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The Impact of Climate Change on Economic Growth in Africa: An Econometric Analysis

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Abstract:

African economics are characterized by strong economic dependency on sectors highly vulnerable to climate change that may make it more susceptible to climate change. This study aims to investigate the effect of climate change on both short and long-run economic growth in Africa using a panel of 34 selected African countries for the period of 1971–2019. The study relies on a dynamic panel model with a multifactor error structure; we estimate the model through the cross-sectionally augmented autoregressive distributed lag (CS-ARDL) and the cross-sectionally augmented distributed lag (CS-DL) approaches. We find clear evidence that climate change is negatively associated with economic growth in both the short and long-run. We establish that a rise in the mean temperature change with one degree would significantly reduce the real GDP per capita in Africa by 1.68% (2.45%) in the short-run (long-run), respectively.

Keywords: climate change; economic growth; Africa; multifactor error structures; cross-section dependence.

JEL Classification: C23, O44, Q54, Q56

1. Introduction:

Climate change is a complex phenomenon with many ramifications and overlaps. That recently stats to capture headlines and gets a growing large consensus in the literature on its negative impact on the whole economic development process and call for adaptation and mitigation. Climate change is already a reality, it is happening and accelerating. Observational evidence from all regions shows that the whole climate system is being affected by climate changes, particularly temperature increases. The estimates show that 1989 to 2019 was the warmest 30-year period in more than 800 years; the most recent decade, 2010-2019, is the warmest decade in the instrumental record so far (National Academy of Sciences, & The Royal Society, 2020). Climate change is having profound impacts on nearly every aspect of our environment, which make it a serious threat to the environment and to the global economy as well. Vastly altered weather patterns and climate extremes affect climate-sensitive sectors output, whether agricultural production, health, water, energy security or conflict. Moreover, temperatures are expected to rise substantially over the next century causing more widespread and rapid changes which highlights the importance of assessing the climate change and economic growth relationship.

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Although global warming is a global issue that all countries have to handle with, the effect of climate change is not homogeneous; the magnitude of impacts tends to vary across the countries and regions with the amount of climate change and the capacity to adapt. Most studies indicate that poor countries are projected to bear the brunt of climate change. In particular, climate change may be more notable in Africa, mainly because of their strong economic dependency on climate-related resources, particularly for the agricultural and water-resources sectors. Food production on the continent is almost entirely rain fed. The situation makes combating hunger and achieving food security more challenging in light of rainfall shortage. Climate change may exacerbate existing stressors and undermines Africa's ability to grow and break the vicious cycle of poverty.

1.1. Research Problematic:

Based on the above observations, the present paper tries to examine the effect of climate change on both short and long-run economic growth in Africa by discussing the following question: **What is the impact of climate change on economic growth in Africa?**

1.2. Research Aims:

This study aims to investigate and model the overall long and short effect of climate change on economic growth in Africa and measure the extent to which climate change burden the growth in the region.

1.3. Research Methodology

Using a selected sample of African countries during 1971 to 2019, we rely on the recent methodology of dynamic common correlated Effects (DCCE), this technique overcomes the methodological issues which the existing literature suffers from and can deal with the issue of dynamics, heterogeneity and cross section dependence jointly.

The rest of the paper is organized as follows. In Section 2, we survey the literature, examining particularly the effect of climate on economic growth in Africa. Section 3 presents the data and methodology used in this paper; in Section 4, we exhibit the empirical results; while Section 5 concludes.

