Climatic factors and economic growth in Africa

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Abstract

Using a recently developed historical weather dataset, this paper investigates the economic effects of rainfall and temperature on a panel of 36 African economies over the 1962-2000 period. We adopt the econometric approach based on Mean Group and Pooled Mean Group estimation of Autoregressive Distributed Lag models and find clear evidence of significant long-run relationships between climatic factors and per-capita GDP: Temperature has strong negative long-run effects, while rainfall enters with a positive sign. Very similar findings are reported for labour productivity, while the evidence for population is weaker. The results are remarkably robust to several extensions and checks on the baseline model.

JEL Classification: O44, Q54

Keywords: Climate; Economic growth; Africa; Pooled mean group estimation

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1. Introduction

The disappointing growth performance of African countries, many of which are among the poorest in the world, has for a long time been the focus of much interest in the literature, lately reinforced by the growing gap with other emerging countries, particularly the fast-growing Asian economies. Several factors have been pointed at as major determinants of this so-called “African growth tragedy” (Easterly and Levine, 1997). These range from political causes, such as badly functioning institutions or markets (Elbadawi and Ndulu, 1996; Mauro, 1995), to exogenous factors associated to the excessive sectoral concentration of the African countries’ exports (Sachs and Warner, 1997) or the inefficient allocation of external aid (Burnside and Dollar, 2000). The empirical evidence so far is, by and large, mixed.

A fairly overlooked aspect and potential determinant of slow growth in Africa relates to the geographical and, particularly, climatic features characterising many African countries. This neglect in the literature is somewhat surprising, since the contention that the climate affects economic activity can be traced back to classic early studies, such as Huntington (1915) and Marshall (1890). Most research on the topic is not directly concerned with the African countries and explores specific aspects of the climate-growth relationship and the individual channels via which climatic features can play a role in constraining or fostering growth and economic development. In particular, several studies focus on the effects of climatic changes on agriculture (e.g. Deschenes and Greenstone, 2007; Mendelsohn et al., 2001), but also crime, civil conflict, mortality and migration attracted much interest (e.g. Brückner and Ciccone, 2010; Deschenes and Moretti, 2007; Jacob et al., 2007; Miguel et al. 2004).

A new strand of this literature adopts a different approach, focused on the overall impact of the climate on economic growth rather than on the individual transmission channels, and exploits recently-developed historical weather datasets. Among these, Dell et al. (2008) investigate the short-term impact of climatic changes around the world and, using data over the 1950-2003 years for 136 countries, find significantly negative effects for both higher precipitation and temperature on per-capita GDP, although the negative effects of warming are significant only for poor countries. Moreover, relying on cross-section estimation, Dell et al. (2008) show that the negative impact of higher temperature in poor countries appears to be even stronger in the long-run, whereas the effects of precipitation turn out to be only temporary and, thus, not significant in the long-term. Using the same climate dataset as Dell et al. (2008), Jones and Olken (2010) focus on trade data and find that higher temperatures have significantly negative effects on poor countries' export growth, predominantly for agriculture and light manufacturing, while there is very little (and not robust) evidence of a positive role for precipitation patterns.[1]

Given the structural characteristics of African economies, there are reasons to expect these climatic effects to be more prominent in Africa than in other parts of the world.[2] In particular, warmer climates and declining precipitation trends can potentially represent significant constraints on the African economies' growth performances, for instance, due to their significant reliance on the agricultural sector. In these countries, water availability for irrigation (and other) purposes is often highly dependent on precipitation, so that rainfall shortages can represent a significant constraint on agricultural production and, by extension, on the economy as a whole. Apart from their direct negative effects (on health, labour productivity, crime rates, etc…), the high

[1] See also Dell et al. (2009).

[2] This view is implicitly or explicitly shared by many studies in the literature, e.g. Brückner (2010), Brückner and Ciccone (2010), Miguel et al. (2004).

temperatures characterising many of the countries in the continent amplify the problems arising from water scarcity, e.g. by reducing the runoff from water-rich areas to arid lands.[3]

Nonetheless, the evidence on the role of climatic factors in Africa is, as yet, not conclusive. For the sub-sample of Sub-Saharan African countries, Dell et al. (2008) find that, as expected, the temperature and precipitation variables enter, respectively, with a negative and positive sign, but both turn out to be not significant suggesting that climatic factors do not play a major role in Africa. However, limiting the attention specifically to Sub-Saharan Africa, Barrios et al. (2010) present evidence to the contrary. They investigate the role of declining trends in rainfall as a potential cause of persistently slow growth in the continent, adopting a conditional convergence approach and using a newly developed dataset based on rainfall data from the Inter-Governmental Panel on Climate Change (IPCC). Barrios et al. (2010) find that the decline in rainfall had a significantly negative effect on growth in Africa. Simulations based on their conditional convergence framework suggest that, depending on the level of rainfall assumed as a benchmark, the per-capita GDP differential between Sub-Saharan African and non-African developing countries could have been 15 to 40 per cent lower than it turned out to be.

Following this recent line of research, this paper investigates the economic impact of climatic factors in Africa. We add to the body of empirical evidence so far gathered by focusing on both rainfall and temperature, the two climatic features singled out in the abovementioned studies, as well as considering not only per-capita GDP but also labour productivity and population as dependent variables. Though we also estimate the short-run impact of changes in rainfall and temperature, our main interest lies in assessing the long-run economic effects of the climate. Thus, we give explicit consideration to the stationarity properties of the series under analysis, an aspect so far neglected in the literature, making use of unit root and panel unit root tests and adopting the

[3] For a more complete discussion of these points, see Barrios et al. (2010).

