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Climate Change in Sub-Saharan Africa's Fragile States

Evidence from Panel Estimations

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Climate Change in Sub-Saharan Africa Fragile States: Evidence from Panel Estimations
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ABSTRACT: Fragile states in sub-Saharan Africa (SSA) face challenges to respond to the effects of climate shocks and rising temperatures. Fragility is linked to structural weaknesses, government failure, and lack of institutional basic functions. Against this setup, climate change could add to risks. A panel fixed effects model (1980 to 2019) found that the effect of a 1◦C rise in temperature decreases income per capita growth in fragile states in SSA by 1.8 percentage points. Panel quantile regression models that account for unobserved individual heterogeneity and distributional heterogeneity, corroborate that the effects of higher temperature on income per capita growth are negative while the impact of income per capita growth on carbon emissions growth is heterogeneous, indicating that higher income per capita growth could help reduce carbon emissions growth for high-emitter countries. These findings tend to support the hypothesis behind the Environmental Kuznets Curve and the energy consumption growth literature, which postulates that as income increases, emissions increase *pari passu* until a threshold level of income where emissions start to decline.

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WORKING PAPERS

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Contents

I. Introduction

Global temperatures have increased significantly over the past-half century and extreme weather events such as cold and heat waves, droughts, floods, and storms have intensified, now dominating the disaster landscape in the 21st century. These changes in the weather patterns (i.e., climate change[1]) are presenting immense challenges and its effects are particularly severe for the populations of poor countries. This is even truer for fragile environments,[2] which may be more vulnerable to humanitarian crisis and instability.

Sub-Saharan Africa (SSA) is one of the regions where climate change is expected to push the most people into poverty (39.7 million) if no concrete climate and development action takes place by 2050 (Jafino et al. 2020). The impacts of climate change could be felt most immensely by those living in fragile and conflict-affected settings in SSA.

The vulnerability of fragile states' populations to climate change and natural disasters is much higher than in other countries (Mason et al., 2015). Fragile states in SSA with high exposure to climate risks face multi-faceted challenges, including physical and livelihood risks for the population. They heavily rely on agriculture, which is climate dependent. Weak governance and conflicts also exert a significant toll on fragile states, thus amplifying their vulnerability to climate change. Burke et al. (2009) found that, in Africa, higher temperatures lead to higher conflict incidence—a 1ºC increase in temperatures leading to a surge in civil conflicts by 4.5 percentage points.

Conflict over land and natural resources, access to basic social services and other measures of fragility have growingly been associated to the effects of climate change (Navone 2021). The Darfur conflict—labeled the "first climate change conflict"—is an important example, given "the convergence of environmental and political factors leading to the conflict" (Sova, 2017).

Temperature shocks and changes in precipitation patterns and/or more frequent and intense weather events imply not just a one-time episode for a fragile state but, more importantly, they could carry implications for the rate of economic growth. Rising temperatures affect agricultural output and determine lower industrial output. Along with higher temperatures, meteorologists and scientists observe in some areas an increase in the intensity of extreme precipitation and lower precipitation trends in others. Temperature and precipitation are considered in this paper as proxies for climate change on the understanding that augmented heating conditions result in greater evaporation, thus increasing the intensity of droughts, the lack of irrigation, and the negative effect on SSA's economic growth.

Fragile states in SSA face challenges to respond to the effects of climate shocks and rising temperatures. According to the Intergovernmental Panel on Climate Change (IPCC, 2012), rising temperatures in Africa affect people's health and livelihoods through: (i) erratic precipitation (more extreme and less predictable rainfall); (ii) extreme events (heat waves, tropical cyclones, extreme rainfall, floods, wildfires, and droughts), and (iii) rising seas (risk of coastal erosion and floods, causing physical damage and injury, threatening health with water-borne diseases, and contaminating drinking water and agricultural land with salt).

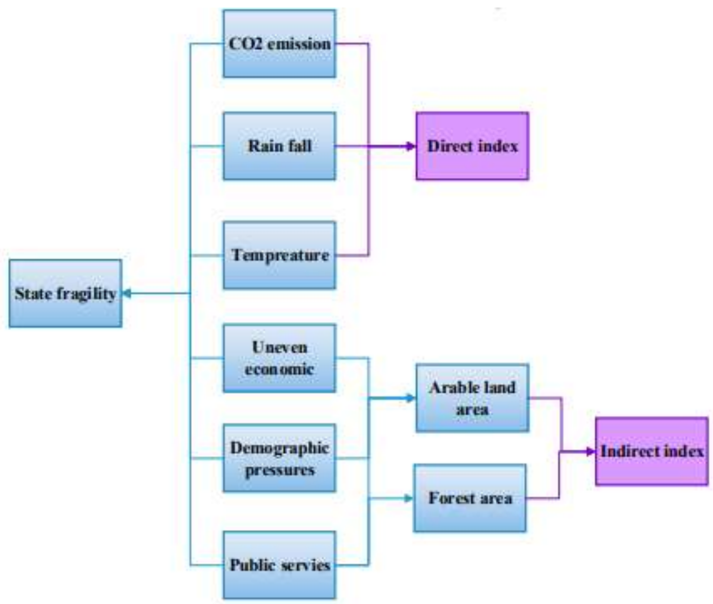
Fragility is linked to structural weaknesses, government failure, and lack of institutional basic functions in a state. In this setup, climate change could add up risks. Climate change can place immense stress in fragile states where governments struggle to provide basic social services, resulting into deeper fragility and creating an environment prone to violent conflict. This stress, in turn, makes it difficult for governments in addressing climate and environmental issues, as they become either distracted with resolving the fragility crisis or are not

[1] IPCC (2014) defines 'climate change' as "a change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer."

[2] The list of fragile and conflict-affected situations is released annually by the World Bank Group. Fragile Situations include countries or territories with: (i) a harmonized CPIA (Country Policy and Institutional Assessment) country rating of 3.2 or less, and/or (ii) the presence of a UN and/or regional peace-keeping or political/peace-building mission, during the last three years.

capable of acting altogether (Navone 2021). Wenya et al. (2020) have proposed the following framework to establish the connection between climate change and state fragility:

Figure 1. Climate Change and Fragile States: Direct and Indirect Influence



Source: Wenya et al. (2020)

Figure 1 shows rain fall, temperature, and CO2 emission as the most significant variables affecting climate change directly. Other variables like demographics, public services, and uneven economic development, together with arable land area and forest area, are found to be of indirect influence.

The tails of distributions could become very informative regarding climate change information. Quantile regression allows understanding relationships between variables outside the mean of the data, making it useful when evaluating data that are non-normally distributed. They also provide a more flexible statistical framework—than the classical regression model—to detect relationships among variables at sections of the tails of distributions in cases of non-normality of the error term. As climate data differ at the upper/lower tails of a distribution, quantile regression offers a useful framework to assess factors (covariates) that may be interacting with climate change.

This paper investigates the impact of temperature anomalies on income per capita growth based on panel fixed effects and panel quantile regression methodologies with the goal to filling the gap on the lack of climate-relates econometric analyses on fragile states. Burke et al. (2015) found that extreme temperatures "have significant negative effects in all cases for poor countries." Hence, our identification approach for fragile states builds on fluctuations in temperature to identify their effects. Then, we reverse the assessment focus to analyze the impact of economic conditions on climate change through their effects on Green House Gas (GHG) emissions growth rate. We use a dynamic-panel model based on twenty fragile states in sub-Saharan Africa from 1980 to 2019. Lastly, we provide a series of scenarios to evaluate the potential impact of policy responses (mitigation) to climate change, focusing on the incidence on fragile states in SSA.

The paper is structured as follows. Sections II and III present a short review of the literature and the data, respectively. Section IV discusses the methodology while Sections V presents a panel fixed effects estimations and quantile panel estimations. Sections VI and VII present and discuss robustness tests and policy implications for fragile states in SSA to tackle climate change mitigation. Section VIII concludes.

II. Review of the Literature

This short review spans over not just the impact of temperature rising on economic activity but, also, its implications for SSA countries. The section ends with a discussion on the impact of economic activity on carbon emissions as well as the rising challenges in econometric modelling of climate change.

Temperature and economic activity

To measure the economic impact of climate change, economists have sought to quantify how temperature changes affect economic activity. Dell et al. (2012) and Kahn et al. (2021) investigate the long-term impact of climate change on economic activity. Dell et al. (2012) uses historical fluctuations in temperature within countries to identify its implications for aggregate economic outcomes. They find substantial effects of temperature shocks, but only in poor countries, where a 1° C rise in temperature in a given year reduces economic growth by 1.3 percentage points on average. The findings further suggest that temperature shocks may affect not only the rate of economic growth but also the level of output.

