PERSISTENCE AND TRENDS IN CO_2 EMISSIONS IN AFRICA: IS CHINESE FDI BEHIND THESE FEATURES?

Gloria Claudio-Quiroga
Universidad Francisco de Vitoria, Madrid, Spain

Luis A. Gil-Alana
University of Navarra, Pamplona, Spain
Universidad Francisco de Vitoria, Madrid, Spain

and

Andoni Maiza-Larrarte
University of the Basque Country, UPV/EHU, Spain

ABSTRACT

In this paper we investigate the statistical features of the CO_2 emissions and CO_2 emissions per capita in a group of 45 African countries by looking at their degree of persistence and also testing for the existence of trends in the data. In addition, we also investigate if this level of emissions is related to the Chinese FDI in Africa. The results are very heterogeneous across countries, observing orders of integration statistically below 1 in a group of countries; in others, the majority of them, the values are around 1, while for some others, the degree of integration is statistically significantly above 1. Linear time trends are observed in approximately half of the countries. These results imply that, in the long term, public measures to reduce CO_2 emissions may be required in the majority of the countries since in the event of shocks the series will not return by themselves to their original levels. If we look at Chinese FDI in these countries, we observe that there seems to be no relationship between the Chinese investment in Africa and the CO_2 emissions persistence, though this result needs to be contrasted in future research.

JEL Classification: C25; F64; F21
Keywords: CO_2 emissions; Africa; China; FDI; persistence, time trends

Corresponding author: Prof. Gloria Claudio-Quiroga
Faculty of Law, Business and Government.
Universidad Francisco de Vitoria, Madrid, Spain.
Email: g.claudio.prof@ufv.es

Prof. Luis A. Gil-Alana gratefully acknowledges financial support from the project from 'Ministerio de Economía, Industria y Competitividad' (MINEIC), `Agencia Estatal de Investigación' (AEI) Spain and `Fondo Europeo de Desarrollo Regional' (FEDER), Grant PID2020-113691RB-I00 funded by MCIN/AEI/ 10.13039/501100011033. He also acknowledges support from an internal Project of the Universidad Francisco de Vitoria. Comments from the Editor and two anonymous reviewers are gratefully acknowledged.

1. Introduction

Global warming is one of the most relevant issues in the world and, as carbon dioxide emissions are the largest determinant of this process, there is a growing academic interest to understand the degree of persistence of CO_2 emissions. It is of utterly relevance to analyse the dynamic behaviour and the stationarity properties of CO_2 emissions, since stationarity would suggest that the effects of the shocks are transitory, and the adoption of public policies should not be as strong as in the case of nonstationary series (Lee and Chang, 2009).

In this paper, we focus on African countries' emissions because the continent is experiencing dynamic economic growth and, even though pollution levels are still very low compared to high income countries' ones, carbon dioxide emissions are growing at a rapid pace since the 60's. Hence, it may be convenient to implement public measures as soon as possible to avoid that the desirable progress of African economies towards higher income levels becomes a new main cause of distress to prevent warming.

GRAPH 1. ROUND HERE.

Additionally, we examine whether China's foreign direct investment (FDI) plays a role in African countries' CO_2 emissions. China's investments in developing countries have attracted much attention from environmental researchers since they are concentrated in areas that are environmentally sensitive. The criticism of China's investments involves mainly mining, infrastructure, forestry and agricultural projects (Bosshard, 2008; Li, 2010; Mol, 2011; Kolstad and Wiig, 2011).

There is an open and intense debate about the impact of FDI in host countries' pollution level. Several authors support the thesis that foreign investment increases pollution, whereas others defend just the opposite, and some others think that the final impact depends on the characteristics of the investment flows and the recipient's conditions. The objectives of the paper are two-fold: first, we want to check the presence of deterministic time trends in the level of the emissions in Africa, along with their orders of integration to determine if shocks in the series have permanent or transitory effects; second, we want to contrast if the presence of Chinese FDI may affect the level of emissions on the continent. The paper contributes to the existing literature because we use some recently developed techniques in the context of time series analysis such as those based on the concepts of fractional integration and long memory processes. The approach represents a significant advantage with previous research since it is useful to obtain relevant conclusions for policy makers about the potential impact of public policies to curb CO_2 emissions.

The rest of the paper is organized as follows: Section 2 describes the literature on both CO_2 emissions and China's FDI in Africa. Section 3 is devoted to the methodology. Section 4 describes the dataset, while Section 5 reports the empirical results. Next, in Section 6 we discuss the main results and, finally, Section 7 contains some concluding remarks.

2. Review of the literature

Researchers have analysed whether CO_2 emissions are nonstationary through a variety of approaches: techniques based on conventional univariate unit-root tests (Christidou et al., 2013, etc.), the Dickey Fuller-GLS test (Aldy, 2006), panel unit-root testing procedures (Strazicich and List, 2003; Perman and Stern, 2003), and threshold autoregressive panel-data unit-root test (Yavuz and Yilanci, 2013) among others. Results are not consensual: some detect that emissions are stationary (Strazicich and List, 2003; Lee and Chang, 2009; Christidou et al., 2013), others find nonstationarity (Perman and Stern 2003; Zerbo and Darné, 2019; Awaworyi et al., 2020; Fallahi, 2020), and some others obtain mixed results depending on time horizon and regional areas (Panopoulou and Pantelidis, 2009; Ordás and Grether, 2011; etc.).

