsilon^2}; y \sim IG\left(N * \frac{T}{2} + a_\varepsilon, \left[0.5 \sum (y_i - M_i\theta_i)' (y_i - M_i\theta_i) + b_\varepsilon \right]^{-1} \right)$$

Step 4: Complete Posterior Conditional for $\sum^{-1}$

$$\textstyle\sum^{-1} | ב_{-\sum^{-1}}; y \sim W\left(\left[\sum (\tilde{\theta}_i - \tilde{\theta}) (\tilde{\theta}_i - \tilde{\theta})' + R\rho_0 \right]^{-1}, N + \rho_0 \right)$$

Where $\tilde{\theta}_i$ refers to only elements of α_i and β_i in the vector θ_i.

Appendix 2: Country Estimates with Model Diagnostics - Posterior mean, Probability that the parameter is less than zero, Posterior standard deviation and Numerical standard errors.

Values	Mean	Pr(:<0|y)	Std	NSE
Algeria	-1.4817	1.0000	0.4779	0.0630
Angola	-1.4637	1.0000	0.4844	0.0644
Benin	-1.5899	1.0000	0.4643	0.0627
Botswana	-1.5332	1.0000	0.4869	0.0600
Burkina Faso	-1.5390	1.0000	0.4664	0.0632
Burundi	-1.6838	1.0000	0.4702	0.0628
Cameroon	-1.7031	1.0000	0.4664	0.0623
Central African Republic	-1.7486	1.0000	0.4640	0.0624
Chad	-1.4842	1.0000	0.4683	0.0633
Congo, Dem. Rep.	-1.8219	1.0000	0.4667	0.0620
Congo, Rep.	-1.6702	1.0000	0.4697	0.0618
Cote d'Ivoire	-1.6393	1.0000	0.4706	0.0629
Egypt, Arab Rep.	-1.4086	1.0000	0.4739	0.0617
Equatorial Guinea	-1.2443	0.9992	0.4806	0.0632
Eritrea	-1.4499	1.0000	0.4882	0.0625
Ethiopia	-1.5365	1.0000	0.4665	0.0625
Gabon	-1.6912	1.0000	0.4837	0.0637
Gambia, The	-1.5744	1.0000	0.4662	0.0623
Ghana	-1.6373	1.0000	0.4690	0.0622
Guinea	-1.6812	1.0000	0.4670	0.0623
Guinea-Bissau	-1.7275	1.0000	0.4624	0.0623
Kenya	-1.5435	1.0000	0.4683	0.0621
Lesotho	-1.5420	0.9996	0.5403	0.0630
Liberia	-1.5825	0.9998	0.5391	0.0674
Libya	-1.5140	1.0000	0.4931	0.0634
Madagascar	-1.7713	1.0000	0.4710	0.0621
Malawi	-1.5489	1.0000	0.4771	0.0623
Mali	-1.5157	1.0000	0.4629	0.0626
Mauritania	-1.5068	1.0000	0.4743	0.0633
Morocco	-1.4915	1.0000	0.4858	0.0633
Mozambique	-1.5721	1.0000	0.4687	0.0623
Namibia	-1.5945	1.0000	0.4983	0.0637
Niger	-1.5340	1.0000	0.4707	0.0633
Nigeria	-1.5810	1.0000	0.4653	0.0629
Rwanda	-1.6280	1.0000	0.4749	0.0628
Senegal	-1.6124	1.0000	0.4634	0.0622
Sierra Leone	-1.8005	1.0000	0.4717	0.0627
Somalia	-1.5703	1.0000	0.4766	0.0621
South Africa	-1.5171	1.0000	0.4830	0.0632
Sudan	-1.4889	1.0000	0.4636	0.0618

Swaziland	-1.5432	1.0000	0.4876	0.0640
Tanzania	-1.7900	1.0000	0.4750	0.0604
Togo	-1.5634	1.0000	0.4670	0.0623
Uganda	-1.5084	1.0000	0.4679	0.0625
Zambia	-1.6850	1.0000	0.4843	0.0633
Zimbabwe	-1.6438	1.0000	0.4727	0.0627