Kahn et al. (2021) found that per-capita real output is negatively affected by constant changes in the temperature, but they do not obtain statistically significant effects for changes in precipitation. Their counterfactual analysis suggests that a constant increase in average global temperature by 0.04°C per year, where there is a lack of mitigation policies, reduces world real GDP per capita by more than 7 percent by 2100. On the other hand, when adhering to the Paris Agreement, limiting the temperature increase to 0.01°C per annum, reduces the loss significantly to about 1 percent. These effects appear to differ significantly across countries depending on the pace of temperature increases and variability of climate conditions.

To understand whether temperature can explain variation in cross-country income, Dell et al. (2009) shows that the negative cross-sectional relationship between temperature and income exists within countries, as well as across countries, though the relationship is substantially smaller in size in the former rather than in the latter. Their theoretical framework suggests that half of the negative short-term effects of temperature are offset in the long run through adaptation. This can be explained by the fact that, in the long run, regions may adapt to their climate. Individuals can modify their behavior to permanent temperature changes; hence the short-run effect could be larger than the longer-run response.

There are other important studies that examine the relationship between climate (temperature, precipitation, storms, and other aspects of the weather) and economic performance (agricultural production, labor productivity, commodity prices, health, conflict, and economic growth) – see Stern (2007), Tol (2009), IPCC (2014), the surveys by Dell et al. (2014), Hsiang (2016), and Cashin et al. (2017).

The impact of climate change on sub-Saharan Africa

There have also been a series of important studies that aim to quantify the impact that climate change has had on sub-Saharan Africa.[3] Okonjo-Iweala (2020) using Kompas et al. (2018) modeling data predicts that climate change is expected to significantly decrease Africa's GDP through lowered crop yields, reduced agricultural and labor productivity, and damage to human health. Okonjo-Iweala 2020 stated: "Assuming no major changes in the world's social, economic, and technological trends, climate change resulting in a 3°C temperature will decrease Africa's GDP by as much as 8.6 percent per year after 2100. If climate change is limited to the 1.5°C agreed to in the Paris Agreement, the decrease in GDP will be significantly less—only 3.8 percent per year after 2100." Against the previous backdrop, Blanc (2012)'s findings are critical: largest temperature increases the largest precipitation changes, thus determining changes in droughts and floods. Based on a panel auto-regressive distributed lag model for SSA countries (1970-2018), Sandalli (2021) showed that countries are adversely affected by temperature variations, although no significant relationship was found between precipitation and income growth. Miguel, Satyanath, and Sergenti (2004), studied African

[3] Ntinyari and Gweyi-Onyango (2021) review published scientific papers on climate change, greenhouse emissions, agricultural fertilizer use, modeling and projections of greenhouse gases emissions affecting SSA.

countries from 1981–1999 to understand civil conflict and found that annual per capita income growth was positively predicted by current and lagged rainfall growth (without controlling for temperature).

The IMF's Regional Economic Outlook (2020) for SSA suggests that economic activity in a given month can decrease by 1 percent when the average temperature is 0.5°C above that month's 30-year average. This effect is 60 percent higher than the average for emerging market and developing economies in other regions, which can be explained by sub-Saharan Africa's agricultural dependence and the temperature sensitivity of its crops. Findings also suggest that climate-related natural disasters have a lasting impact, especially droughts. For example, medium-term economic activity can decrease by 1 percentage point when one additional drought occurs. This effect is about eight times that in emerging market and developing economies in other regions.

While diminishing rainfall affects economic growth in Africa, there is no clear impact for temperature. Barrios et al., (2010) found that, depending on the level of rainfall assumed as a benchmark, the per-capita GDP differential between SSA and other non-African developing countries would have been 15-40 percent lower than it was. Further, Fjelde and von Uexkull (2012) found that negative rainfall shocks are associated with (communal) conflict in subnational regions in Africa. Nonetheless, Lanzafame (2014), taking account explicitly of parameter heterogeneity and cross section dependence, used a panel autoregressive distributed lag (ARDL) model and found evidence of short- and long-run relations between temperature and economic growth in SSA. Tol (2019) emphasizes that there are only 27 estimates of the total economic impact of climate change, which show that global warming of 2.5°C would make the average person feels as if she had lost 1.3 percent of her income.

The impact of economic activity on carbon emissions

To measure the impact of economic activity on carbon emissions, Zhu et al. (2016) examine the effect of foreign direct investment (FDI), economic growth, and energy consumption on carbon emissions in five selected countries in the Association of Southeast Asian Nations (ASEAN-5). They apply a panel quantile regression model, which reveals that the effect of the independent variables on carbon emissions is heterogenous across quantiles. Contrary to the effect of FDI which appears to be negative and significant at higher quantiles, energy consumption shows to increase carbon emissions with the strongest effects happening at higher quantiles. In addition, higher economic growth and population size appear to reduce emissions among the high-emissions countries. (inverted U-shape hypothesis). The results of the study also support the validity of the halo effect hypothesis in higher-emissions countries.[4] However, they find little evidence in support of an inverted U-shaped curve in the ASEAN-5 countries.

According to Stern (2007), the environmental Kuznets curve (EKC) shows that there is an inverted U-shape relation between pollution and other indicators of environmental degradation, meaning that pollution emissions increase in the early stages of economic growth and then the trend reverses course in the later stages, leading to less environmental degradation. Nevertheless, there is also evidence that suggest that the EKC hypothesis is a linear relationship (Alkhathlan & Javid, 2013) and an N-shaped relationship as well (Allard et al., 2017), while some find that the EKC hypothesis is invalid (Dasgupta et al. 2002).

Zhang et al. (2016) explores the relationship between corruption and CO2 emissions. Using a quantile regression approach, they show that, first, the effect of corruption on CO2 emissions is heterogeneous among APEC (Asia-Pacific Economic Cooperation) countries. Specifically, there is significant negative effect in lower emission countries, but insignificant in higher emission countries. Second, there exists an inverted U-shaped Environmental Kuznets Curve (EKC) between corruption and CO2 emissions, and the per capita GDP at the turning point of the EKC may increase when CO2 emissions increase.

[4] The halo effect hypothesis refers to foreign companies using better management practices and advanced technologies that are conducive to a clean environment in host countries (Zarsky, 1999).

Challenges in econometric modelling of climate change

Both Weitzman (2012) and Stern (2016), among others, have warned that current economic modeling may seriously underestimate the impacts of potentially catastrophic climate change and emphasize the need for a new generation of models that give a more accurate picture of damages. In particular, Stern (2016) has pointed out two key weaknesses of the current class of economic models: (i) their limited spatial coverage, including averaged impacts across countries and regions, and (ii) unreasonable assumptions on the discount rate, which translate into a relative lack of forward-looking behavior in economic forecasts and resulting negative impacts on future generations.

According to Kompas et al. (2018), there have been relatively few attempts to examine the full global, disaggregated, and intertemporal effects of climate change on GDP using large-scale economic modeling, which would capture all of the trading patterns, spillover effects, and economic linkages among countries in the global economic system over time. Kompas et al. (2018) highlight that, given its computational complexity, computable general equilibrium (CGE) modeling has largely concentrated on individual country effects or on dynamic models with limited numbers of countries or regions and an absence of forward-looking behavior.

Hendry and Pretis (2013) stress the dangers of approaches that fail to address all the complications inherent in statistical analyses of observational data by relying on the example of the relationship between greenhouse gases and temperature. They warn that before any statistical inference can be conducted, a model must be congruent, or well-specified in that it satisfies the assumptions on which the statistical analysis relies. In addition, using data series that come from a variety of different sources can lead to higher measurement errors and false interpretations of the data properties.

Pindyck (2013) points to a plethora of integrated assessment models to estimate the social cost of carbon (SCC) and evaluate alternative abatement policies, which present major flaws making them close to useless as tools for policy analysis. These flaws include certain inputs (e.g., the discount rate) as arbitrary, but with significant effects on the SCC estimates produced by the models. The models' descriptions of the impact of climate change are completely *ad hoc*, with no theoretical or empirical foundation; and the models can tell us nothing about the most important driver of the SCC, the possibility of a catastrophic climate outcome.

However, one important aspect that needs to be considered—following Tol (2019)—is the fact that climate varies only slowly over time. The identification of the impact of climate, therefore, comes from cross-sectional variation, and as the climate varies only slowly over space, the cross-section needs to be large. This is problematic as so many other critical indicators vary over space too. This method is therefore vulnerable to spurious associations because of confounding variables. This can be partly overcome with panel data, for confounders that vary over time. Panel data with cross section fixed effects cannot help with confounders that do not change much over time. A random effects model is not vulnerable to this critique, although it faces other weaknesses: the correlation between equation errors and explanatory variables yields inconsistent estimators. Nonetheless, instrumental variables estimation can mitigate against this problem.