Much less research has been done specifically in Africa concerning the hypothesis of mean reversion. Gil-Alana (2017) found evidence against this hypothesis, implying that in the event of exogenous shocks producing negative economic effects, strong measures should be adopted by the authorities to recover the original trends. On the other hand, Tiwari et al. (2016) obtained evidence of mean reversion in the per capita CO_2 emissions for 27 of the countries in Sub-Saharan Africa. Our paper contributes to the existing research by investigating the statistical properties of CO_2 emissions in a group of 45 African countries through alternative developments in econometrics that permit us to examine the time series properties of carbon dioxide emissions.

Additionally, we also look at the potential connection between China's FDI and CO_2 emissions to contrast whether western stakeholders' concern about China's environmental practices in Africa is justified. There is a high degree of consensus about the fact that economic growth -measured in per capita gross domestic product-, and population growth have been the main drivers of the upwards trend in CO_2 emissions. Three global studies by Bacon and Bhatthacharya (2007), Wang et al. (2018) and Dong et al. (2018) evidenced this strong link. More precisely, Dong et al. (2018) detected that, while economic growth is the main responsible for the growth of CO_2 emissions in high- and middle-income countries, in low-income countries it is population growth what drives the upward trend in carbon emissions.

Instead, empirical evidence about the link between FDI flows and CO_2 emissions is still controversial and uncertain. The pollution haven hypothesis (PHH) originally proposed by Pethig (1976) and Walter and Ugelow (1979) has been confirmed by several researchers (Xing and Kolstad, 2002; Shahbaz et al., 2019a and 2019b; Singhania and Saini, 2021; Nguyen-Thanh et al. 2022; etc.), supporting the idea that some countries transfer their polluting activities through FDI to take advantage of host countries' weak environmental regulations.[1] Nevertheless, other researchers have determined that FDI can contribute to the adoption of advanced technologies reducing the environmental impact of economic activity (Birdsall and Wheeler, 1993; Pazienza, 2015; Zhang and Zhou, 2016; Twerefou et al., 2019; Demena and Afesorgbor 2020; etc.). Interestingly, some researchers have obtained mixed results suggesting that the impact of FDI on the environment depends on the level of development of host countries (Hoffman et al., 2005; Pao and Tsai, 2011).

Studies on the environmental impacts of Chinese foreign investment in African countries are scarce. Nevertheless, we find some papers whose results show that Chinese foreign direct investment improves the environment in Africa, especially in non-resource countries. (Tawiah et al., 2021). Zakari et al. (2021) apply Panel Driscoll-Kraay Standard Errors (PDSE) and System-Generalized Method of Moment (S-GMM) estimators for yearly data spanning the period of 1992–2018 and conclude that the Chinese investment is associated with improving environmental quality through the transfer of green technologies across borders. Huang et al. (2022) also confirm the pollution halo hypothesis demonstrating that the effect of Chinese foreign direct investment in Africa is negative and significant.

A growing number of voices are building their own discourse within Africa and demanding sustainable environmental policy from Chinese companies (Adem, 2014; Sautman and Hairong, 2009a,b). If these claims turned out to be right, African countries should examine the qualifications for China’s (and other countries’) foreign investment and protect the environment through coordinated know-how and technological transfer with foreign companies. Our paper contributes to previous research examining the

[1] Research finds that sometimes low-income countries engage in a “race to the bottom” using lax environmental regulations to compete in the FDI arena (due to their lack of infrastructure and skills), while other unintended pollution havens may arise just because low-income countries are less able to implement and monitor environmental regulations.

relationship between the level of carbon emissions in African countries and their associated degrees of persistence with the Chinese FDI in these economies.

3. Methodology

We focus on fractional integration. This is a very flexible methodology that allows us to consider fractional orders of differentiation or I(d) behaviour in the series of interest. In fact, by allowing for such an approach we can consider a variety of modelling specifications, including the case of I(0) stationarity (or short memory) if d = 0, and long memory models if d > 0. Moreover, we can also consider nonstationary though mean reverting processes, if the order of integration d is in the interval [0.5, 1). Nonstationary, non-mean-reverting patterns are obtained if d ≥ 1.

The estimation of the differencing parameter d is carried out by using the Whittle function in the frequency domain as proposed in Dahlhaus (1989) and presented in a testing-procedure form in Robinson (1994). Robinson's (1994) tests are very general, including cases with multiple orders of integration at different frequencies in the series. In this work we use a very simple version of his tests, widely employed in empirical applications and which functional form can be found, for example, in Gil-Alana and Robinson (1997). One of the advantages of this method is that is not restricted to be in the stationary range (i.e., d < 0.5) and thus we do not need preliminary differentiation if we believe the series is nonstationary.