2. Literature review:

Recent studies have enriched the literature with confident evaluation of the relationship between climate change and economic growth. For instance, Nordhaus (2005), applied the G-Econ database, which measures economic activity for all large countries, measured at a 1° latitude by 1° longitude scale, to analyze the impact of climatic and geographic factors on economic activity. He found a negative relationship between temperature and economic output when measured on a per capita basis and strongly positive on a per area basis and that geography is an important factor in explaining the African poverty. Dell et al. (2008) used a panel of 136 countries over the 1950-2003 period to examine the impact of climatic changes on economic activity; they found large negative effects of higher temperatures on both the level and growth rate of economic growth, but only in poor countries, with 1C rise in temperature in a given year reduces economic growth by 1.1 percentage points on average, while the precipitation was found have no substantial effects on growth in either poor or rich countries. In another study, Dell et al. (2009) examined the temperature-income relationship based on sample of 12 countries in the Western Hemisphere. They found strong negative short-run effects of temperature, while the theoretical framework suggests that half of the negative short-run effects of temperature are mitigated through long run adaptation. The negative effect of climate change on economic growth was confirmed by the study of Dell et al. (2012) that found substantial effects of temperature shocks, but only in poor countries. Similarly, Lanzafame (2012), explored empirically the aggregated effects of temperature and rainfall on per-capita GDP growth in Africa using annual data spanning the period 1962-2000 for 36 African countries, using autoregressive distributed lag model and panel estimators with multifactor structures. He provided strong evidence that economic growth in Africa is significantly affected by temperature, while the evidence is less unambiguous for rainfall. In the same line, Abidoye and Odusola (2015) applied a Bayesian hierarchical modeling approach to investigate the effects of climate changes on economic growth in Africa. Using annual data for 34 countries from 1961 to 2009, they found that one unit rise in climate change proxy reduces GDP growth by 0.667 percentage point and that the impact is not homogenous across countries. Similarly, Based on annual data for 103 countries covering the period of 1961-2010, Martin Henseler et al. (2019) investigated empirically the effect of temperature and precipitation on GDP growth. They found that GDP growth and its factors of production are negatively affected by higher temperatures, and the effect depends on a country's level of growth, with more damage effect for poor countries.

3. Data and methodology:

This empirical paper relies on panel annual dataset collected from different data sources from 1971 to 2019 for 34 African countries.[1] The choice of the countries was determined by issues of data availability.

The proxy for climate change in this study is the annual mean surface temperature change from baseline, using temperatures between 1951 and 1980 as a baseline. The data series are taken from the Economic Activity and Climate Indicators of the International Monetary Fund, except for Rwanda and Burundi for which the Climatic Research Unit database was used instead. Economic growth is measured as the real GDP per-capita obtained from the Penn World Table version 10.0. As control variables, we include: population (in millions) and the share of gross capital formation at current PPPs, the data series are taken from PWT10. We also consider trade openness, defined as the sum of import and exports as a percentage of GDP to control for international trade activity. Data is obtained from the world development indicators (WB-WDI). The variables of this study are presented with more detailed statistics in table 1.

Table (01): Summary statistics of the variables

Variables	Observations	Mean	Median	Minimum	Maximum	Std.Dev.
Ln Real GDP per capita	1666	7.825	7.728	5.586	10.400	0.853
Mean Temperature Change	1666	0.586	0.556	-1.294	2.378	0.534
Ln Population	1666	2.278	2.315	-0.811	5.303	1.159
Ln Share of gross capital formation	1666	-1.979	-1.907	-4.424	-0.051	0.654
Ln Trade Openness	1626	4.018	4.019	1.843	5.239	0.472

Source: Authors' Computation Using STATA 13.

2.1. Empirical framework and estimators:

For empirical analysis, we consider the dynamic heterogeneous panel estimators built on the auto-regressive distributive lag (ARDL) approach. With the panel specification of lag orders (p_y, p_x):

$$y_{i,t} = \alpha_i + \sum_{l=1}^{p_y} \varphi_{il} y_{i,t-l} + \sum_{l=0}^{p_x} \beta'_{il}\, x_{i,t-l} + u_{i,t}, \qquad (1)$$

We specify $u_{i,t}$ as follows to allow for cross-sectional dependence of the error terms:

$$u_{i,t} = \gamma'_i f_t + \varepsilon_{i,t}, \qquad (2)$$

For i = 1, 2, … , N indicates the cross sections and t = 1, 2, …, T the time periods. $y_{i,t}$ is log real GDP per capita and its lags are used as an independent variables and $x_{i,t}$ includes the mean temperature change and the log of the control variables mentioned above, the p_y and p_x are the lag orders of y and x respectively. The error term is specified such that to allow for cross-sectional correlation of the error terms. The CSD is captured by a set of unobservable common factors f_t with country-specific factor loadings γ_i. ε_{it} is the idiosyncratic errors term with mean 0 and variance σ^2.

Different conventional panel data techniques have been used by previous studies like PMG (pooled mean group), and fixed effect (FE) models. However, these methodologies does not adequately address the possibility of the parameters heterogeneity across countries that could be rise do to country-specific factors which effect the rate of convergence and make these estimators no longer consistent. Moreover, panel-data models are likely to exhibit substantial cross-sectional dependence, whereby all units in the same cross-section are correlated, for instance by sharing unobserved common factors, common to all units and affecting each of them. The standard panel data techniques such as fixed/random effects can lead to inconsistent and even inefficient estimators when the observed explanatory variables and the unobserved common factors are correlated. Furthermore, the common correlated effect (CCE) approach used in previous studies does not cover the case where the panel includes a lagged dependent variable or weakly exogenous regressors. To tackle such issues, we apply the recent panel data methodology, "dynamic common correlated effects (DCCE)" by Chudik and Pesaran (2015). This approach considers main issues which are not recognized by other conventional methods, it can deal with the issue of dynamics, heterogeneity and CSD jointly.