In recent years, there have also been several papers that estimate the impact of weather on a range of economic indicators. According to Tol (2019) the impact of a weather shock is not the same as the impact of climate change. In other words, weather studies estimate the short-run elasticity, whereas climate change is estimated based on long-run elasticities. Extrapolating the impact of weather shocks to the impact of climate change is unlikely to lead to credible results. Juselius (2007) makes the case for analyzing climate data with integrated-cointegrated vector autoregressive processes (VARs).

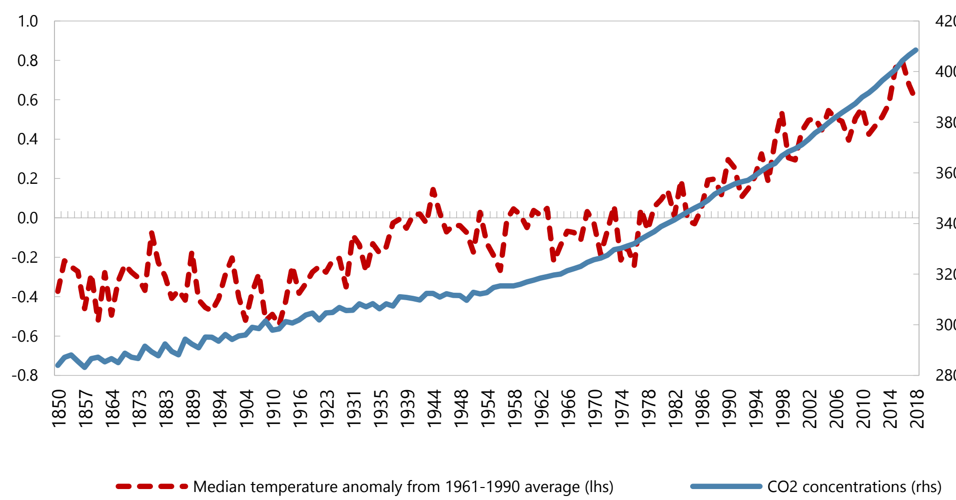
III. Stylized Findings

The increase in temperatures around the globe is being accompanied by concomitant surges in carbon dioxide. Among the main drivers of climate change, human emissions of carbon dioxide and greenhouse gases are the most significant. Figure 2 shows the median temperature anomaly relative to the average of the period between 1961-1990 along with CO2 concentrations.

Median temperature anomalies have been steadily increasing along with carbon dioxide in recent years. Although these figures are aggregate in nature, they convey information about the risks of rising temperatures, which might generate rising sea levels, droughts, and unstable climate responsible for storms, floods, hurricanes, and cyclones. One third of the world's droughts occur in SSA and the frequency of storms and flows is growing fast in this region (IMF, 2020).

Although the pace and scale of global warming generated by greenhouse gases emissions (CO2) is a worldwide phenomenon (IPCC 2014), the data from fragile states is particularly worrisome (Zhou et al., 2018). Liu et al. (2018) worked on a metric system to assess state fragility, including climate change, cohesion, economy, policy, and society, aiming at calculating the Fragile States Index of 132 states from 2007 to 2017. Their results show that countries in Africa and South America experienced worse conditions than Europe arising from climate change. [5]

Figure 2. Global Temperature and Carbon Dioxide, 1850-2019



Source: OurWorldInData.org

During the period 1980 to 2019, real GDP data in SSA is positively associated with higher CO2 emissions and GHG (Figures 3 and 4).

[5] Greenhouse gas (GHG) emissions data is sourced from the Climate Watch CAIT dataset, including Land-use, land use-change and forestry.

Figure 3. SSA Fragile States CO2 emissions and GDP, 1980-2019

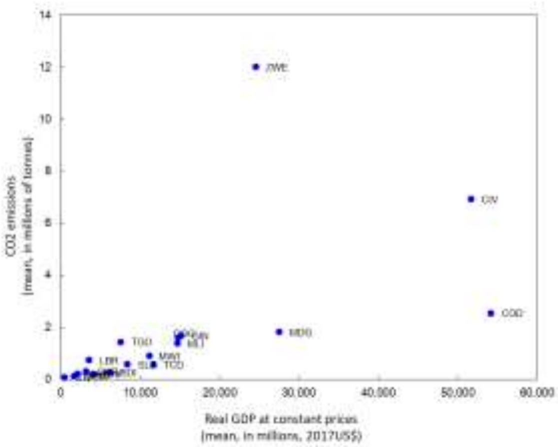
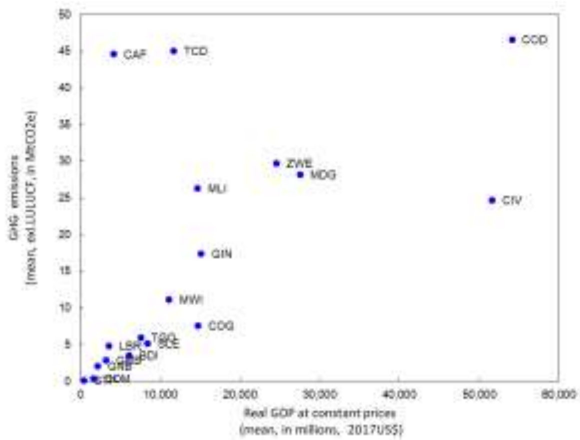


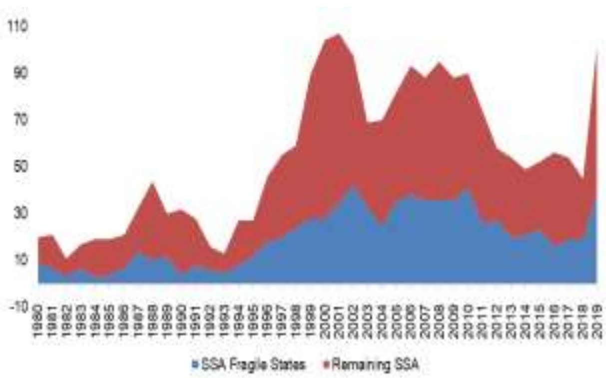
Figure 4. SSA Fragile States GHG and GDP, 1980-2019



Source: Author's Calculations using Global Carbon Project data for the CO2 emissions; Climate Watch Database for the GHG emissions and Penn World Tables for the Real GDP data.
(Note: BDI=Burundi; CAF=Central African Republic; TCD=Chad; COM=Comoros; CIV= Côte d'Ivoire; COD=Democratic Republic of the Congo; GIN=Guinea; GNB=Guinea-Bissau; LBR=Liberia; MDG=Madagascar; MWI=Malawi; MLI=Mali; COG=Republic of Congo; STP =Saõ Tomé and Príncipe; SLE=Sierra Leone; GMB=The Gambia; TGO=Togo; ZWE=Zimbabwe)

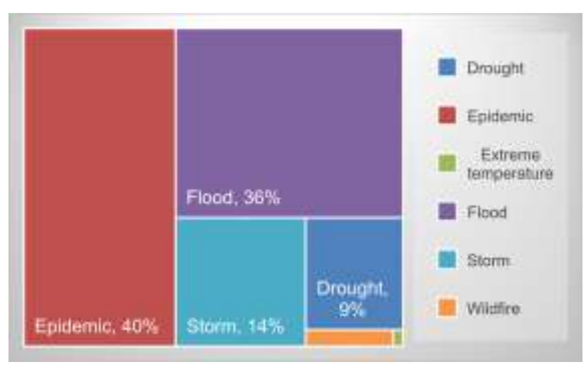
Rising temperatures along with rising sea levels and rainfall anomalies have translated into an acceleration of climate-induced natural disasters in the fragile states (Figure 5). Over the period of 1980-2019, almost 40 percent of these events in the sub-Saharan Africa occurred in the fragile states. Floods, epidemics, and storms make 90 percent of the total climate-related natural disasters (Figure 6). Throughout the period 1980-2019, average rising temperatures in sub-Saharan Africa's fragile states were associated with an increased number of climate-related events (Figure 7). These findings are critical for fragile states: as Burke et al. (2015) mentioned a strong negative correlation between income and temperature indicates that warming may amplify global inequality because hot, poor countries will probably suffer the largest reduction in growth.