The model examined in the empirical section is the following one,

$$y_t \;=\; \beta + \gamma t \;+\; x_t, \qquad t \;=\; 1, 2, \ldots \tag{1}$$

$$(1 - L)^d \, x_t \;=\; u_t, \qquad t \;=\; 1, 2, \ldots, \tag{2}$$

where y_t is the log of the CO_2 emissions and the CO_2 emissions per capita in each of the 45 countries examined; β and γ are unknown parameters to be estimated and corresponding to a constant and a (linear) time trend; d is the order of integration of the series, which may be any real value and thus potentially fractional, and u_t is the I(0) error term that will be modelled in terms of both white noise and autocorrelation, in the latter case, by means of the exponential spectral model of Bloomfield (1973).[2]

4. Data

Our study involves yearly data from 1960-2014 on CO_2 emissions[3] (kt) and CO_2 emissions (metric tons per capita) taken from the World Development Indicators (World Bank, 2020). The data correspond to the following 45 African countries: Algeria, Angola, Benin, Burkina Faso, Burundi, Cameroon, Central African Republic, Cote d'Ivoire, Chad, Comoros, Congo (Democratic Republic of the), Congo (Republic of), Cabo Verde, Egypt, Equatorial Guinea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea Bissau, Kenya, Liberia, Libya, Madagascar, Maldives, Mali, Mauritania, Morocco, Mozambique, Niger, Nigeria, Rwanda, South Africa, Sao Tome, Senegal, Seychelles, Sierra Leone, Somalia, Sudan, Tanzania, Tunisia, Uganda, Zambia and Zimbabwe.

We obtain GDP yearly data (current US$) from World Development Indicators database (World Bank, 2020). Finally, as it refers to data concerning China's FDI in the African continent, we use yearly data from 2003 to 2014 from Johns Hopkins University SAIS China-Africa Research Initiative database, which collects investment data from the Statistical Bulletin of China's Outward Foreign Direct Investment published by China's MOFCOM (current US$). We obtain FDI data for 51 African countries, including all the countries for which we have CO_2 emissions data except for the Maldives and Somalia.

[2] See Gil-Alana (2004) for the convenience of the model of Bloomfield (1973) for autocorrelation in the context of fractional integration.
[3] Carbon dioxide emissions include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring, and they are those stemming from the burning of fossil fuels and the manufacture of cement.

5. Empirical results

Tables 1 – 4 report the results for the CO_2 emissions while Tables 5 – 8 refer to the CO_2 emissions per capita. Tables 1 and 5 display the estimates under the assumption of uncorrelated (white noise) errors, while Tables 2 and 6 contain the results under the assumption of autocorrelation, throughout the model of Bloomfield (1973). Finally, Tables 3 and 4 (and 7 and 8) present some summary values for the CO_2 emissions (and CO_2 emissions per capita).

We estimate d in the model given by equations (1) and (2), that is,

$$y_t = \beta + \gamma t + x_t, \qquad (1 - L)^d x_t = u_t, \qquad t = 1, 2, ... \tag{3}$$

under the three standard cases of no deterministic terms (i.e., $\beta = \gamma = 0$ in (3)); with an intercept (i.e., $\gamma = 0$ in (3)), and with an intercept and a linear time trend, and choose the specification that produces significant coefficients in the joint representation of the two equations in (3), i.e.,

$$\tilde{y}_t = \beta \tilde{1}_t + \gamma \tilde{t}_t + u_t, \qquad t = 1, 2, ... \tag{4}$$

where $\tilde{y}_t = (1 - L)^d y_t$; $\tilde{1}_t = (1 - L)^d 1$; and $\tilde{t}_t = (1 - L)^d t$. Note that since u_t in equation (4) is I(0) by assumption, standard LS estimates β and γ hold and t-values apply.

CO_2 emissions

We start by presenting the results for the CO_2 emissions. Table 1 displays the estimates of the d-coefficient under the assumption that u_t is a white noise process. We first observe that the time trend is required in a number of cases, in particular in 35 out of the 45 countries examined, the constant being sufficient in the remaining cases. If we focus now on the estimated values of d for the selected models, we see that the values are relatively high in all cases, rejecting the null of d = 0 (short memory) in all countries. Statistical evidence of mean reversion (i.e., $d < 1$) is found in only 11 countries: Comoros, Ghana, Senegal, Angola, Cameroon, Somalia, Madagascar, Mauritania, Chad, Morocco and Equatorial Guinea. For the remaining countries, the estimated values of d are around 1 or above it (in fact, it is statistically significantly higher than 1 for Niger, Gabon and Uganda). The time trend is statistically insignificant in 10 countries: Congo Democratic Republic, Gabon, Liberia, Libya, Mozambique, Rwanda, Sierra Leone, Uganda, Zambia and Zimbabwe. The highest time trend coefficients are obtained in the cases of Benin (0.701), Angola (0.728), Burkina Faso (0.734), Seychelles (0.829), Niger (0.988) and Equatorial Guinea (1.046). (See Tables 3 and 4 for a summary of the results in terms of both persistence and time trends respectively).