Autoregressive Distributed Lag approach to cointegration analysis via Mean Group and Pooled Mean Group estimation (Pesaran and Smith, 1995; Pesaran et al., 1997, 1999).

To preview our results, we find significant evidence of a long-run equilibrium relationship for (both the level and growth rate) of per-capita GDP and labour productivity with, respectively, negative long-run effects for higher temperature and a positive long-run impact of higher precipitation. Moreover, there is only weak evidence of a significant relationship of climatic factors with either the level or growth rate of population. This outcome is remarkably robust to several extensions and checks performed on the baseline model, by splitting the sample of countries according to different criteria, allowing for non-linear behaviour, asymmetries and cross-section dependence.

The remainder of the paper is organised as follows. Section 2 describes the data and methodology used in this paper, while Section 3 presents and discusses the results from the baseline models. Section 4 and its subsections present a number of extensions and robustness checks on the benchmark models. Section 5 concludes.

2. Data

To investigate the economic impact of climatic changes in Africa we make use of panel regression techniques and a panel dataset of annual data over the 1962-2000 period for 36 African countries.[4] The panel is slightly unbalanced, as there are some gaps in the per-capita GDP and labour productivity series. The dataset on rainfall and temperature used in this paper is that developed by Dell et al. (2008) and also used by Jones and Olken (2010), which is built on data taken from the *Terrestrial and Air Temperature and Precipitation: 1900-2006 Gridded Monthly Time Series,*

[4] For a list of the countries included in the panel dataset, see Appendix A.

Version 1.01 (Matsuura and Willmott, 2007).[5] The latter provides worldwide (terrestrial) monthly mean precipitation and temperature data at 0.5 x 0.5 degree resolution (approximately 56km x 56km at the equator), which Dell et al. (2008) aggregate to the country-year level, weighting by population distribution, using geospatial software.[6]

As in other studies, per capita GDP is our main variable of interest, but we also consider labour productivity and population as alternative dependent variables in our models, as both play a relevant role in relation to economic growth. According to standard growth theory, labour productivity can be considered a proxy for technological progress, the main driver of long-run growth. Population, on the other hand, can influence both per-capita GDP and productivity, either positively or negatively, according to whether or not population growth gives rise to some type of increasing returns (e.g. via human capital accumulation) as postulated by endogenous growth theory (e.g. Romer 1986, 1989). Our empirical work will consider both the levels and growth rates of the variables under analysis. Data on per capita GDP, labour productivity and population are taken from the *Penn World Tables, Version 6.3* (Heston et al., 2009).

2.1. Econometric methodology: The ARDL approach

There is a large consensus in the literature on cointegration analysis as the most appropriate approach to study long-run relations in panels. When the series under investigation are non-stationary, several panel cointegration techniques are now available to test whether they share a common long-run (cointegrating) relationship (e.g. Pedroni, 1999, 2001, 2004; Westerlund, 2007). However, due to power problems, panel cointegration tests can lead to potentially misleading

[5] We are grateful to Ben Jones for kindly making the dataset available.

[6] For a detailed description of the construction of the dataset, see the Appendix I in Dell et al. (2008).

inference if a fraction of the series are stationary (Karlsson and Löthgren, 2000; Gutierrez, 2003). Thus, ascertaining the order of integration of the variables under analysis is an essential precondition to establish whether the use of panel cointegration tests is warranted.

A suitable alternative, which we will rely upon, is to adopt the Autoregressive Distributed Lag (ARDL) framework proposed by Pesaran et al. (1997, 1999) and carry out the analysis using the Mean Group (MG) and/or Pooled Mean Group (PMG) estimators. Both the MG and the PMG provide consistent estimates in a dynamic panel context even in the presence of potentially non-stationary regressors. Moreover, the ARDL approach allows the researcher to retrieve both the short-run and the long-run parameters of the model within the same estimation framework.

The general $ARDL\left(p, q_1, ..., q_k\right)$ panel specification can be formalised as follows

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta_{ij}^{'} X_{i,t-j} + \mu_i + \varepsilon_{it} \qquad (1)$$

where $i = 1, 2, ..., N$ indicates the cross-sections (groups); $t = 1, 2, ..., T$ the time periods; X_{it} is a $k \times 1$ vector of explanatory variables; δ_{ij} are the $k \times 1$ coefficient vectors; the coefficients of the lagged dependent variables, λ_{ij}, are scalars; μ_i represents the (group-specific) fixed effect. If the variables are I(1) and cointegrated, the short-run dynamics of the model will be influenced by any deviation from equilibrium, so that it is common to express (1) using the following error correction representation:

$$\Delta y_{it} = \phi_i \left(y_{i,t-1} - \beta_i^{'} X_{it} \right) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij}^{*'} \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \qquad (2)$$

where $\phi_i = -\left(1 - \sum_{j=1}^{p} \lambda_{ij}\right)$, $\beta_i = \sum_{j=0}^{q} \delta_{ij} \Big/ \left(1 - \sum_k \lambda_{ik}\right)$, $\lambda_{ij}^* = -\sum_{m=j+1}^{p} \lambda_{im}$ with $j = 1, 2, ..., p-1$, $\delta_{ij}^* = -\sum_{m=j+1}^{q} \delta_{im}$ with $j = 1, 2, ..., q-1$. The parameter ϕ_i is the speed of adjustment of the error-correction process, which is significantly negative when the variables display reversion to a long-run equilibrium. The vectors $\beta_i^{'}$ and $\delta_{ij}^{*'}$ contain, respectively, the long-run and short-run parameters of the model. Lag selection in the ARDL model can be performed using single-equation estimation for each of the panel units. Removing serial correlation, the selection of an appropriate lag order also eliminates the problems arising from potential (regressor) endogeneity. However, particularly when the analysis of the short-run parameters is also of interest, it is recommended that all of the panel cross-sections be imposed the same lag order, chosen in accordance to the model and data limitations (Loayza and Ranciere, 2006).