Figure 5. Total Number of climate-related natural disasters



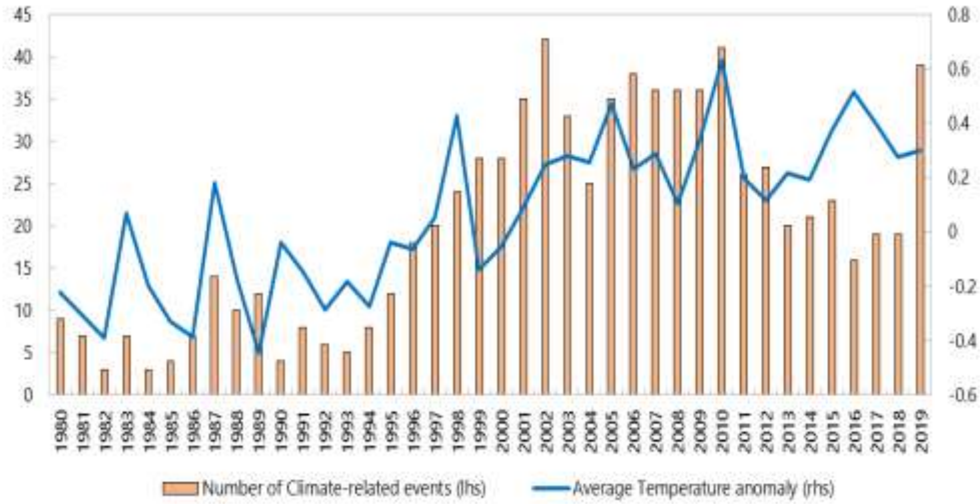
Source: Authors' calculations using EM-DAT Database
(Note: Climate-related disasters include: Drought, Epidemic, Extreme Temperature, Flood, Storm and Wildfire)

Figure 6. Share of climate-related natural disasters in SSA Fragile States, 1980-2019



Source: Authors' calculations using EM-DAT Database

Figure 7. SSA Fragile States Temperature anomaly and climate-related events



Source: Author's calculations using Harris et al. (2020) & EM-DAT Database (Note: Temperature anomaly was constructed as the difference from the average temperature of 1980-2010 time period).

IV. Methodology and Data Description

Methodology

The purpose of this paper is to investigate the relationship between income per capita, carbon emissions, temperature anomaly, and other control variables.

1) Panel autoregressive distributed lag approach

The existence of cointegration could provide relevant long-run information about the relationship between income per capita and drivers of climate change. Following Pesaran et al. (1999), we examine the relationship between real GDP per capita and drivers of climate change for the 20 fragile states in our sample, covering the period of 1980-2019. We capture the possible nonlinearities in the relationship within each group differences by allowing for heterogeneity effect in the cross sections. Hence, we propose a panel autoregressive dynamic linear (ARDL) model, examining the predictability of the linear and nonlinear panel ARDL models. The ARDL methodology is suitable for testing cointegration when all underlying series are weakly exogenous and taken as explanatory variables, *i.e*., when there is a long-run relationship among the response and covariates and there are no long-run relations in the conditional error correction form of the covariates in terms of the response (Frimpong and Oteng-Abayie, 2006).

To proceed with the estimation of ARDL, we first test whether the variables used are stationary. We conduct two panel unit root tests. Pesaran (2003) t-test for unit roots in heterogenous panels with cross-section dependence and, also, the Im, Pesaran, Hashem and Shin (2003) test, which is based on the null hypothesis that all the panels contain a unit root.

The two main techniques then used in the estimation of a dynamic heterogenous panel data model are the Pooled Mean Group (PMG) and the Dynamic Fixed Effects (DFE) estimators. The pooled mean group estimator constrains long-run coefficients to be identical but allows short-run coefficients and error variances to differ across groups. Hence, the short-run adjustment is country-specific due to the widely impact of the vulnerability to climate change. Pesaran et al. (1999) showed that PMG estimators are asymptotically and normally distributed. The Mean Group (MG) model introduced by Pesaran, Hashem, and Smith (1995) estimates separate regression for each country and calculates the coefficients for each country as unweight means. The MG approach avoids imposing restrictions, and, hence, all coefficients may vary heterogeneously in the long and short run. While the PMG estimator involves the combination of pooling and averaging of coefficients, the Dynamic Fixed Effects (DFE) estimator restricts the speed of adjustment, slope coefficient and short-run coefficient to exhibit non-heterogeneity across countries. Hence, the DFE assumes that countries responses are the same in the short-run and long-run. We select the most efficient method by relying on the Hausman test under the null hypothesis of homogeneity to compare between the PMG, DFE, and MG estimators.

In principle, a panel-ARDL model, like those proposed by Pesaran, Hashem and Smith (1995) and Pesaran et al. (1999) seem to be suitable for dealing with the panel of fragile states. The PMG and MG may generate more consistent estimates as they are allowed to vary across countries. The ARDL (n, m) model with a lag m for exogenous variables, $\boldsymbol{X} = (x_1, x_2, \dots, x_p)$, with a lag n for the response variable (Y) can be formulated as:

$$Y_{it} = \sum_{j=1}^{n} a_{ij} Y_{i,t-j} + \sum_{j=0}^{m} \boldsymbol{c}'_{ij} \boldsymbol{X}_{i,t-j} + \mu_i + \epsilon_{it} \quad (1)$$

where *X* is the vector of explanatory variables, $\boldsymbol{c}_i = (c_{i1}, c_{i2}, \dots, c_{ip})$ shows the effects of both the current and lagged exogenous variables on the response variable *Y* at moment *t* and the coefficients $(a_i, \dots, a_n)$ are the autoregressive effects of past realizations of variable *Y*; α_0 is the intercept term and ϵ_{it} is a white noise error. By reparametrizing the model, we obtain:

$$\Delta\, GHG_{it} = \phi_i \left(GHG_{i,t-1} - \beta'_i X_{it} \right) + \sum_{j=1}^{n-1} \alpha^*_{ij} \Delta\, GHG_{i,t-j} + \sum_{j=0}^{m-1} \boldsymbol{c}'_{ij} \boldsymbol{X}_{i,t-j} + \mu_i + \epsilon_{it} \quad (2)$$

where the coefficients β_i depict the long-run estimates of the impact of the explanatory variables on Green House Gasses (GHG), μ_i captures country-specific effects, and ϕ_i is the error correction mechanism. All the other parameters represent short-run coefficients while ϵ_{it} are the disturbances, which are assumed to be independently distributed across time. Against this backdrop, we test the null hypothesis of the absence of cointegration ($H_0: c_{1i} = \cdots = c_{mi} = 0$) versus the alternative hypothesis ($H_0: c_{1i} \neq \cdots \neq c_{mi} \neq 0$).

The second part of the study focuses on utilizing panel quantile regression models

2) Panel Quantile Estimations

The panel quantile regression model is given in equation (3):

$$Q_{GDP_{it}}(\tau_k | \alpha_i, x_{it}) = \alpha_i + x_{it}\beta(\tau_k) \quad (3)$$

where *i* and *t* denote, respectively, country and year while α_i represents unobservable individual effects. The coefficients for the $\tau - th$ quantile of the conditional distribution is derived from equation (4):

$$\hat{\beta}(\tau) = \arg\min \textstyle\sum_{i=1}^{n} \rho_\tau (y_i = x_i^T \beta) \quad (4)$$

where $\rho_\tau(u) = u\big(\tau - I(u < 0)\big) = \begin{cases} 1. u < 0 \\ 0. u \geq 0 \end{cases}$ is the check function, and $I(..)$ is an indicator function. For the methodology, this paper follows Koenker (2004), treating the unobservable individual effect, α_i, as a regression parameter. Hence, the estimation equation for long-run relations for the different quantiles—equation (4)—becomes:

$$\left(\hat{\beta}(\tau_k, \lambda), \{\alpha_i(\lambda)\}_{t=1}^{N}\right) = \arg\min \textstyle\sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{n=1}^{N} w_k\, \rho_{\tau k}(y_i - \alpha_i - x_{it}^T \beta(\tau_k)) + \lambda \sum_{i=1}^{N} |\alpha_i| \quad (5)$$

where $\omega_k$are the weights of the $k - th$ quantile.

In reviewing methodologies, datasets, and recent findings on climate factors affecting economically related outcomes and other relevant variables, Dell et al. (2014) suggested as "best practice" to include credibly exogenous regressors as control variables (such as terms of trade shocks and weather-related variables). Dell et al. (2014) pointed out also that "potentially endogenous regressors should typically only be included if there is a strong argument that these variables are not affected by climate or can otherwise be modeled appropriately in a credible structural context." Furthermore, they suggest to "control for the interactions of those other characteristics with the climate shocks." On our empirical search, we follow this strategy and include a set of control variables to address endogeneity and avoid specification bias that might arise from non-controlling for relevant explanatory variables.