TABLES 1 AND 2 ABOUT HERE

Table 2 refers to the case of autocorrelated errors. That is, we suppose u_t in (3) is time dependent; however, instead of using the classical AutoRegressive Moving Average (ARMA) representation, we use a non-parametric approach due to Bloomfield (1973), widely used in empirical applications involving fractional integration. The time trend is now significant in 32 countries and the highest coefficients correspond to Benin (0.720), Burkina Faso (0.732), Angola (0.737), Libya (0.786), Seychelles (0.822) and especially, Niger (1.471) (see Table 6). Dealing with persistence, mean reversion ($d < 1$) takes place in the cases of Cabo Verde, Comoros, Senegal, Sierra Leone, Ghana, Madagascar and Cameroon, and evidence of $d > 1$ is found in the cases of Mozambique, Niger and Burundi.

TABLES 3 AND 4 ABOUT HERE

The results displayed across Tables 3 and 4 show that there are some patterns in common in the results for the two cases of uncorrelated and autocorrelated errors. Thus, for example, and starting with the level of persistence (measured by d), we see in Table 3 that for Comoros, Senegal, Ghana, Madagascar and Cameroon, we obtain evidence of mean reversion, while for Niger, both models suggest that d is statistically higher than 1. If we look now at the levels of the time trends, we observe that for Congo Democratic Republic, Gabon, Liberia, Mozambique, Rwanda, Uganda, Zambia and Zimbabwe the time trend is unrequired in the two models, and for Benin, Angola, Burkina Faso, Seychelles and Niger, the time trend coefficients display the highest values.

CO_2 emissions per capita

We next focus on the CO_2 emissions per capita. Starting with the white noise results, we observe in Table 5 that the time trend is significant in only 22 countries (compared with the 35 countries in Table 1), and there are 11 countries showing evidence of mean reversion: Senegal, Ghana, Comoros, Cameroon, Somalia, Angola, Madagascar, Chad, Mauritania, Morocco and Egypt, i.e. the same 10 countries as in the CO_2 emission series along with Egypt instead of Equatorial Guinea, while d is statistically above 1 in Gabon, Niger and Uganda, once more the same three countries as with the CO_2 emissions.

TABLES 5 AND 6 ABOUT HERE

Table 6 reports the results for the case of autocorrelated (Bloomfield) errors. The time trend is required in 21 countries, and the highest coefficients correspond to Angola, Benin, Burkina Faso, Cabo Verde, Libya, Seychelles and Niger.

TABLES 7 AND 8 ABOUT HERE

Tables 7 and 8 summarize the results in terms of persistence (Table 7) and time trends (Table 8). We observe that Niger displays one of the highest degrees of persistence in the two cases (d = 1.20 in case of no autocorrelation, and d = 1.37 with autocorrelation) and at the same time also presents one of the highest coefficients for the time trend (0.0677 with white noise errors and 0.1156 under autocorrelation). On the other hand, there is a group of five countries (Senegal, Ghana, Comoros, Cameroon and Madagascar) with evidence of mean reversion in all cases under consideration.

Chinese FDI and CO_2 emissions persistence

China's investing role on the African continent has become critical for the financing of several urgent infrastructure projects since the end of the 90's. China has extended large sums in commercial loans to African governments and state-owned entities and, as a result, China has become the region's largest creditor.

Nevertheless, despite its dynamic growth, in 2014 the stock of China FDI (US$ 32,000 Million), was still far from the top investors in Africa: the UK (US$ 66,000 Million), USA (US$ 64,000 Million), and France (US$ 52,000 Million), according to the World Investment Report (UNCTAD, 2018). In 2014, the degree of China's investment penetration (FDI Stock / GDP ratio) ranks from little more than 0.01% of the GDP in Tunisia and Burkina Faso to more than 8% in Zambia, Seychelles and Zimbabwe.

TABLE 9 ABOUT HERE

In this last section of the paper, we examine the potential relationship between the degree of persistence in CO_2 emissions and the stock of China's FDI in African countries. For this purpose, in Table 9 we group the 51 countries for which we have collected data in five categories according to the percentage of China's FDI stock related to their GDP. In our previous exercise we obtained estimates of persistence by means of "d" values of the series under examination. In Tables 10, 11, 12 and 13 we classify these countries according to the % China FDI stock/GDP and the degree of persistence in CO_2 emissions (Tables 10 and 11) and CO_2 per capita emissions (Tables 12 and 13).

TABLES 10 - 13 ABOUT HERE

Then, we estimate the R^2 correlation coefficient between the % FDI Stock/GDP and the CO_2 emissions/GDP variables in 2014. Figure 1 shows that the correlation coefficient is very small (0.024). Finally, we obtained the R^2 coefficient between the percentage of China FDI Stock/GDP and the persistence in CO_2 emissions ("d" values).

Figures 2 and 3 display these two variables observing a non-significant relationship between the relevance of China' FDI stock in the host country and the degree of persistence in CO_2 emissions. Nevertheless, we acknowledge that this is just a preliminary result that will be contrasted in future research through other specific techniques, since there could be other variables influencing the link among these two variables.

6. Discussion of results

The results of this study have important implications for the African governments and policy makers. In terms of CO_2 emissions, they are heterogeneous among African countries, so it provides a basis for each of them to explore their individual characteristics that gives guidance to different governments and policy makers.