Provided that both *N* and *T* are sufficiently large, estimation of dynamic panel models, such as that formalised in (1), can be performed with several alternative approaches, which differ according to the degree of parameter heterogeneity allowed for. On one extreme, the pooled estimator imposes full-homogeneity of slope and intercept coefficients, while the fixed-effects estimator allows only the intercepts to differ across groups. If the coefficients are in fact heterogeneous, these estimators will produce inconsistent and misleading results. At the other extreme, the fully heterogeneous-coefficient model is fitted separately for each group, imposing no cross-group parameter restrictions. The mean of the long- and short-run parameters across groups can, then, be estimated consistently by the simple arithmetic average of the coefficients: This is the MG estimator introduced by Pesaran and Smith (1995). Between the two extremes, the PMG estimator, developed by Pesaran et al. (1999), combines both pooling and averaging, allowing the intercept and short-run coefficients (including the speed of adjustment) to differ across groups (as the MG estimator), but restricting the long-run slope coefficients to be the same across groups (as the fixed-effects estimator).

The choice among the MG and PMG estimators depends on the trade-off between consistency and efficiency. The PMG estimator imposes cross-group homogeneity of the long-run parameters, yielding consistent and efficient estimates and, thus, dominating the heterogeneous MG estimator in terms of efficiency when the restrictions are valid. If, however, the hypothesis of long-run parameter homogeneity is invalid, the PMG estimates are inconsistent while the MG estimator remains consistent. This suggests the use of a standard Hausman test on the long-run parameter-homogeneity restriction to choose the most appropriate between the MG and PMG estimators (Pesaran et al., 1999).

3. Econometric Results

We start by assessing the stationarity properties of the series under analysis: temperature (*T*), rainfall (*R*), per-capita GDP (*Y*), labour productivity (*LP*) and population (*P*). We make use of the classic univariate Augmented Dickey-Fuller (ADF) test, as well as three well-known panel unit root (PUR) tests.[7] The first is the widely-used IPS test proposed by Im et al. (2003) which, however, is suitable only for balanced panels, so that it cannot be applied to the per-capita GDP and labour productivity series in our panel. Thus, we also make use of the Fisher-type test developed by Maddala and Wu (MW, 1999), which is suitable for unbalanced panels and is based on the pooling of individual *p*-values from univariate unit-root tests (e.g. ADF tests).

Both the MW and IPS tests are first-generation PUR tests, which have been shown to suffer from power problems and size distortion in the presence of cross-section dependence (e.g. Banerjee et al., 2005). In contrast, the third PUR test we make use of, the (standardised version of the) CIPS test developed by Pesaran (2007), is an example of the so-called second-generation PUR tests,

[7] To save space, we do not describe in detail the PUR tests. The reader is referred to the relevant references.

which are built to explicitly control for cross-section dependence in various ways. Specifically, the CIPS test assumes that cross-section dependence arises from the presence of a common factor and corrects for it via the inclusion of cross-section means as additional regressors in an ADF-type regression.[8]

Table 1. ADF unit root tests

Country	*T*	*R*	*Y*	*LP*	*P*
Algeria	-0.610	-6.958**	-2.816^	-3.210*	-3.881**
Benin	-1.793	-4.845**	-1.613	-2.450	3.566
Burkina Faso	-1.245	-2.664^	-0.927	-1.272	-1.204
Burundi	-0.957	-2.098	-2.091	-2.674^	-0.046
Cameroon	-4.923**	-1.983	-1.832	-1.772	-1.945
Central African Republic	-1.806	-4.910**	-0.449	-0.537	-0.426
Chad	-2.128	-2.480	-2.133	-1.762	4.147
Congo, Dem. Rep.	-0.189	-4.254**	1.680	1.658	0.006
Congo, Rep. Of	-3.872**	-6.253**	-1.467	-1.570	7.136
Cote d`Ivoire	-4.441**	-5.389**	-3.099*	-3.124*	-3.188*
Djibouti	-2.920*	-5.929**	-1.612	-1.646	-5.317**
Egypt	-4.776**	-4.724**	-0.154	-0.376	-0.300
Equatorial Guinea	-5.030**	-4.620**	-1.220	-1.138	-0.336
Gabon	-4.309**	-6.097**	-4.038**	-4.016**	-0.047
Gambia	-1.680	-4.727**	-1.174	-1.427	2.369
Ghana	-5.155**	-5.812**	-2.380	-2.449	0.199
Guinea	-5.060**	-2.183	-2.537	-2.508	1.461
Kenya	-4.016**	-5.235**	-2.877*	-3.709**	-2.683^
Liberia	-5.107**	-1.850	-1.500	-1.504	-0.774
Madagascar	-3.090*	-3.523**	-3.291*	-3.398*	-0.480
Mali	-4.315**	-4.295**	0.437	0.483	0.489
Mauritania	-4.601**	-3.756**	-6.943**	-6.983**	4.204
Mauritius	-2.856^	-4.690**	0.747	0.625	-1.864
Morocco	-1.821	-5.052**	-2.346	-3.354*	-1.020
Mozambique	-1.635	-6.911**	-1.863	-2.303	-0.118
Niger	-2.236	-4.296**	-0.906	-0.879	2.031
Nigeria	-2.031	-4.340**	-2.165	-2.305	-3.216*
Senegal	-4.763**	-4.935**	-1.984	-2.180	-0.507
Sierra Leone	-4.880**	-3.747**	-0.226	-0.428	0.031
Somalia	-3.887**	-5.195**	-0.442	-0.317	-1.150
Sudan	-1.402	-3.867**	-1.534	-1.514	-0.518
Tanzania	-1.389	-5.905**	-3.397*	-3.457**	-1.047
Togo	-4.838**	-5.489**	-1.735	-1.902	0.688
Tunisia	0.107	-6.807**	-1.156	-2.100	-2.014
Uganda	-3.610**	-6.562**	-1.091	-1.011	0.964
Zambia	-0.975	-5.874**	-0.296	-0.188	-2.042

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level

[8] The CIPS is, thus, a cross-sectionally augmented version of the IPS test.