Data Description

Our analysis covers in total twenty fragile states in the sub-Saharan Africa (*i.e*., Burundi, Central African Republic, Chad, Comoros, Democratic Republic of the Congo, Republic of Congo, Côte d'Ivoire, Eritrea, The Gambia, Guinea, Guinea-Bissau, Liberia, Madagascar, Malawi, Mali, Saõ Tomé and Príncipe, Sierra Leone, South Sudan, Togo, Zimbabwe). Based on data availability, an annual sample observation from 1980 to 2019 was selected. The variable descriptions, data definitions and data sources are shown in Annex 1. To address endogeneity problems, we considered a strong set of control variables.

Dependent variables

For estimating the effects on economic activity using panel regressions as well as quantile regressions, we use the logarithm of real GDP per capita as our main dependent variable. GDP per capita is constructed using real GDP expressed in constant 2017 US$ prices and dividing it by the population of the country. Both real GDP and population data are sourced from the Penn World Table version 10.0 (updated as of June 21st, 2021).

For estimating the effects on emissions through quantile regressions, we use the logarithm of Greenhouse gas (GHG) emissions as our main dependent variable, sourced from the Climate Watch CAIT dataset, including Land-use, land use-change and forestry (LULUCF).

Explanatory variable

In estimating the effects of climate change on economic activity, we use historical temperature data as our key explanatory variable. Temperature data are sourced from the gridded Climatic Research Unit (CRU) Time-series data version 4.04 at the University of East Anglia. This dataset provides month-by-month variations in climate over the period 1900-2019 on high-resolution (0.5x0.5 degree) grids. We used geospatial software to aggregate the temperature data to the country-month level. We then averaged the monthly variations to construct annual data for the twenty fragile countries in the sub-Saharan Africa over the period of 1980-2019. In addition, we constructed the temperature anomaly variable as the difference from the average temperature of 1980-2010 time period, following the NOAA methodology.

Other control variables

The model incorporates other variables in addition to the log of GDP per capita, temperature anomaly and log of carbon emissions. The other explanatory variables considered in the model are the following: log of trade as the sum of imports and exports of goods and services, log of gross fixed capital formation, mobile cellular subscriptions (per 100 people) as a proxy for technology, human capital (proxied by secondary school education), and life expectancy sourced from the WDI Database, log of population by country sourced from the Penn World Table, and armed conflict expressed as a dummy variable for 1-armed conflict and 0-otherwise sourced from the Uppsala Conflict Data Program (UCDP) Dataset. A variable depicting the quality rate of institutions was included in the model (polity score). A dummy variable was also included to differentiate oil producers and non-oil producers in the dataset.

V. Panel Estimations

Panel Unit Root Tests and Cointegration

To proceed with the estimation of panel regression models, we first test whether the variables used are stationary. We conduct two panel unit root tests. Pesaran (2003) t-test for unit roots in heterogenous panels with cross-section dependence and, also, the Im, Pesaran and Shin (IPS, 2003) test, which is based on the null hypothesis that all the panels contain a unit root.

Table 1 reports the Im-Pesaran-Shin unit-root test and Pesaran's cross-section dependence. These results indicate that the null hypothesis of the existence of a unit root could not be rejected for all the variables at the selected level. Also, the unit root null hypothesis for all the variables at the first difference could be completely rejected at the 1 percent level.

Table 1. Panel Unit Root and Cross-Sectional Independence Tests

Variable	Co2	Real GDP per capita	GHG	Population	Temp. Anomaly	Trade	Investment	Life expectancy	Technology	Secondary School	Polity score
Levels											
CSD	-0.152	-2.380	-2.220	3,692	-2.067	-2.306	-0.711	-4.735	-8.362	-0.495	-0.729
	(0.440)	(0.423)	(0.668)	(1.000)	(0.079)	(0.538)	(0.239)	(0.000)	(0.000)	(0.310	(0.233)
IPS Statistic	-1.1975	-0.9826	-0.9804	-1.0499	-1.3368	-0.2317	0.8250	-1.1071	-0.347	4.9914	-1.4526
	(0.9622)	(0.9971)	(0.9999)	(0.9998)	(0.0906)	(0.4084)	(0.7953)	(1.000)	(1.000)	(1.000)	(0.0732)
First Difference											
CSD	-13.262	-4.033	-3.390	-4.274	-5.669	-3.975	-9.091	-6.259	-8.571	-3.652	-8.096
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IPS Statistic	-6.367	-5.4077	-5.0363	-2.5956	-8.8959	-9.6611	-14.524	-0.9473	-5.8281	-3.648	-14.315
	(0.0000)	(0.0000)	(0.0000)	(0.0047)	(0.0000)	(0.0000)	(0.000)	(0.9994)	(0.000)	-	(0.000)

Note. IPS: Im-Pesaran-Shin unit-root test. P-values are reported in parentheses
CSD: Pesaran's test of cross-sectional independence. p-value indicate the rejection of null hypothesis of no cross-sectional independence.

Given that the time series contain a panel unit root (non-stationary), we look for a stable, long-run relationship in the panel data. We use Westerlund (2007) to examine if there is a long-run relationship between temperature anomaly and log of GDP per capita and other explanatory variables by examining whether error-correction is present for individual panel members and for the panel. The null hypothesis of no cointegration under Westerlund test for cointegration is rejected at a *p*-value of 0.0321 with a variance ratio statistic equal to 1.8509, removing cross-sectional means. We run the same test for examining whether there is a long-run relationship between logarithm of GDP per capita and logarithm of Greenhouse Gas Emissions and other explanatory variables. The null hypothesis of no cointegration under Westerlund test for cointegration is rejected at a *p*-value of 0.0124 with a variance ratio statistic equal to -2.243.

ARDL Model

Table 2 presents the long-, short-run results together with the error correction term.[6] The PMG model shows that, for the long-run equation, real GDP per capita, temperature anomalies and technology significantly contributes to climate change measured by GHG emissions. A 1 percent increase in real GDP per capita increases GHG by 25 percentage points in the long run. Also, if there is a 1 percent increase in temperature anomalies, then there is an increase in GHG emissions by 19 percentage points. Similarly, for the DFE model, we observe that a 1 percent increase in real GDP per capita leads to a 85 percentage points increase in GHG emissions in the long run. Economic growth in SSA is highly pollutive. Given the overall use of fossil fuels in economic activity in SSA, it could be assumed that by using renewable forms of energy consumption, emissions of carbon dioxide—one of the most critical determinants of global warming—could be reduced.

Table 2: ARDL results under Pooled Mean Group and Dynamic Fixed Effects

Variable	Pooled Mean Group	Dynamic Fixed Effects
Long-run equation		
Real GDP per capita	.247***	.849***
	(.08)	(.253)
Temperature Anomalies	.188***	.295
	(.068)	(.258)
Technology	.032***	.008
	(.006)	(.021)
Error Correction Term	-.199***	-.145***
	(.046)	(.028)
Short-run equation		
Δ: Log of Real GDP per capita	-.057	-.01
	(.132)	(.095)
Δ: Temperature Anomalies	-.048	-.01
	(.058)	(.028)
Δ: Technology	-.002*	-.001
	(.001)	(.001)
Constant	.176**	-.494*
	(.087)	(.272)
Observations	497	497

Standard errors are in parentheses; Δ is the first difference operator

**** p<.01, ** p<.05, * p<.1*

[6] We test the PMG estimator versus the MG estimator (that allows heterogeneity in the short and long run estimators) by means of the Hausman, which provided evidence that the PMG is consistent and more efficient.

Hausman (1978) specification test	
	Coef.
Chi-square test value	.20
P-value	.977

Brini (2021) underlined the potential role to play by renewable energy consumption in SSA to contain climate change. Nonetheless, both temperature anomalies and technology are no longer significant in the dynamic fixed effects model. The error correction terms under PMG and DFE are negative and statistically significant at the 1 percent level. The error correction term indicates that, if there is a deviation from the long-run equilibrium, they will correct at a 20 percent and 15 percent speed of adjustment, respectively for PMG and DFE. These results confirm the existence of a process, which converges over the long run, returning to equilibrium. However, all the coefficients for short-run equations show non-significant effects on GHG.