The fact that the estimated values of d are relatively high, except for Comoros, Ghana, Senegal, Angola, Cameroon, Somalia, Madagascar, Mauritania, Chad, Morocco and Equatorial Guinea (for CO_2) and Egypt (for CO_2 per capita) where the value of d is low, indicates that there is a need for green FDI policies that, stimulating economic growth, slow down the increase in CO_2 that they cause. If there were a shock with a strong environmental deterioration, governments would be forced to apply strong policies to allow the situation to be reversed because by itself the situation would not be reversed. Green FDI policies should change the investment structure and apply a policy of unauthorized practices, while investment must be accompanied by foreign environmental technology that allows the hypothesis to be effectively met (Gong et al., 2021). These countries should also introduce carbon emission tax and emission ceiling (Gyamfi et al., 2021).

We have also shown in this paper that there seems to be no relationship between Chinese FDI and CO_2 emissions persistence in Africa, though our results should be contrasted with other specific techniques. From these results we might infer that China is not profiting from African countries’ weak environmental regulations to transfer its polluting activities. That would mean that the pollution haven hypothesis (PHH) would not hold as it concerns China’s investments in Africa. It might also be the case that China’s investments in Africa, no matter how substantial their environmental impact, do not have a substantially different impact compared to other foreign countries’ investments or even to domestic investments. Hence, Western countries’ criticism would not be justified unless accompanied by self-critical messages.

Further research is needed to confirm or reject the main conclusions of this paper. It is of utmost importance for international sustainability practices to determine precisely the time trends and degrees of persistence of CO_2 emissions in Africa, and also to detail the impact that China’s and other main investors’ FDI have on African countries’ emissions.

7. Conclusions

In this paper we have shown that the level of persistence of CO_2 emissions is heterogeneous across African countries. In most of them “d-persistence” values are around one implying that the series contain unit roots. Nevertheless, evidence of mean reversion is found for Comoros, Senegal, Ghana, Madagascar and Cameroon under both white noise and autocorrelated specifications. In the former case (white noise errors) there is another group of six countries displaying reversion to the mean (Angola, Somalia, Mauritania, Chad, Morocco and Equatorial Guinea) while under autocorrelation this property is also satisfied for Sierra Leone and Cabo Verde. This implies that shocks affecting the series in these countries will have transitory effects, returning to their long run projections in the future. This is good in the case of negative shocks increasing the number of emissions, since the series will return by themselves to their original levels.

On the other hand, caution should be taken in those countries undergoing positive shocks reducing the emissions since the series should revert unless policy actions are adopted.

Linear time trends are observed in half of the countries. The time trend is unrequired for Congo Democratic Republic, Gabon, Liberia, Libya, Mozambique, Rwanda, Uganda, Zambia and Zimbabwe, and the coefficients (positive in all cases) display the highest values in three neighbouring Western African countries (Niger, Benin, and Burkina Faso), Angola and Seychelles.

Finally, we find no significant correlation between the relevance of China's FDI stock measured as the percentage of GDP and CO_2 emissions. This result does not reject *per se* the pollution haven hypothesis, but shows that if China is transferring its polluting activities to African countries, it is acting in a similar way to the other main investors in Africa, therefore western countries' criticism and concerns are by no means justified unless they are accompanied by self-critical messages.

We consider that future research should deepen into the main results of this paper including other potentially relevant variables such as the emitter of CO_2 (industrial processes, households, etc.), and the origin of carbon emissions (fossil fuels combustion, cover cement processes, etc.). The availability of a more detailed set of data for African countries would allow to enrich the analysis of the causality between Chinese FDI and African countries' emissions. This study should also be completed with others that focus on emissions that come from investments by local companies or FDI from countries other than China. From an econometric viewpoint, alternative approaches can be implemented for the analysis of these data, including for instance structural breaks (Gil-Alana, 2008) and/or non-linear structures (Cuestas and Gil-Alana, 2016) within the context of fractional integration. Work in these directions is now under progress.

References

Adem, S. (2014). Decoding the Discourse on China in Africa. *Journal of African Foreign Affairs* 2, 93-106.

Aldy, J. E. (2006). Per capita carbon dioxide emissions: convergence or divergence? *Environmental & Resource Economics*, Vol. 33, 534–555.

Awaworyi, S., Inekwe, J., Ivanovski, K. and Smyth, R. (2020). Stationarity properties of per capita CO2 emissions in the OECD in the very long-run: A replication and extension analysis, *Energy Economics*, Volume 90, 2020.

Bacon R.W. and S. Bhattacharya (2007). Growth and CO_2 emissions: how do different countries fare. Environment Department Papers. 2007;113.

Birdsall, N. and Wheeler, D. (1993). Trade policy and industrial pollution in Latin America: where are the pollution Havens? *The Journal of Environment and Development* 2, 137-149.

Bloomfield, P. (1973). An exponential model in the spectrum of a scalar time series. *Biometrika* 60, 217-226.

Bosshard, P. (2008). China's Environmental Footprint in Africa. SAIS Working Papers in African Studies. The Johns Hopkins University, Washington.

Christidou, M., Panagiotidis, T. and Sharma, A. (2013). On the stationarity of per capita carbon dioxide emissions over a century. *Economic Modelling* 33:918–925

Cuestas, J.C. and Gil-Alana, L.A. (2016). A Non-Linear Approach with Long Range Dependence Based on Chebyshev Polynomials. *Studies in Nonlinear Dynamics and Econometrics*, 23, 445–468.