Table 2. PUR tests

	T	*R*	*Y*	*LP*	*P*
IPS	-9.945**	-23.738**	-	-	1.996
MW	295.22**	463.61**	142.18**	147.16**	38.55
CIPS	-8.770**	-20.572**	1.823	0.235	-0.789

Notes: ** indicates significant at the 1% level.

As common in the literature, the IPS, MW and CIPS consider the null of a unit root for all the cross-sections in the panel against the heterogeneous alternative hypothesis that at least a positive fraction of them are stationary. Rejection of the null, therefore, cannot be considered as evidence that all the cross-section units are I(0), but rather it indicates that at least some of them are, while the remaining may be non-stationary.

The unit-root test results for the series in our panel dataset are reported in Tables 1 and 2. The optimal lag length selection was performed using the general-to-specific procedure suggested by Ng and Perron (1995). Throughout the econometric work in this and the following sections, all the data used were transformed to natural logarithms.

The univariate ADF tests (Table 1) indicate that we are dealing with are a mix of I(1) and I(0) variables. Temperature and, particularly, precipitation appear to be stationary for the majority of countries, while the opposite is true for per-capita GDP, labour productivity and population. This outcome is confirmed by the use of 1^{st}- and 2^{nd}-generation PUR tests. The PUR null hypothesis is strongly rejected by the IPS, MW and CIPS tests for temperature and precipitation, while none of the tests reject it for population and only the MW test supports the view that (at least some of) the labour productivity series are I(0). As mentioned, in this context the use of panel cointegration tests would be inappropriate and likely to lead to misleading inference.

We, thus, proceed implementing the ARDL approach via MG and PMG estimation methods, as laid out in the previous section. Following a common practice in the literature (Loayza and Ranciere, 2006), we impose a common lag-structure to all the panel cross-sections adopting the ARDL(1,1,1) throughout our econometric work as, using the Schwarz Bayesian Criterion (SBC), we find that, for most of the cross-sections in our panel, the ARDL (1,1,1) is the appropriate model. This choice is consistent with the use of annual data and minimises the loss of degrees of freedom, which is a concern in our case given the relatively short time-series in our panel.[9] Moreover, measuring climatic features, both temperature and rainfall can be confidently considered strictly exogenous for the African countries, so that endogeneity issues are irrelevant in our case.[10]

Table 3. Panel ARDL estimations

Dependent Variable	*Y*	*ΔY*	*LP*	*ΔPL*	*P*	*ΔP*
Estimator	PMG	MG	PMG	MG	PMG	PMG
LR Coefficient						
R	0.353**	0.063**	0.299**	0.066**	0.012	-0.008**
T	-1.870*	0.254	-2.477**	0.152	0.331	-0.042^
SR Coefficient						
EC	-0.103**	-0.993**	-0.108**	-0.984**	0.0004	-0.308*
ΔR	-0.019	-0.022	-0.157	-0.022	-0.004	-0.001
ΔT	-0.237^	-0.402*	-0.219^	-0.376*	0.024	0.037
Constant	1.310**	-0.553	1.690**	-0.234	0.022	0.055**
Hausman statistic	1.54	6.35	2.37	7.62	4.51	0.03
p-value	0.46	0.04	0.30	0.02	0.10	0.98

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level

[9] Notice that the PMG estimator, which turns out to outperform the MG technique in most of our regressions, has been shown to be robust to the choice of lag order, as well as to outliers (e.g. Pesaran et al.,1999, and Martínez-Zarzoso and Bengochea-Morancho, 2004). This greatly reduces any concerns regarding the selection of the lag order.

[10] This would be different in a study not limited to Africa, but considering the global economic effects of the climate, in which case the current debate and growing body of empirical evidence on man-made global warming would require a thorough consideration of endogeneity issues.

Table 3 reports the estimation results.[11] The error-correction coefficient turns out to be negative and significant in all estimations, except the case in which the log-level of population is taken as dependent variable. As regards per-capita GDP, the Hausman test indicates that the long-run coefficient-homogeneity assumption cannot be rejected, so the PMG estimator is preferred to the MG method – a result that is common to 6 of the 8 models considered in Table 3. The long-run elasticities to rainfall and temperature are both significant and have the expected sign. The sizes of the coefficients suggest fairly strong negative effects for temperature, with a 1 per cent increase leading to about a 1.9 per cent fall in per capita GDP in the long-term, while the impact of a 1 per cent precipitation shock is in the order of 0.35 percentage points. The short-run elasticities, however, turn out to be not significant (in the case of rainfall) and significant only at the 10 per cent level (temperature). This result is consistent with the evidence uncovered by Dell et al. (2008) and is, by and large, confirmed in all of the estimations we carry out in this paper: While the short-term coefficients turn out to be not significant in most cases, the long-run elasticities are usually strongly significant, indicating that the effects of precipitation and temperature shocks are persistent and accumulate over time.