The ARDL-PMG and DFE approaches were used to assess the long- and short-term relationship among greenhouse gas emissions, income per capita, temperature anomalies and technology. Given the existence of cointegration among these variables—and, hence, the existence of a long-term relationship—we found that, in the long run, income per capita, temperature anomalies, and technology carry a positive and statistically significant impact on greenhouse emissions. These results may suggest that the use of renewable energy consumption (and, also, achieving higher energy efficiency), could potentially contribute to a reduction in GHG emissions in SSA's fragile states, hence mitigating the negative effects on climate change.[7]

Panel Regression: Effects of Temperature on Income per capita growth

Building on the representations in Section IV, this section assesses different panel regression models in first differences (*d*), as an alternative exploration to the previous cointegration outcome. We compared fixed effects estimates with estimates obtained using fixed and time effects, random effects (to check for robustness), apply the Hausman test for the validity of the random effects model assumptions, and using a dynamic model that includes lags of selected independent variable that the variation across states remains random. Nonetheless, to capture the unobserved heterogeneity across different states, fixed effects regression models were also run. The alternative estimation techniques reveal a qualitatively similar picture—although the coefficients and statistical significance of different indicators vary across methods.

Table 3 shows the estimates of panel regression results for the period 1980-2019 for the 20 fragile states in SSA. We assess the impact of temperature anomaly on income per capita growth after accounting for the impact of other variables that are also likely to affect income. Specifically, we run an expanded GDP per capita growth regression on panel data, where the dependent variable is the GDP per capita growth rate and the explanatory variables include, temperature anomaly, and macroeconomic variables that can affect short or long-term GDP dynamics such as trade, investment and other variables like human capital, technology, quality of institutions (polity score), incidence of an armed conflict and a dummy variable for differentiating an oil producer country.[8]

The results reveal that temperature anomaly negatively affects the growth rate of income per capita on average across all countries. Temperature anomaly shows a significant negative effect through all the models assessed. Findings reveal that the effect of a 1◦C rise in temperature decreases income per capita growth in fragile states in SSA by −2.4 percentage points. Most of the other explanatory variables, including the incidence of an armed conflict, have the expected sign and are significant. The new variable interaction depicts the interplay between

[7] This is an avenue for further research as the model tested here does not consider the effects of renewable energy on GHG emissions.

[8] We have also considered interaction terms of the climate intensity variable with other variables that may have constituted important channels through which climate change may have affected growth of income per capita. Nevertheless, the results were not significant.

quality of institutions (*polity_score*) and GDP per capita growth, exhibiting a significant positive effect on income per capita growth.

To decide whether to use a random or fixed effect estimation, we apply the Hausman test where the null hypothesis is that the preferred model is random effects vs. the alternative the fixed effects. Results show a significant *p*-value of 0.00 which corroborates the possible use of fixed effects.

Table 3. Panel Regression Estimates: Effects on Income per capita growth, 1980-2019

	Pooled_OLS	Fixed_Effects	Random_Effects
dtemp	-.024***	-.024***	-.024***
	(.008)	(.008)	(.008)
dlpop	.169	.179	.169
	(.312)	(.359)	(.312)
dltrade	.074***	.07***	.074***
	(.015)	(.015)	(.015)
dtechnology	.002***	.002***	.002***
	(.001)	(.001)	(.001)
Dhuman capital	.002	.001	.002
	(.002)	(.002)	(.002)
polity_score	.001	.001*	.001
	(0)	(.001)	(0)
armed_conflict	-.017**	-.032***	-.017**
	(.007)	(.008)	(.007)
interaction	.045***	.042***	.045***
	(.009)	(.009)	(.009)
oil_producer	.01*		.01*
	(.006)		(.006)
dlinvestment_cu~t	.043***	.042***	.043***
	(.008)	(.007)	(.008)
_cons	-.013	-.005	-.013
	(.009)	(.01)	(.009)
Observations	487	487	487

***Significant at the 1 percent level
**Significant at the 5 percent level
*Significant at the 10 percent level
Standard errors are in parentheses

Panel Quantile Regression: Effects of Temperature on Income per capita growth

The results of the panel quantile regression presented in Tables 4 and 5 confirm the significant and negative effect of temperature anomaly on income per capita growth with some variability but significant effect across the quantile distribution (15, 25, 50, 75, and 90 percent). In addition, other controlling variables confirm a significant effect across the quantile distribution.[9]

Integrating over the quantile estimated, Table 5 shows that an increase in temperature reduces growth of income per capita by 1.8 percentage points (average effect estimate).[10]

[9]Specifically, we study the simultaneously changes in specific parts of the distribution of the dependent variable with quantile regressions, independently of the change and variability experienced by the rest of the distribution.

[10] We tested for weak cross-sectional dependence in a panel data's error term to check whether dependence between cross sectional units in a regression is not accounted for—as the dependence between units violates the basic OLS assumption of an independent and identically distributed error term. The test statistic is 13.25 and the *p*-value is 0, therefore rejecting the null hypothesis of weak cross-sectional dependence.

Table 4. Quantile Panel Regressions: Effects on Income per capita growth, 1980-2019

	Quantile				
	15	25	50	75	90
dtemp	-.029***	-.022***	-.02***	-.012***	-.037***
	(0)	(.001)	(.002)	(.001)	(0)
dlpop	.31***	.161***	-.41***	-.557***	-.614***
	(.014)	(.04)	(.048)	(.038)	(.012)
dltrade	.068***	.056***	.022***	.041***	.049***
	(.001)	(.005)	(.002)	(.001)	(0)
dtechnology	.002***	.002***	.002***	.001***	.004***
	(.001)	(.002)	(.002)	(.001)	(0)
Dhuman capital	.003***	.001***	.002***	0	.002***
	(0)	(0)	(0)	(0)	(0)
polity_score	.002***	.001***	.001***	0***	0***
	(0)	(0)	(0)	(0)	(0)
armed_conflict	-.021***	-.012***	-.003***	-.004***	-.007***
	(0)	(.001)	(.001)	(.001)	(0)
interaction	.028***	-.025***	-.02***	.034***	.042***
	(.001)	(.002)	(.002)	(.001)	(0)
oil_producer	.007***	0	.005***	.011***	.026***
	(0)	(.001)	(.001)	(.001)	(0)
dlinvestment_cu~t	.031***	.028***	.039***	.04***	.034***
	(.001)	(.001)	(.001)	(.001)	(0)
Observations	487	487	487	487	487

***Significant at the 1 percent level
**Significant at the 5 percent level
*Significant at the 10 percent level
Standard errors are in parentheses

Table 5. Average Effect Estimates

dtemp	-.018***
	(.004)
Observations	487

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Panel Quantile Regression: Effects of Income per capita growth on Carbon Emissions growth

Raising greenhouse gas (GHG) emissions are the natural consequence of human activities and economic growth. Elevated GHG emissions would thus imply a direct effect on climate change. The impact of income per capita growth on carbon emissions growth rate is heterogeneous, indicating that higher growth rate of income per capita could mitigate the increase in carbon emissions in high-emission countries.

Table 6 presents the results of the panel quantile regression estimation for GHG emissions growth rate. The results are reported for the 5th, 10th, 15th,20th, 50th, 70th, 85th, 90th percentiles of the conditional emissions distribution. The three variables—GDP per capita, trade, technology, and population—have significant and positive impact on the change in GHG emissions. Similar effect is reported for the oil producer dummy variable till the 50th quantile. Overall, the empirical results indicate that the impacts of various factors on carbon emissions are heterogeneous. The results show that the coefficient of GDP per capita growth is negative and significant at the 5 percent level for the 90th quantile, suggesting that higher growth of income per capita could help reduce carbon emissions for high-emitter countries. These results provide a more informative portrait of the effect of GDP per capita growth on carbon emissions growth rate in fragile states *vis-à-vis* simple regression outcomes. These findings tend to support the hypothesis behind the Environmental Kuznets Curve (EKC) and the energy consumption growth literature, which postulates that as income increases, emissions increase pari passu until a threshold level at which emissions start to decline.