Dahlhaus, R. (1989). Efficient parameter estimation for self-similar processes. Annals of Statistics 17, 1749-1766.

Demena, B. A., and Afesorgbor, S. K. (2020). The effect of FDI on environmental emissions: Evidence from a meta-analysis. *Energy Policy*, 138, 111192.

Dijk, M. P. v. (Ed.). (2009). The new presence of China in Africa (EADI). Amsterdam: Amsterdam Univ. Press. https://nbn-resolving.org/urn:nbn:de:0168-ssoar-271450

Dong, K., Hochman, G. and Timilsina, G. R. (2018). Are Driving Forces of CO2 Emissions Different across Countries?: Insights from Identity and Econometric Analyses. Policy Research Working Paper; No. 8477. World Bank, Washington, DC. World Bank.

Fallahi, F. (2020). Persistence and unit root in CO2 emissions: evidence from disaggregated global and regional data, *Empirical Economics*. 58, pp. 2155–2179.

Gil-Alana, L.A. (2004). The use of the Bloomfield (1973) model as an approximation to ARMA processes in the context of fractional integration, *Mathematical and Computer Modelling* 39, 429-436.

Gil-Alana, L.A. (2008). Fractional integration and structural breaks at unknown periods of time. *Journal of Time Series Analysis,* 29, 163–185.

Gil-Alana, L.A. (2017). CO_2 emissions in Africa. Persistence and economic implications. *African Journal of Economic and Sustainable Development* 6, 4, 280-291.

Gil-Alana, L.A. and Robinson, P.M. (1997). Testing of unit roots and other nonstationary hypotheses in macroeconomic time series. *Journal of Econometrics* 80, 241-268.

Gong, M., Zhen, S. & Liu, H. (2021). Research on the nonlinear dynamic relationship between FDI and CO2 emissions in the “One Belt, One Road” countries. *Environmental Science and Pollution Research* 28, 27942–27953. https://doi.org/10.1007/s11356-021-12532-6.

Gyamfi, B.A. et al. (2021). Investigating the pollution haven hypothesis in oil and non-oil sub-Saharan Africa countries: Evidence from quantile regression technique. *Resources Policy* 73, 102119, https://doi.org/10.1016/j.resourpol.2021.102119.

Hoffmann, R., Lee, C.-G., Ramasamy, B. and Yeung, M. (2005). FDI and pollution: a Granger causality test using panel data. *Journal of International Development* 17, 311–317.

Huang, J., Berhe, M. W., Dossou, T. A. M., and Pan, X. M. (2022). The heterogeneous impacts of Sino-African trade relations on carbon intensity in Africa. *Journal of Environmental Management*, 316, 115233.

Kolstad, I. and Wiig, A. (2011). Better the Devil You Know? Chinese Foreign Direct Investment in Africa, *Journal of African Business* 12, 1, 31-50

Lee C. and Chang, C. (2009) Stochastic convergence of per capita carbon dioxide emissions and multiple breaks in OECD countries, *Economic Modelling* 26, 1375–1381.

Li, P. (2010). The myth and reality of Chinese investors: A case study of Chinese investment in Zambia’s copper industry. Occasional Paper No. 62. South African Institute of International Affairs. May 2010.

Mol, A. P. (2011). China’s ascent and Africa’s environment. *Global Environmental Change* 21(3), 785–794.

Nguyen-Thanh, N., Chin, KH. and Nguyen, V. (2022). Does the pollution halo hypothesis exist in this “better” world? The evidence from STIRPAT model. *Environmental Science and Pollution Research,* https://doi.org/10.1007/s11356-022-21654-4.

Ordás, C. and Grether, J.-M. (2011). Convergence in per capita CO2 emissions: A robust distributional approach. *Resource and Energy Economics* 33, 637–665.

Pao, H-T. and Tsai, C-M. (2011). Multivariate Granger causality between CO2 emissions, energy consumption, FDI (foreign direct investment) and GDP (gross domestic product): Evidence from a panel of BRIC (Brazil, Russian Federation, India, and China) countries. *Energy* 36, 685-693.

Panopoulou, E. and Pantelidis, T. (2009). Club convergence in carbon dioxide emissions. *Environmental and Resource Economics* 44, (1), 47–70.

Pazienza, P. (2015). The relationship between CO2 and Foreign Direct Investment in the agriculture and fishing sector of OECD countries: Evidence and policy considerations, *Intellectual Economics* 9, 1, 55-66.

Perman R. and Stern, D. I. (2003). Evidence from panel unit root and cointegration tests that the environmental Kuznets curve does not exist. *The Australian Journal of Agricultural and Resource Economics*, Vol. 47, 325–347.

Pethig, R. (1976). Pollution, welfare and environmental policy in the theory of comparative advantage. *Journal of Environmental Economics and Management* 2, 160-169.

Robinson, P.M. (1994). Efficient tests of nonstationary hypotheses. *Journal of the American Statistical Association* 89, 1420-1437.

Sautman, B. and Hairong, Y. (2009a). Trade, investment, power and the China-in-Africa discourse. *Asia-Pacific Journal* 7, 52, 3. Article ID 3278.