This reading of the results is reinforced by the comparison between the “log-level” and “growth-rate” specifications. The speed of adjustment to rainfall and temperature shocks is always faster for the growth rates than for the levels of the variables under consideration, indicating that, for per-capita GDP and labour productivity, more than 90 per cent of the correction takes place within the year. The estimated long-run elasticities, however, are smaller in the “growth-rate” specifications, while the short-run coefficients are larger and, in the case of temperature, also significant (with the exclusion of the population-growth model). This suggests that rainfall and temperature shocks have significant, rapid and permanent effects on the growth rates of per-capita

[11] To save space, in this paper we report solely the results from the preferred estimator between the MG and PMG methods, chosen according to the Hausman test. The complete set of estimation results is available from the author upon request.

GDP, labour productivity and population. These effects gradually build up over time, so that the long-term impact on the levels of the variables considered is larger than on the growth rates.

This picture fits fairly closely particularly the results for the per-capita GDP and labour productivity models. Moreover, looking at the preferred estimations (chosen according to the Hausman statistic), in these two cases the sizes of the estimated long-run coefficients are very similar and their signs always those expected, with the exception of the long-run elasticities to temperature in the growth-rate specifications. Thus, it appears that the climatic features under analysis influence per-capita GDP primarily via their impact on productivity, rather than population. Indeed, if the estimated long-run elasticities are significant (though small) in the population-growth model, the short-run coefficients are not and we do not find any evidence of a significant long-run relationship in the log-level specification for population.[12]

Overall, therefore, our results provide strong support for the hypothesis that long-run economic growth in Africa is significantly affected by climatic conditions. To qualify and reinforce this evidence, in the next section we extend the econometric analysis carried out so far and perform a series of robustness checks.

4. Extensions and robustness of the results

We start our assessment on the robustness of the results by excluding the North African countries from the sample, to limit the analysis to Sub-Saharan Africa. Subsequently, we split the complete sample along the high/low temperature and rainfall divides, to ascertain the possible presence of non-linearities triggered by high/low values of temperature or precipitation. We, then, also assess

[12] As seen later on, this result is partly reversed when we take account of cross-section dependence in the MG and PMG estimations.

the role of asymmetries in the ARDL model, allowing for heterogeneous effects between positive and negative changes in temperature and rainfall. Finally, we investigate the effects of the possible presence of cross-section dependence in the panel ARDL model at the basis of our MG and PMG estimations.

4.1. Sample splitting

Many studies in the literature on growth and development in Africa focus on Sub-Saharan countries, leaving aside the North African economies on the (explicit or implicit) assumption that the latter, for a variety of reasons, belong to a different "club". In the context of our analysis, it is not immediately clear that this distinction is warranted, as the climatic factors at the centre of our investigation can certainly have important effects on Northern African countries too (e.g. Tropp and Jägerskog, 2006).[13] Thus, to maximise panel size we included in our sample four North African countries (i.e. Algeria, Egypt, Morocco and Tunisia). We now investigate whether this has any significant bearing on the results rerunning all of the regressions on the sub-sample of 32 Sub-Saharan countries.

As can be seen from Table 4, despite the reduced number of observations, the results barely change. In particular, the significance and size of the error-correction coefficients reflect very closely those reported in Table 3, while the order of magnitude of the estimated long-run elasticities is appreciably different only for the temperature elasticities of per-capita GDP and population: In both cases, the impact of temperature appears to be stronger in the subset of Sub-Saharan countries.

[13] The World Bank, for instance, talks openly of a water crisis in Middle East and North African (MENA) countries, where in many cases more water is consumed on average than is received in rainfall (e.g. Bucknall, 2007). According to current estimates, population growth, increasing urbanisation and climate change will all contribute to a halving of per-capita water availability in the MENA region by 2050.

This suggests that the long-run relationships linking climatic features and the economy are not very dissimilar across African countries, both North and South of the Sahara desert.

Table 4. Panel ARDL estimations, Sub-Saharan African countries

Dependent Variable	*Y*	*ΔY*	*LP*	*ΔLP*	*P*	*ΔP*
Estimator	PMG	MG	PMG	MG	PMG	PMG
LR Coefficient						
R	0.353**	0.064*	0.287**	0.066**	0.046	0.024
T	-2.495**	0.302	-2.649**	0.198	1.514*	-0.009^
SR Coefficient						
EC	-0.107**	-0.968**	-0.111**	-0.965**	0.027	-0.323*
ΔR	-0.020	-0.021	-0.017	-0.021	-0.004	-0.002
ΔT	-0.212	-0.433*	-0.221	-0.407*	0.024	0.030
Constant	1.573**	-0.655	1.793**	-0.338	0.020**	-0.010**
Hausman statistic	1.21	6.92	1.54	7.20	4.41	0.06
p-value	0.55	0.03	0.46	0.03	0.11	0.97

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level

A further distinction which could affect significantly this relationship is that between countries characterised by high *vis-a-vis* low temperature and/or precipitation. That is, the phenomena under investigation may be subject to non-linearities, giving rise to different effects on the economy when temperature or precipitation are above (or below) a certain threshold value. Ideally, the critical temperature and/or precipitation threshold values should be estimated directly from the data, via threshold or smooth transition regression techniques for panel models, such as those proposed by Hansen (1999) and González et al. (2005). Unfortunately, both the non-stationarity present in our data and the dynamic nature of the relations (and model) we focus on make these estimators unfeasible in our case.

Thus, we resort to a common practice in the literature and split the sample according to the median values of temperature and precipitation to fit the ARDL model to high- and low-temperature countries, as well as high- and low-precipitation countries. That is, we re-estimate all the specifications of the ARDL model using four sub-samples including 18 countries each.