The DCCE approach is an extension of the CCE approach estimation developed by Pesaran (2006) and is designed on the principles of pooled mean group (PMG) technique developed by Pesaran et al. (1996) and Mean group (MG) estimation developed by Pesaran and Smith (1995). Chudik and Pesaran provide that with the inclusion of $p_T = \sqrt[3]{T}$ lags of the cross-sectional averages for the heterogeneous panel data models with lagged dependent variables or weakly exogenous variables, the CCE estimators gain consistency.

The equation of DCCE model can be written as follows:

$$y_{it} = \alpha_i + \sum_{l=1}^{p_y} \varphi_{il} y_{i,t-l} + \sum_{l=0}^{p_x} \beta'_{il}\, X_{i,t-l} + \sum_{l=0}^{p_T} \psi'_{il}\, \bar{z}_{t-l} + u_{it}, \qquad (3)$$

Where $\bar{z}_t = (\bar{y}_t, \bar{x}'_t)'$ is the cross-sectional averages, and p_T is the number of lags of the cross-sectional averages to be included, it is not necessarily equal to the lag orders p_y or p_x, as well as one could allow for different lag orders for $\bar{y}_t$, and $\bar{x}_t$, and all the other variables are as defined in equations (1) and (2).

Chudik and Pesaran propose the CS-ARDL estimator for the above equation. The estimator augments the individual ARDL regressions appropriately with additional lags of cross-sectional averages to control common factors. The approach estimates first the short run coefficients in the ARDL relation, and then computes the estimates of long-run effects using the short run estimation with the following formula:

$$\hat{\theta}_{CS-ARDL,i} = \frac{\sum_{l=0}^{p_x} \hat{\beta}_{il}}{1 - \sum_{l=0}^{p_y} \hat{\varphi}_{il}} \qquad (4)$$

The coefficients can be estimated by pooled estimator or mean group where the mean long-run effects are estimated as $N^{-1} \sum_{i=1}^{N} \hat{\theta}_{CS-ARDL,i}$.

The long-run coefficients can be estimated consistently, irrespective of whether the regressors are strictly exogenous or jointly determined with y_{it}, and whether the underlying variables are integrated of order one or integrated of order zero. However, as can be seen from (4), the sampling uncertainty could rise when the speed of convergence towards the long-run relation is rather slow and the time dimension is not sufficiently long. When the $\sum_{l=0}^{p_y} \hat{\varphi}_{il}$ is close to unity, the calculation of the long-run estimates could be sensitive to outlier estimates (Chudik & Pesaran, 2015).

An alternative approach proposed by Chudik and Pesaran (2015) as complementary to the ARDL approach to estimate the long effect directly is the cross-section augmented distributed lag (CS-DL) approach. This approach based on a transformation to the ARDL model, (1), to a distributed lag by augmenting the regression with the differences of the explanatory variables (x), their lags and the cross-sectional averages. The CS-DL estimator is based on the following equation:

$$y_{i,t} = \alpha_i + \theta_i x_{i,t} + \sum_{l=0}^{p_x - 1} \delta'_{i,l} \, \Delta \, x_{i,t-l} + \sum_{l=0}^{p_{\bar{y}}} \gamma_{il} \bar{y}_{i,t-l} + \sum_{l=0}^{p_{\bar{x}}} \psi'_{il} \, x_{i,t-l} + u_{i,t}, \qquad (5)$$

Where $p_{\bar{y}}$ and $p_{\bar{x}}$ are the number of lags of the cross-sectional averages. Under the assumption that φ_{il} lies in the unit circle, the long-run unit-specific impacts, θ_i, are directly estimated, and the mean group estimates are calculated as $\hat{\theta}_{MG} = N^{-1} \sum_{i=1}^{n} \hat{\theta}_i$. The CS-DL is robust to residual serial correlation, breaks in error processes and dynamic misspecifications.

3. Finding and discussion:

This section presents the results and discussion of the estimated relationship between climate change and economic growth in Africa. Since we are dealing with large linear panel data models which often found to be subject to cross-sectional dependence and nonstationary variables, we first conduct cross section dependence tests to determine the features of each cross-section. Next we investigate the integration order of the variables. Then, we determine the optimal lag length selection of ARDL specification and evaluate the heterogeneity of the coefficients using slope homogeneity test. In the final step, we estimate the short and long-run relationships using the relevant and efficient techniques.