Sautman, B. and Hairong, Y. (2009b). African Perspectives on China–Africa Links. *The China Quarterly* 199, 728-759

Shahbaz, M., Gozgor, G., Adom P.K. and Hammoudeh, S. (2019a). The technical decomposition of carbon emissions and the concerns about FDI and trade openness effects in the United States. *International Economics* 159, 56-73.

Shahbaz, M., Balsalobre-Lorente, D. and Sinha, A. (2019b). Foreign direct Investment-CO2 emissions nexus in Middle East and North African countries: Importance of biomass energy consumption. *Journal of Clearer Production* 217, 603-614.

Singhania, M., and Saini, N. (2021). Demystifying pollution haven hypothesis: Role of FDI. *Journal of Business Research*, *123*, 516-528.

Strazicich, M.C. and List, J. A. (2003). Are CO2 emission levels converging among industrial countries? *Environmental & Resource Economics*, Vol. 24, 263–271

Tawiah, V. K., Zakari, A., and Khan, I. (2021). The environmental footprint of China-Africa engagement: an analysis of the effect of China–Africa partnership on carbon emissions. *Science of the Total Environment*, 756, 143603.

Tiwari, A.K., Kyophilavong, P. and Albulescu, C.T. (2016). Testing the stationarity of CO2 emissions series in Sub-Saharan African countries by incorporating nonlinearity and smooth breaks. *Research in International Business and Finance* 37, 527-540.

Twerefou, D.K., Akpalu, W. and Mensah, A.C.E. (2019). Trade-induced environmental quality: the role of factor endowment and environmental regulation in Africa, *Climate and Development*, 11:9, 786-798.

UNCTAD (2018). World Investment Report 2018: Investment and New Industrial Policies, UN, New York, https://doi.org/10.18356/ebb78749-en.

Walter, I. and Ugelow, J.L. (1979). Environmental policies in developing countries. Ambio 8, No. 2/3, 102-109.

Wang S, Li, G. and Fang, C. (2018). Urbanization, economic growth, energy consumption, and CO2 emissions: Empirical evidence from countries with different income levels. Renewable and Sustainable Energy Reviews, Vol. 81:2, 2144-2159.

World Bank (2020). World Development Indicators.

Xing, Y. and Kolstad, C.D. (2002). Do Lax Environmental Regulations Attract Foreign Investment? *Environmental and Resource Economics* 21, 1–22.

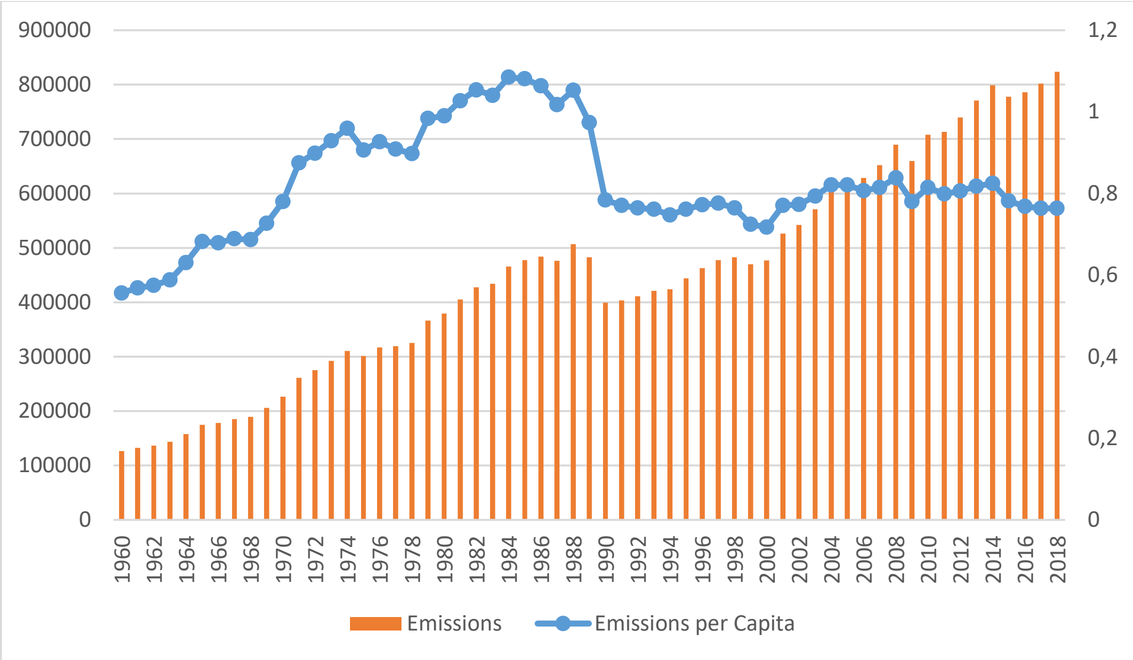
Yavuz, N.C. and Yilanci, V. (2013). Convergence in per capita carbon dioxide emissions among G7 countries: a TAR panel unit root approach. *Environmental Resource & Economics*, Vol. 54, 283–291.

Zakari, A., Li, G., Khan, I., Jindal, A., Tawiah, V., & Alvarado, R. (2022). Are abundant energy resources and Chinese business a solution to environmental prosperity in Africa? *Energy Policy*, 163, 112829.