Table 6. Quantile Panel Regressions: Effects on Carbon Emissions growth, 1980-2019

	Quantile							
	5	10	15	20	50	70	85	90
dlrgdp_ca	.195***	.174***	.171***	.148***	.1***	.049***	.094***	-.042*
	(.006)	(.007)	(.003)	(.01)	(.003)	(.008)	(.012)	(.024)
dltrade	.065***	.019***	.04***	.021***	.007	.003	.032***	.062***
	(.001)	(.002)	(.001)	(.002)	(.005)	(.004)	(.004)	(.008)
dtechnology	.002***	.001***	0***	0***	0***	0***	0***	0**
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
dlife	.007**	.003***	-.018***	-.006***	-.006***	-.003***	0	.017***
	(.003)	(.001)	(0)	(.001)	(.001)	(.001)	(.003)	(.003)
armed_conflict	.013***	.016***	.02***	.022***	.003*	.007***	-.004	-.022***
	(.003)	(.001)	(0)	(.001)	(.002)	(.001)	(.005)	(.002)
dlpop	-.381***	.176***	.869***	1.016***	.789***	.742***	1.348***	1.408***
	(.037)	(.038)	(.027)	(.047)	(.024)	(.038)	(.089)	(.14)
polity_score	-.001***	.002***	.001***	.001***	0***	.001***	-.002***	-.003***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(.001)
interaction	.017***	.006***	.035***	.025***	.017***	.008***	.004	.008**
	(.001)	(.001)	(.001)	(.001)	(.001)	(.002)	(.004)	(.004)
oil_producer	.035***	.024***	.013***	.019***	.006***	-.011***	-.015***	-.021***
	(.001)	(.001)	(.001)	(0)	(.001)	(.001)	(.003)	(.002)
dlinvestment_cu~t	-.02***	-.008***	-.001**	.005***	-.002**	-.002***	-.013***	-.005**
	(.002)	(.001)	(0)	(.002)	(.001)	(.001)	(.004)	(.002)
Observations	399	399	399	399	399	399	399	399

***Significant at the 1 percent level
**Significant at the 5 percent level
*Significant at the 10 percent level
Standard errors are in parentheses

VI. Robustness Tests

To test the validity of the previous results and outcomes, several robustness checks are proposed. This section provides a detail of these checks, which are conducted for both panel and quantile panel regressions. The results of panel regressions are consistent for alternative data and model specification. Table 7 shows the results from adding Co2 as an independent variable in the panel regression (columns 1-3). In addition, Table 7 also includes an interaction term for temperature anomaly and pollution in each country. On the one hand, comparing with Table 2, these results show that results are almost invariant to the addition of Co2, with similar results in terms of the effects on income per capita growth as those from Table 2. On the other hand, the inclusion of an interaction term for temperature anomaly and population carries a significant increase in the effect of this variable on income per capita growth. In particular, these findings show that the effect of a 1°C rise in temperature anomaly decreases GDP per capita growth rate in fragile states in SSA by 2.2 percentage points under Pooled OLS. Most of the other explanatory variables, including the incidence of an armed conflict, have the expected sign and are significant.

Table 7. Panel Regression Robustness Tests: Effects on Income per capita growth, 1980-2019

	Pooled_ OLS	Fixed_ Effects	Random Effects	Pooled_ OLS	Fixed_ Effects	Rando m_Effe cts	MLE
dtemp	-.022***	-.022***	-.022***				-.022***
	(.008)	(.007)	(.007)				(.007)
dlco2	.028*	.024*	.026*	.028*	.025*	.026*	
	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)	
dltrade	.074***	.07***	.072***	.075***	.071***	.073***	.074***
	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
dtechnology	.002***	.001***	.002***	.002***	.001***	.002***	.002***
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
dlife	.006	.008	.007	.006	.009	.007	.007
	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)
armed_conflict	-.016**	-.032***	-.024***	-.016**	-.032***	-.024***	-.024***
	(.007)	(.008)	(.007)	(.007)	(.008)	(.007)	(.008)
polity_score	.001	.001	.001	.001	.001	.001	.001*
	(0)	(.001)	(0)	(0)	(.001)	(0)	(0)
interaction	.042***	.04***	.041***	.042***	.039***	.04***	.041***
	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)
oil_producer	.011**		.012	.011**		.012	.012
	(.005)		(.008)	(.005)		(.008)	(.008)
dlinvestment_cu~t	.04***	.039***	.039***	.04***	.038***	.039***	.04***
	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)
dtemp_x_dlpop				-.632**	-.644**	-.639**	
				(.268)	(.262)	(.263)	
_cons	-.009**	-.002	-.008	-.009**	-.002	-.008	-.007
	(.004)	(.003)	(.005)	(.004)	(.003)	(.005)	(.005)
Observations	525	525	525	525	525	525	525

***Significant at the 1 percent level
**Significant at the 5 percent level
*Significant at the 10 percent level
Standard errors are in parentheses

Further, Table 7 includes (column 7) the results of conducting the panel regression analysis by using a maximum-likelihood random-effects estimator. The effect of a 1°C rise in temperature anomaly decreases GDP per capita growth in fragile states in SSA by −2.2 percentage points. Most of the other explanatory variables, including the incidence of an armed conflict, trade, technology, and investment still carry the expected sign and remain statistically significant. Results from this robustness check—assuming a change in model specification to a maximum-likelihood estimation procedure—largely support the robustness of the previous results.

For the quantile panel regression models, the robustness testing also involves adding a new variable (the interaction of temperature anomaly and population). The coefficient for temperature anomaly and population remains negative at all quantiles (Table 8), like in Table 4. All other covariates kept their sign and a similar coefficient when compared against Table 4.

Table 8. Quantile Panel Regressions Robustness Tests: Effects on Income per capita growth, 1980-2019

	Quantile				
	15	25	50	75	90
dtemp_x_dlpop	-1.048***	-.649***	-.242***	-.348***	-.521***
	(.015)	(.011)	(.048)	(.019)	(.032)
dltrade	.076***	.051***	.034***	.038***	.067***
	(.001)	(.001)	(.002)	(.001)	(.008)
dtechnology	.001***	.001***	.001***	.001***	.001***
	(0)	(0)	(0)	(0)	(0)
dlife	.01***	.007***	.004***	.004***	.013***
	(0)	(0)	(.001)	(0)	(.001)
armed_conflict	-.015***	-.014***	-.013***	.006***	-.003
	(0)	(0)	(.001)	(0)	(.003)
polity_score	.002***	.001***	.001***	0***	0***
	(0)	(0)	(0)	(0)	(0)
interaction	.014***	-.029***	-.014***	.044***	.062***
	(0)	(.001)	(.001)	(.002)	(.004)
oil_producer	.014***	.008***	.014***	.001	.039***
	(0)	(0)	(.001)	(.001)	(.004)
dlinvestment_cu~t	.023***	.028***	.031***	.031***	.041***
	(0)	(0)	(0)	(0)	(.002)
Observations	525	525	525	525	525

***Significant at the 1 percent level
**Significant at the 5 percent level
*Significant at the 10 percent level
Standard errors are in parentheses

VII. Policy Implications

Based on the results from the previous section, there are plausible implications for policy making that could be pursued to address climate change in SSA's fragile states. Specific challenges for fragile states include: (i) low capacity to propose, legislate, or manage regulations and carbon taxes; (ii) carbon emissions may be limited to specific sectors or firms, which may facilitate enforcement and collection. Further, if emissions are very concentrated—as opposed to other contexts where household energy use constitutes a large portion of emissions—this could enhance political feasibility. These measures could also generate much-needed revenue for fragile states.

Our analysis so far showed that there are instances where, as income increases, emissions increase *pari passu* until a threshold level at which emissions start to decline (relatively higher-developed countries). This seems to support the notion that countries using more efficient means of production (the *halo* effect) could pollute relatively less. This calls for further reviews of the environmental impact of the different forms of industrial production—for instance, a careful analysis of foreign direct investment coming into the country.

Each fragile state could develop its own strategy for energy consumption—how to shift from being an economy consuming fossil fuels (oil, carbon) to a clean and renewable source. Some fragile states could benefit from increasing the level of economic growth and population. However, for fragile states, high economic growth does not contain but increase Co2 emissions. Hence, a uniform policy for controlling Co2 emissions does not seem to be an efficient answer from the policy perspective—a tailored policy is superior in this regard, taking into consideration the particular developmental characteristics of each state.

Countries in the SSA region have pledged to adopt a range of mitigation measures in the recent decade to address climate change. Almost all fragile states in the SSA region, along with other developed and developing countries, have submitted their national post-2020 climate action commitments, known as the Nationally Determined Contributions (NDCs). These commitments form the foundation of the 2015 climate agreement.

Commitments under the Paris pledges vary in terms of target variables, baseline years, the size of reductions and whether they are conditional on financing or not. A handful of the fragile states have pledged in reducing CO2 emissions by more than 30 percent in 2030 *vis-à-vis* the BAU (Business-as-Usual) scenario emissions conditional on receiving international support (Chad, Republic of Congo, Malawi, and Zimbabwe). The goal of this section is to build on the findings from the previous econometric exercise to outline a mitigation strategy for fragile states.

How much mitigation effort is needed?

We analyze quantitatively the effectiveness of carbon taxes in reducing long-term emissions in the fragile states of sub-Sahara Africa. We follow the IMF's Carbon Pricing Assessment Tool (CPAT) and its *Multiscenario Tool* to estimate the mitigation efforts needed to deliver emission reductions in the region.