3.1. Cross section dependence:

The first step of our empirical analysis is the cross-sectional dependence test to analyse the contemporaneous cross-correlations across the countries in order to decide in the estimation method. This paper uses two methods to identify cross-sectional dependence. The first developed by Pesaran (2004/2015) to test the existence of cross section dependence while the second presented by Bailey et al. (2016), estimate the exponent of the dependence. Pesaran's test is applicable to both balanced and unbalanced panel data, and robust to the presence of nonstationary processes, parameter heterogeneity or structural breaks. The tests are based on simple averages of pair-wise correlation coefficients of OLS residuals. [2] The degree of cross-sectional dependence is presented by the rate at which the average pairwise error correlation coefficient, tend to zero in N. This rate is defined by alpha, as the exponent of cross-sectional dependency. The values of alpha in the range [0, 1/2) correspond to different degrees of weak cross-sectional dependence, while the values of in the range (1/2, 1] relate to different degrees of strong cross-sectional dependence.

The table 2 represents a strong evidence of a dependency between the cross-sections of the panel. The Pesaran CD test rejects the null hypothesis in favour of the alternative hypothesis and the estimated exponent of cross-sectional dependence is well above 0.5. Hence, strong cross-section dependence for all variables is detected.

Table (02): Results of cross-sectional dependence tests.

	Ln RGDPPC	Mean Temperature	Ln Population	Ln Share of gross	Ln Trade Openness
Pesaran,	40.361	125.226	163.579	28.004	19.641
p-value	0.000	0.000	0.000	0.000	0.000
Cross-	0.98	1.00	1.00	0.92	0.93

Note: The STATA command xtcse2 developed by Ditzen (2021) is used for the CSD estimation.
Source: Authors' Computation Using STATA 13.

3.2. Unit root tests:

Due to the presence of CSD, two of the second generation panel unit root tests that deal with cross-section dependence have been used to analyze the stationarity features; the cross-sectionally augmented Im-Pesaran-Shin (CIPS) test and the Pesaran cross-sectional augmented Dickey-Fuller test (Pescadf test). The results shown in Table 3 indicate the failure to accept the null hypothesis of the presence of unit root for mean temperature change, population and share gross capital formation. While both RGDP per capita and trade openness were found to be integrated of order one.

Table (03): Second Generation Panel Unit Root Tests

	CIPS Test		**Pescadf Test**	
	Constant	**Constant & Trend**	**Constant Z[t-bar] (Prob)**	**Constant & Trend Z[t-bar] (Prob)**
Tests in levels				
Ln RGDP per capita	-1.670	-2.435	0.777 (0.762)	-0.635 (0.263)
Mean Temp Change	-5.245*	-5.458*	-12.755* (0.000)	-10.359* (0.000)
Ln Population	-2.766*	-3.121*	-12.753* (0.000)	-13.668* (0.000)
Ln Share of gross capital formation	-2.265*	-3.005*	-3.013* (0.001)	-3.791* (0.000)
Ln Trade Openness	/	/	-1.300 (0.097)	-1.374 (0.085)
Tests in first differences				

D. Ln RGDP per capita	-5.130*	-5.367*	-15.162 (0.000)	-14.229 (0.000)
D. Ln Trade Openness	/	/	-18.803* (0.000)	-16.375* (0.000)

Note: * denotes the rejection of the null of a unit root for 99% .
Critical values: Without trend: −2.23 (1%), −2.11 (5%), −2.05 (10%). With trend: −2.72 (1%), −2.6 (5%), −2.55 (10%).
Source: Authors' Computation Using STATA 13.

3.3. Lag selection:

To find the optimal lags, single-equation estimations for each of countries was used. It was found that the ARDL (1, 0, 0, 0, 0) model is the most appropriate for the majority of countries. Accordingly, we rely our model on an ARDL (1, 0, 0, 0, 0) specification.

3.4. Slope homogeneity:

Homogeneity analysis is used to test whether the climate change effect on growth varies across countries. Given the presence of cross-sectional dependence in the panel of our model, we used the cross sectional-dependence robust version proposed by Bersvendsen and Ditzen (2021) that perform best in the presence of CSD to analyse the homogeneity features. The CSD robust version is an extension of the delta test proposed by Pesaran and Yamagata, 2008. Under its null, slope coefficients are homogeneous across cross-sectional units; the test adopts the same methodology used in the CCE estimator to take out strong CSD by approximating it with cross section averages CSA (Bersvendsen & Ditzen, 2021). The result of the slope homogeneity test is presented in Table 5. The results give us sufficient evidence for the presence of country-specific heterogeneity in our model.