Table 5. Panel ARDL estimations, high-temperature countries

Dependent variable	*Y*	*ΔY*	*LP*	*ΔLP*	*P*	*ΔP*
Estimator	PMG	PMG	PMG	PMG	PMG	PMG
LR Coefficient						
R	0.413**	0.048*	0.324**	0.050*	0.055	-0.009*
T	-3.115**	-0.239	-3.162**	-0.387^	1.355	0.103*
SR Coefficient						
EC	-0.121**	-0.951**	-0.128**	-0.949**	0.0005	-0.380**
ΔR	-0.024	-0.009	-0.020	-0.009	-0.004	-0.003
ΔT	-0.266	-0.353^	-0.291	-0.315	0.044	0.018
Constant	2.026**	0.654**	2.315**	1.111**	0.019	-0.117**
Hausman statistic	3.67	3.79	3.22	4.33	4.37	0.05
p-value	0.16	0.15	0.20	0.11	0.11	0.97

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level

Table 6. Panel ARDL estimations, low-temperature countries

Dependent variable	*Y*	*ΔY*	*LP*	*ΔLP*	*P*	*ΔP*
Estimator	PMG	PMG	PMG	PMG	PMG	PMG
LR Coefficient						
R	0.240*	0.018	0.211	0.012	-0.008	-0.007^
T	-0.734	-0.236*	-1.769*	-0.334**	-0.411	-0.102**
SR Coefficient						
EC	-0.093**	-0.963**	-0.094**	-0.949**	0.005	-0.245**
ΔR	-0.012	-0.002	-0.009	0.002	-0.002	0.0003
ΔT	-0.179	-0.148	-0.130	-0.118	0.004	0.035
Constant	0.864	0.664**	1.259**	0.951**	0.023	0.087**
Hausman statistic	0.79	4.03	0.13	4.85	2.99	0.13
p-value	0.67	0.13	0.94	0.09	0.22	0.94

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level

As shown in Tables 5 and 6, in no case does estimating the ARDL model separately for high- and low-temperature countries affect the significance and speed of adjustment of the error correction mechanism with respect to the complete sample estimates of the previous section. Hence, the main result of the analysis, i.e. the existence of a significant long-run equilibrium relationship in 6 of the 7 models considered, is confirmed. However, there is also some evidence of non-linear effects of temperature on per-capita GDP and labour productivity, as the size of the estimated long-run elasticities are larger for high- than for low-temperature countries.

Table 7. Panel ARDL estimations, high-precipitation countries

Dependent variable	*Y*	*ΔY*	*LP*	*ΔLP*	*P*	*ΔP*
Estimator	PMG	MG	PMG	MG	PMG	PMG
LR Coefficient						
R	0.221^	0.086*	0.149	0.090*	0.059	0.006
T	-1.104	0.545	-1.157	0.420	1.454	0.012
SR Coefficient						
EC	-0.102**	-0.933**	-0.103**	-0.930**	0.0003	-0.346**
ΔR	-0.005	-0.014	-0.001	-0.015	-0.007^	-0.007^
ΔT	-0.057	-0.246	-0.034	-0.191	0.021	0.044
Constant	1.067**	-1.245	1.340**	-0.883	0.025**	-0.010**
Hausman statistic	0.34	7.07	0.44	7.09	3.62	0.27
p-value	0.845	0.03	0.84	0.03	0.16	0.87

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level

Table 8. Panel ARDL estimations, Low-precipitation countries

Dependent variable	*Y*	*ΔY*	*LP*	*ΔLP*	*P*	*ΔP*
Estimator	PMG	PMG	PMG	PMG	PMG	PMG
LR Coefficient						
R	0.410**	0.026*	0.333**	0.023^	-0.171*	-0.009**
T	-2.271*	-0.214*	-2.744**	-0.331**	-1.513	-0.075**
SR Coefficient						
EC	-0.109**	-1.016**	-0.119**	-1.003**	0.0003	-0.273**
ΔR	-0.029^	-0.021	-0.026	-0.019	0.0003	0.002^
ΔT	-0.434**	-0.478**	-0.433*	-0.463*	0.026	0.027
Constant	1.528**	0.653**	1.988**	1.027**	0.015	0.077**
Hausman statistic	5.21	1.18	3.79	1.85	4.56	0.16
p-value	0.07	0.55	0.15	0.40	0.10	0.92

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level

The results do not change much when we consider separately high- and low-precipitation countries (Tables 7 and 8). The error correction coefficients maintain the previous significance levels and size. Moreover, as before, we find some support for the hypothesis of non-linear effects, as the estimated long-run parameters for both rainfall and temperature are larger and/or more significant in low- than in high-precipitation countries.

Overall, therefore, we find that the results reported in Section 3 remain remarkably robust when splitting the sample according to various criteria, though the role played by precipitation and temperature seems to be somewhat stronger in high-temperature and low-precipitation countries.[14] Next we assess the potential impact of another type of non-linear effects, namely asymmetries.

4.2. An asymmetric ARDL approach

Building on Pesaran and Shin (1998) and Pesaran et al. (2001), Shin et al. (2009) generalise the ARDL model to allow for asymmetric cointegration behaviour. Briefly stated, in a time-series framework the approach is based on the following asymmetric long-run regression

$$y_t = \beta^{+'} x_t^+ + \beta^{-'} x_t^- + u_t \tag{3}$$

$$\Delta x_t = \upsilon_t \tag{4}$$

where y_t and x_t are scalar I(1) variables, x_t is a $k \times 1$ vector of regressors decomposed as

$$x_t = x_0 + x_t^+ + x_t^- \tag{5}$$

[14] This similarity in the results for the high-temperature and low-precipitation countries may be partly explained by the partial overlap between the two sub-samples, which occurs for 11 out of 36 countries.