CPAT provides projections of fuel use and CO2 emissions by major energy sector by country. This tool starts with use of fossil fuels and other fuels by the power, industrial, transport, and residential sectors and then projects fuel use forward in a baseline case using: GDP projections; assumptions about the income elasticity of demand and own-price elasticity of demand for electricity and other fuel products; assumptions about the rate of technological change that affects energy efficiency and the productivity of different energy sources; and future international energy prices. In these projections, current fuel taxes/subsidies and carbon pricing are held constant in real terms.[11] The model generates emission projections for 20 fragile states in sub-Sahara Africa under both baseline scenarios (business as usual, or BAU) and three carbon pricing measures.

We estimate the amount of emissions in a country that can be reduced by 2030 against the BAU scenario with carbon tax rates of $25, $50, and $75 per ton. The carbon tax level is assumed to be reached only gradually in 10 years. The IMF staff estimated that the $75 tax would lead to the amount of emissions that scientists estimate is consistent with containing global warming to below 2 degrees Celsius (IMF, 2020). More specifically,

- ✓ Simulation exercises with a carbon tax as the main mitigation tool indicate a wide range of tax rates that can help achieve the NDCs (Figure 8). For countries with relatively high-emission reduction targets such as the Central African Republic, São Tomé and Príncipe, Liberia and Mali, a carbon tax of more than $75 per ton of GHG emission would be needed, assuming that the carbon tax is the only instrument used.

- ✓ Assuming that the 20 countries introduce a carbon tax of $50 and $75 per ton, regional emissions would decrease by 26, and 33 percent on average, respectively. The dispersion of the needed carbon tax rates mainly reflects underlying cross-country differences in commitment levels and energy sources, which calls for stronger international coordination in mitigation targets across the region.

- ✓ Carbon taxes can also mobilize additional fiscal revenue. At $25 per ton of GHG, additional revenue from a carbon tax is estimated to be 0.35 percent of GDP, on average, in the region (Figure 9). The additional revenue is 0.66 percent of GDP for a tax rate of $50, and 0.95 percent of GDP for $75. The marginal gain from higher tax rates declines due to erosion of the tax base caused by higher energy prices. The revenue from carbon taxes (Figure 9) can, in turn, be used for compensating those affected negatively by carbon taxes, financing priority spending including health, education, infrastructure, green investment, and adaptation spending; and reducing distortionary taxes that reduce incentives to work and invest.

[11] CPAT was developed by IMF and World Bank staff and evolved from an earlier IMF tool used, for example, in IMF (2019a and b). For descriptions of the model and its parameterization, see IMF (2019b Appendix III, and Parry and others (2021), and for further underlying rationale see Heine and Black (2019).

Figure 8: Emissions reductions and NDC goals by scenario (percent vs BAU in 2030)

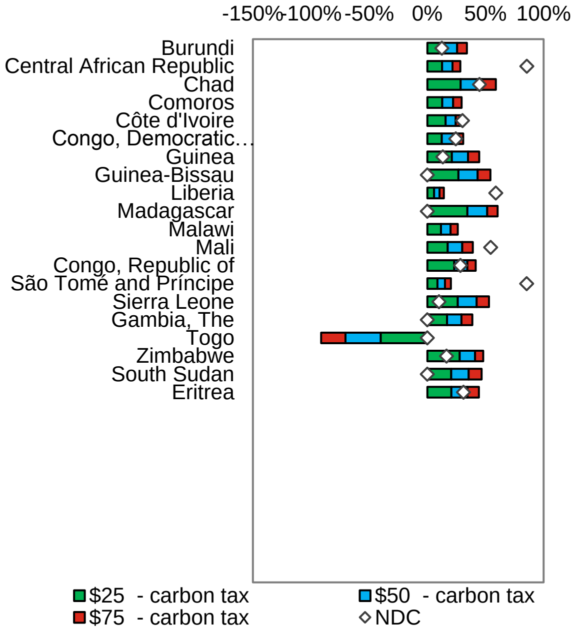
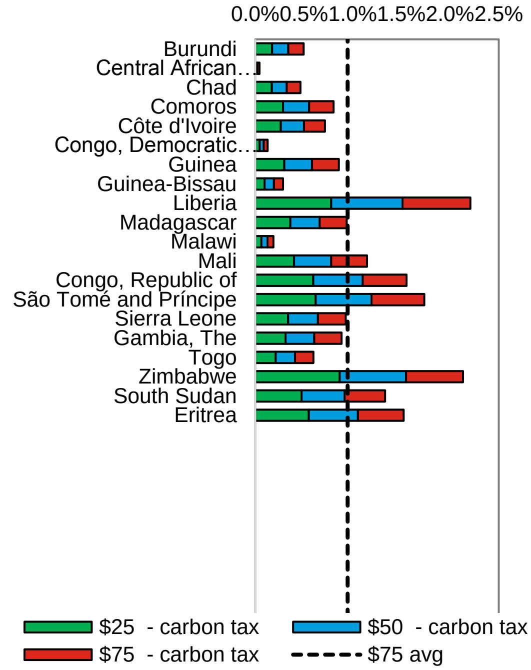


Figure 9: Fiscal revenues by scenario (percent of GDP), compared to a baseline in 2030



Source: IMF CPAT and Multiscenario Tool

VIII. Conclusion

Based on a panel quantile regression model that accounts for unobserved individual heterogeneity and distributional heterogeneity, the estimates identified a significant, contemporary causal effect of temperature anomaly on income per capita growth. The effects of higher temperature on income per capita growth are negative while the impact of income per capita growth on carbon emissions growth is heterogeneous, indicating that higher GDP per capita growth could help reduce carbon emissions growth for high-emitter countries.

Temperature anomaly shows a significant negative effect through all the models assessed. The other variables, except for life expectancy, were also significant in their effects on GDP per capita growth and have the expected signs. Findings reveal that the effect of a 1◦C rise in temperature decreases income per capita growth in fragile states in SSA by −1.8 percentage points. Moreover, the results of the panel quantile regression confirm the significant and negative effect of temperature anomaly on income per capita growth with some variability but significant effect across the quantile distribution (15, 25, 50, 75, and 90 percent). In addition, other controlling variables confirm a significant effect across the quantile distribution.

The results also provide a more informative description of the effect of GDP per capita growth on greenhouse gas emissions in fragile states in SSA. The estimates of GHG emissions—at different quantiles—tend to vary significantly when compared with the panel fixed effect estimates. The estimates displayed show the distributional impact of GDP per capita growth on GHG emissions growth rates. The results show that the coefficient of GDP per capita growth is negative and significant at the 5 percent level for the 90th quantile, suggesting that higher income per capita growth will reduce carbon emissions growth for high-emitter countries.

Policy coordination is critical to avoid a uniform policy for controlling Co2 emissions across states—which does not seem to be an efficient answer from the policy perspective. Fragile states could benefit from tailoring climate policies, taking into consideration their particular developmental characteristics.

Annex I. Data description and sources

Variable	Description	Source
Dependent variables		
Log of GDP per capita	Real GDP at constant 2017 national prices (in mil.2017US$) divided by population	PWT 10.0 | Penn World Table | Groningen Growth and Development Centre | University of Groningen (rug.nl)
Log of GHG emissions	Greenhouse Gas (GHG) Emissions, Total including LUCF- in MtCO2e	World | Total including LUCF | Greenhouse Gas (GHG) Emissions | Climate Watch (climatewatchdata.org)
Explanatory variables		
Temperature anomaly	The difference from an average, or baseline, temperature. The baseline temperature is computed by averaging 1980-2010 temperature data.	Dataset Record: CRU TS4.04: Climatic Research Unit (CRU) Time-Series (TS) version 4.04 of high-resolution gridded data of month-by-month variation in climate (Jan. 1901- Dec. 2019) (ceda.ac.uk)
Other control variables		
Log of Population	Number of persons (millions)	PWT 10.0 | Penn World Table | Groningen Growth and Development Centre | University of Groningen (rug.nl)
Log of Trade	Imports + Exports of goods and services (current US$)	World Bank Open Data | Data
Technology	Mobile cellular subscriptions (per 100 people)	World Bank Open Data | Data
Log of Investment	Gross fixed capital formation (current US$)	World Bank Open Data | Data
Secondary school	School enrollment, secondary (percent gross)	World Bank Open Data | Data
Life expectancy	Life expectancy at birth, total (years)	World Bank Open Data | Data
Conflict	1-armed conflict 0-no armed conflict	UCDP Dataset Download Center (uu.se)
Polity_score	from -10 (hereditary monarchy) to +10 (consolidated democracy)	INSCR Data Page (systemicpeace.org)
Oil producer	1- oil producer 0-non-oil producer	World Economic Outlook Databases (imf.org)

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PUBLICATIONS

Climate Change in Sub-Saharan Africa's Fragile States: Evidence from Panel Estimations

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