Table 5 : Slope Homogeneity Test

H_0: slope coefficients are homogenous	
Δ	Δ adj
8.042*	9.583*

Note: * refers to the level of significance at 1 percent. The STATA command xthst developed by Bersvendsen and Ditzen (2021) is used for the homogeneity test.
Source: Authors' Computation Using STATA 13.

3.5. Estimation:

3.5.1. The cross sectionally augmented autoregressive distributed lag (CS-ARDL):

The presence of the cross-sectional dependence implies that estimates obtained using standard panel ARDL models might be misleading. To overcome this problem, we employ the CS-ARDL approach, based on Chudik and Pesaran (2013), which augments the ARDL regressions with cross-sectional averages of the regressors, the dependant variable and a sufficient number of their lags, which in our case is set to 3 regardless of p, the lag order chosen for the underlying ARDL specification.

Table (06): The CS-ARDL Estimation

Dependent Variable: Ln Real gross domestic product per capita			
	CS-ARDL (a)	**CS-ARDL (b)**	**CS-ARDL (c)**
Short-Run Coefficients			
L. Real GDP per capita	0.575* (0.045)	0.606* (0.040)	0.606* (0.040)

Mean Temp Change	-0.016***	-0.017**	-0.017**
	(0.008)	(0.008)	(0.008)
Ln Population	0.632**	0.227	0.227
	(0.315)	(0.175)	(0.175)
Ln Share of gross capital formation	0.052*	0.046*	0.046*
	(0.010)	(0.009)	(0.009)
Ln Trade Openness	-0.006	0.002	0.002
	(0.019)	(0.017)	(0.179)
Trend	-0.006	/	/
	(0.014)		
Intercept	1.202	1.066	/
	(1.294)	(0.709)	
Adjust. Term	-0.424*	-0.393*	0.393*
	(0.045)	(0.408)	(0.048)
Long-Run Coefficients			
Mean Temp Change	-0.104***	-0.091**	-0.091**
	(0.062)	(0.443)	(0.044)
Ln Population	0.206	0.483	0.483
	(1.851)	(0.744)	(0.744)
Ln Share of gross capital formation	0.311*	0.215*	0.215*
	(0.113)	(0.058)	(0.058)
Ln Trade Openness	0.166	0.083	0.083
	(0.160)	(0.081)	(0.081)
Constant	5.454	1.167	/
	(5.142)	(2.682)	
CD test	-1.29	-1.55	-1.55
α	0.555	0.547	0.547

Note: Coefficients are reported with standard errors in brackets. ***, **, and * indicate significance at 1, 5 and 10% levels, respectively. The STATA command xtdcce2 developed by Ditzen (2018) is used for the CS-ARDL estimation.
Source: Authors' Computation Using STATA 13.

The estimation results are summarized in Table 06, where we provide MG estimates for the three specifications, (a), (b), and (c), Panel (a) depicts the results when relying on specifications including a country-specific trend, panel (b) when we rely on standard no-trend DCCE estimation, and panel (c) with no trend no constant specification.

The deterministic component is introduced to control for possibly idiosyncratic time effects, but it turns out to be non significant. Thus, the results from the no-trend- no constant specification of the DCCE model may be more reliable. However, all three specifications show significantly (at the 5% level) strong negative effects of temperature on growth, both in the short and long-run. A rise in the mean temperature change with one degree lowers the GDP per capita by 1.68 percent in the short term. The long run effect is more sever with a decrease of 8.69%, this estimate is much larger than those obtained for the short term.

The estimation suggests also a strong positive and significant association between real GDP per capita and the share of gross capital formation, exhibiting the results in an increase of 1 percent in the share of gross capital we find it corresponds to a 0.046 (0.215) percentage point increase in the real GDP per capita in the short term (long term). The population turns out to be significant only in the short run when the model includes a country-specific time trend. The trade, in all our specifications does not appear to have a statistically significant influence on the outcome. The partial adjustment to the long run equilibrium implies that 39.3% of the disequilibrium is adjusted every period. The estimated exponent of cross-sectional dependence is about 0,55 and very close to the threshold of 0,5.which confirms a substantial decline in the average pair-wise correlation of residuals after the cross-section augmentation of the ARDL models.