where x_t^+ and x_t^- are partial sum processes of positive and negative changes in x_t, so that

$$x_t^+ = \sum_{j=1}^{t} \Delta x_j^+ = \sum_{j=1}^{t} \max\left(\Delta x_{j,} 0\right),\ x_t^- = \sum_{j=1}^{t} \Delta x_j^- = \sum_{j=1}^{t} \min\left(\Delta x_{j,} 0\right) \tag{6}$$

while β^+ and β^- are the associated asymmetric long-run parameters. Assuming the error data generating process follows a general p-th order stationary Vector Autoregression (VAR), Shin et al. (2009) show that it is possible to derive the following error correction model associated with asymmetric cointegration

$$\Delta y_t = \phi u_{t-1} + \sum_{j=1}^{p-1} \varphi_j \Delta y_{t-j} + \sum_{j=0}^{p} \left(\pi_j^+ \Delta x_{t-j}^+ + \pi_j^- \Delta x_{t-j}^- \right) + e_t \tag{7}$$

which can be rearranged as

$$\Delta y_t = \phi y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \sum_{j=1}^{p-1} \varphi_j \Delta y_{t-j} + \sum_{j=0}^{p} \left(\pi_j^+ \Delta x_{t-j}^+ + \pi_j^- \Delta x_{t-j}^- \right) + e_t \tag{8}$$

where $\theta^+ = -\rho\beta^+$, $\theta^- = -\rho\beta^-$, and π^+ and π^- are the asymmetric short-run parameters. This is an equivalent transformation of an $ARDL(p,q,q)$ model for y_t, x_t^+ and x_t^- with $q = p+1$. The null hypotheses of symmetric long-run $\left(\beta^+ = \beta^-\right)$ and short-run $\left(\pi^+ = \pi^-\right)$ cointegration relationships can be tested via standard Wald statistics following the chi-squared distribution and the bounds-testing approach proposed by Pesaran et al. (2001).

Adapting the model in (8) to a panel framework and rearranging it in error-correction form, we obtain

$$\Delta y_{it} = \phi_i \left(y_{i,t-1} - \beta_i^{+'} x_{i,t-1}^{+} + \beta_i^{-'} x_{i,t-1}^{-} \right) + \sum_{j=1}^{p-1} \varphi_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{p} \left(\pi_{ij}^{+'} \Delta x_{i,t-j}^{+} + \pi_{ij}^{-'} \Delta x_{i,t-j}^{-} \right) + \mu_i + e_t \tag{9}$$

Relying on the MG and PMG estimators, we use the model in (9) to investigate whether the effects of rainfall and temperature changes in Africa give rise to asymmetric equilibrium relationships . As before, we impose the same lag structure to all the panel cross-section fixing $p=1$. The results are reported in Table 9.

Table 9. Panel Asymmetric ARDL estimations

Dependent variable	*Y*	*ΔY*	*LP*	*ΔLP*	*P*	*ΔP*
Estimator	PMG	PMG	PMG	PMG	MG	PMG
LR Coefficient						
R+	-0.083*	0.019**	-0.092**	0.020**	0.662	-0.004**
R-	-0.085*	0.019**	-0.092**	0.019**	-0.147	-0.004**
T+	-0.441*	-0.052*	-0.543**	-0.052*	-2.013	0.001
T-	-0.471**	-0.043^	-0.600**	-0.044^	6.417	0.002
SR Coefficient						
EC	-0.120**	-1.009**	-0.123**	-1.008**	-0.008	-0.350**
ΔR+	0.027	0.031*	0.027	0.033*	-0.001	0.002
ΔR-	-0.014	0.0002	-0.012	0.001	-0.001	-0.003
L1(ΔR+)	-0.003	-0.012	-0.001	-0.013	0.004^	0.003
L1(ΔR-)	0.003	-0.014	0.004	-0.012	-0.002	0.001
ΔT+	-0.180^	-0.230*	0.104	-0.047	-0.008	-0.017
ΔT-	-0.087	-0.062	-0.229	-0.195	0.029	0.014
L1(ΔT+)	0.013	-0.084	-0.046	-0.086	-0.025	-0.007
L1(ΔT-)	-0.126	-0.051	-0.108	-0.56	0.014	0.003
Constant	0.873**	0.004	1.013**	0.001	0.082	0.009**
Hausman statistic	3.55	1.72	1.86	1.63	21.44	3.08
p-value	0.47	0.79	0.76	0.19	0.00	0.54
Long-run symmetry tests						
Wald Test on *R*	0.55	1.78	0.01	1.97	1.18	2.50
p-value	0.46	0.18	0.93	0.16	0.27	0.11
Wald Test on *T*	0.62	1.75	2.34	1.68	1.12	2.21
p-value	0.43	0.19	0.13	0.19	0.29	0.14

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level. L1 indicates lag of order 1.

With the usual partial exception of the population models, the asymmetric ARDL estimations confirm the presence of significant error correction mechanisms and produce significant estimates of the long-run elasticities for both water and rainfall, even though these coefficients do not always turn out to have the expected sign. Apart from a few cases, the short-run parameters are always insignificant, again confirming the evidence gathered in the previous sections. Thus, in assessing whether the relationships under consideration are subject to significant asymmetric behaviour, we focus solely on the long-run parameter estimates. In this respect, the Wald test results, reported at the bottom of Table 9, are clear-cut: they indicate that in no case the null hypothesis of symmetric long-run coefficients is rejected by the data. There is, thus, no significant evidence of asymmetric effects of rainfall or temperature on per-capita GDP, labour productivity or population.