3.5.2. The cross-sectionally augmented distributed lag (CS-DL):

We rely next on the CS-DL estimator as a direct approach to estimate the long-run relationships. This method has better small sample performance for moderate values of T, and the speed of convergence towards the long-run relation is rather slow.

Table (07): The CS-DL Estimation

Dependent Variable: Ln Real gross domestic product per capita			
	CS-DL (a)	**CS-DL (b)**	**CS-DL (c)**
Mean Temp Change	-0.017*** (0.009)	-0.025** (0.116)	-0.025** (0.011)
Ln Population	-0.102 (0.894)	0.104 (0.831)	0.104 (0.831)
Ln Share of gross capital formation	0.069* (0.017)	0.059* (0.019)	0.059* (0.019)
Ln Trade openness	-0.026 (0.032)	-0.016* (0.036)	-0.016 (0.036)
Trend	0.037 (0.049)	/	/
Constant	4.752 (3.347)	3.069 (2.066)	/
CD test	-2.13	-1.82	-1.82
R^2	0.97	0.96	0.96

Note: Coefficients are reported with standard errors in brackets. ***, **, and * indicate significance at 1, 5 and 10% levels, respectively. The STATA command xtdcce2 developed by Ditzen (2018) is used for the CS-DL estimation.

Source: Authors' Computation Using STATA 13.

The Table 07 presents the estimation results of equation 5; it provides more evidence that climate change reduces the growth in Africa. The long-run relationship between climate change and real GDP per capita is always negative and statistically significant (across different specification). An increase of one degree in the mean temperature change corresponds to a 2.45% percentage increase in the African real GDP per capita in the long run. However, the long-run effect of temperature by the CS-DL approach is comparatively lower as compared to the estimate of CS-ARDL; we expect the exact magnitude of the effects to be somewhere in between the two estimates (CS-ARDL and CS-DL) but much more close to the CD-DL estimation.

The estimation also supports the positive relationship between real GDP per capita and the and the share of gross capital formation, an increase of 1 percent in the share of gross capital rises the real GDP per capita with 0.055 percentage in the long term. However, the population and trade openness are found to be non significant.

5. Conclusion:

This research aimed to expand prior research on the relationship between climate change and economic growth in Africa. For this purpose, a panel of 34 African countries for the period 1971-2019 was used to evaluate the short and long run effect of climate on economic growth in the region. Our analysis paid special attention to cross-sectional dependence issues; we apply the recent developed panel data methodology, "dynamic common correlated effects (DCCE)". This approach considers main issues which are not recognized by other conventional methods, it can deal with the issue of dynamics, slopes heterogeneity and CSD jointly. We estimate the effect of climate change using the CS-ARDL that confirms the negative association between climate change and the real GDP growth in Africa, a rise in the mean temperature change with one degree lowers the real GDP per capita by 1.68 (8.69%) percent in the short run (long run) respectively. We also rely on the CS-DL estimator as a direct approach to estimate the long-run relationships, this method has better small sample performance for moderate values of T, and the speed of convergence towards the long-run relation is rather slow, this approach provides evidence on the negative effect on climate change on African economic growth with a decrease of 2.45% percentage in the African real GDP per capita for every one degree increase in the mean temperature change. The results indicate that climate change damages the African economic performance and that is one of African most significant long-term policy challenges, so that keeping climate change at the forefront of government decision agendas will be critical and inevitably.

Given that temperatures in Africa are rising, and are set to rise faster than the global average and the capacity of African countries to overcome the effects of climate change is expected to be challenged, it will be necessary to present the future horizons of the African countries in the light of climate change and to state, strength and carry out the strategies of climate change adaptation and mitigation across the continent that make people, ecosystems, infrastructure and the whole economy less vulnerable to the impacts of climate change.

6. Endnotes:

[1] The sample consists of Algeria, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Democratic Republic of the Congo, Republic of the Congo, Côte d'Ivoire, Egypt, Eswatini, Gabon, Ghana, Guinea, Kenya, Madagascar, Malawi, Mali, Mauritania, Morocco, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, Sudan, Tanzania, Togo, Tunisia, Uganda and Zimbabwe.

[2] The Pesaran CD test statistic is defined by: $CD_{NT} = \left[\frac{TN(N-1)}{2}\right]^{1/2} \hat{\bar{p}}_N;\ where\ \hat{\bar{p}}_N = \frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{p}_{ij}$, and the pij is the pair-wise correlation of errors terms.

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