4.3. Cross-sectional dependence

The presence of cross-section dependence reduces the efficiency of the ARDL estimates obtained via the MG and PMG methods and could even lead to biased results, if the dependence arises from unobserved common factors correlated with the regressors. Coakley et al. (2004) propose two different methods to overcome this drawback in the context of MG estimation. The first method (SUR-MG) is to correct for cross-section dependence via Seemingly Unrelated Regressions (SUR) estimation of the ARDL models. The second method (CS-MG) relies on the approach put forward by Pesaran (2003, 2007) and corrects for cross-section dependence via the inclusion of cross-sectional means of the dependent and independent variables as additional regressors in the ARDL model.[15] The Monte Carlo evidence in Coakley et al. (2004) shows that CS-MG outperforms SUR-MG in most situations, so that we choose to rely on the former. Moreover, extending the approach put forward in Coakley et al. (2004) to the PMG estimator, in this paper we also introduce a cross-sectionally augmented PMG (CS-PMG) estimator, which is robust to the presence of cross-section dependence. Under the null hypothesis of long-run homogeneity, which, as usual, can be tested via the Hausman test, the CS-PMG estimator is expected to be consistent and more efficient than the CS-MG estimator. Both the CS-MG and CS-PMG estimation techniques are, thus, used to assess the robustness of the results to the possible presence of cross-section dependence.

Table 10. Panel ARDL estimations robust to cross-section dependence

Dependent Variable	*Y*	*ΔY*	*LP*	*ΔLP*	*P*	*ΔP*
Estimator	CS-PMG	CS-PMG	CS-PMG	CS-PMG	CS-PMG	CS-PMG
LR Coefficient						
R	0.229**	0.022^	0.207**	0.026*	-0.005	-0.003*
T	-2.560**	-0.309**	-2.041**	-0.213*	0.054	-0.019
SR Coefficient						
EC	-0.151**	-1.000*	-0.172**	-0.999**	-0.067**	-0.425**
ΔR	-0.050	-0.040	-0.046	-0.044	-0.004	-0.002
ΔT	0.188	-0.008	0.072	-0.011	0.023	0.036
Constant	1.280**	0.450	1.152*	0.119	-0.053	0.030
Hausman statistic	1.78	3.72	2.68	4.62	1.22	1.34
p-value	0.41	0.16	0.26	0.10	0.54	0.51

Notes: ** and * indicate, respectively, significant at the 1% and 5% level

The estimation results, reported in Table 10, show that in every case the CS-PMG method outperforms the CS-MG and, more importantly, support the outcome of the previous econometric analysis and reinforce the interpretation of the evidence laid out in Section 3. More precisely, for

[15] Pesaran (2003) shows analytically that this method produces consistent estimates even when the latent common factor is nonstationary, correlated with the regressors or has heterogenous effects on the panel groups.

per-capita GDP and labour productivity the long-run parameter estimates in Table 10 are always significant and have the expected positive sign for rainfall and negative sign for temperature. For the two population models, although the long-run elasticities are significant in only one case, both the error correction coefficients turn out to be significant, so that we now find significant evidence of a long-run relationship with temperature and rainfall for all the variables and in all the models considered.

Thus, it appears that, correcting for cross-section dependence, the CS-PMG method does increase somewhat the efficiency of the estimates and removes the few exceptions to the general picture painted in the Section 3. Both per-capita GDP and labour productivity in Africa are confirmed to be significantly affected by the climatic factors considered while, though uncovering evidence of a long-run relationship, we still find that the role played by rainfall and temperature is much less relevant in shaping population trends.

5. Conclusion

The poor economic performance of African countries has received much attention in the literature, spurring a lively debate on the determinants of the ‘African Growth Tragedy’. Following a recent line of research, this paper investigates the role played by climatic factors in restraining economic progress in Africa, contributing to the fairly modest body of empirical evidence so far available on the topic.

Contrary to previous studies in the literature, we take account explicitly of the stationarity properties of the data used and, relying on the cointegration approach based on Mean Group and Pooled Mean Group estimation methods, investigate whether there exist significant long-run equilibrium relationships between both temperature and rainfall and the three dependent variables of per-capita GDP, labour productivity and population, both in log-level and growth-rate specifications. While the population models produce mixed results, we find clear supportive evidence of significant long-run relations for both per-capita GDP and labour productivity. In particular, temperature and rainfall turn out to have, respectively, negative and positive effects on the levels and growth rates of per-capita GDP and labour productivity. Moreover, the economic impact of climatic shocks in Africa appears to be long-term and permanent, subject to a gradual build-up over time.

We extend the initial analysis in several respects: by focusing solely on Sub-Saharan African countries; splitting the sample to assess possible non-linear effects between countries characterised by high *vis-à-vis* low temperature or precipitation levels; examining whether the relationships under consideration are influenced by asymmetric behaviour or cross-section dependence. Overall, the results prove remarkably robust, though we do find some evidence of non-linear behaviour, as the negative effects of temperature and the positive effects of rainfall appear to be stronger for countries characterised by high temperature and/or low rainfall levels.

Providing qualified support for the hypothesis that long-run economic growth in Africa is significantly affected by climatic conditions, the evidence gathered in this paper suggests that, far from adapting quickly to climatic shocks, the African economies can be permanently damaged by them. Thus, in the absence of corrective measures, the current trends in climate change, typified by declining rainfall levels and rising temperatures, may impose a progressively heavier burden on African economies.

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Appendix A

List of countries

Algeria, Benin, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Democratic Republic of Congo, Republic of Congo, Cote d`Ivoire, Djibouti, Egypt, Equatorial Guinea, Gabon, The Gambia, Ghana, Guinea, Kenya, Liberia, Madagascar, Mali, Mauritania, Mauritius, Morocco, Mozambique, Niger, Nigeria, Senegal, Sierra Leone, Somalia, Sudan, Tanzania, Togo, Tunisia, Uganda and Zambia.