Zerbo, E. and Darné, O. (2019). On the stationarity of CO2 emissions in OECD and BRICS countries: a sequential testing approach. *Energy Economics*. 83, 319–332.

Zhang, C. and Zhou, X. (2016). Does foreign direct investment lead to lower CO2 emissions? Evidence from a regional analysis in China. Renewable and Sustainable *Energy Reviews* 58, 943–951.

Graph 1. CO2 emissions (Kt) and CO2 per capita emissions (metric tons) in Sub-Saharan Africa.



Source: World Development Indicators. World Bank. Extracted: 25th September 2021.

Table 1: Estimated coefficients in an I(d) model with white noise errors

Series	No terms	An intercept	A time trend
ALGERIA	0.97 (0.84, 1.15)	8.665 (54.77)	0.0587 (3.06)
ANGOLA	0.66 (0.50, 0.86)	6.394 (27.19)	0.0728 (6.63)
BENIN	0.71 (0.47, 1.04)	4.876 (31.77)	0.0701 (8.63)
BURKINA FASO	0.77 (0.56, 1.07)	3.859 (27.40)	0.0734 (8.32)
BURUNDI	0.85 (0.73, 1.02)	3.746 (26.01)	0.0415 (3.50)
CAMEROON	0.67 (0.51, 0.91)	5.605 (16.63)	0.0609 (3.75)
CENTR. AF. REP.	0.83 (0.58, 1.15)	4.443 (29.54)	0.0232 (2.09)
CÔTE D'IVOIRE	0.97 (0.84, 1.16)	6.068 (33.68)	0.0580 (2.65)
CHAD	0.77 (0.64, 0.93)	4.011 (16.63)	0.0432 (2.86)
COMOROS	0.49 (0.30, 0.79)	2.407 (20.11)	0.0507 (12.38)
CONGO DEM. R.	1.07 (0.90, 1.30)	7.748 (44.37)	---
CONGO REP.	0.83 (0.61, 1.13)	5.386 (17.25)	0.0459 (1.95)
CABO VERDE	0.79 (0.48, 1.30)	2.991 (9.93)	0.0601 (3.00)
EGYPT	0.83 (0.61, 1.10)	9.646 (115.98)	0.0480 (7.67)
EQU. GUINEA	0.80 (0.66, 0.99)	2.915 (6.37)	0.1046 (3.33)
ETHIOPIA	1.02 (0.83, 1.27)	5.798 (37.14)	0.0651 (2.87)
GABON	1.15 (1.01, 1.36)	4.843 (18.38)	---
GAMBIA	1.01 (0.89, 1.19)	2.845 (31.62)	0.0618 (4.91)
GHANA	0.44 (0.27, 0.66)	7.168 (88.02)	0.0406 (15.37)
GUINEA	1.02 (0.67, 1.88)	5.977 (89.57)	0.0334 (3.45)
GUINEA BISSAU	0.94 (0.75, 1.16)	2.899 (19.27)	0.0481 (2.93)
KENYA	0.81 (0.58, 1.11)	7.758 (69.81)	0.0323 (4.11)
LIBERIA	1.16 (0.99, 1.41)	5.060 (22.29)	---
LIBYA	1.25 (0.96, 1.63)	6.411 (18.98)	---
MADAGASCAR	0.71 (0.52, 0.98)	5.983 (35.06)	0.0349 (3.86)
MALDIVAS	0.82 (0.62, 1.05)	5.794 (70.46)	0.0258 (4.08)
MALI	0.79 (0.57, 1.11)	4.772 (45.05)	0.0431 (6.12)
MAURITUANA	0.74 (0.55, 0.98)	5.185 (36.18)	0.0585 (7.11)
MOROCCO	0.80 (0.69, 0.97)	8.144 (114.01)	0.0532 (10.86)
MOZAMBIQUE	1.18 (0.99, 1.48)	7.502 (44.81)	---
NIGER	1.20 (1.06, 1.38)	3.181 (22.03)	0.0998 (2.47)
NIGERIA	1.04 (0.89, 1.28)	8.059 (34.75)	0.0627 (1.73)
RWANDA	1.08 (0.93, 1.29)	4.664 (21.86)	---
SOUTH AFRICA	1.04 (0.89, 1.25)	11.460 (246.26)	0.0298 (4.11)
SAO TOME	0.89 (0.74, 1.11)	2.339 (17.99)	0.0440 (3.68)
SENEGAL	0.52 (0.30, 0.86)	6.682 (37.47)	0.0425 (6.69)
SEYCHELLES	0.97 (0.81, 1.17)	1.909 (7.48)	0.0829 (2.60)
SIERRA LEONE	0.73 (0.49, 1.12)	6.355 (28.86)	---
SOMALIA	0.71 (0.60, 0.84)	4.518 (19.09)	0.0368 (2.94)
SUDAN	0.93 (0.80, 1.10)	7.178 (48.41)	0.0443 (2.84)
TANZANIA	0.88 (0.74, 1.05)	6.661 (47.09)	0.0472 (3.76)
TUNISIA	0.91 (0.80, 1.04)	7.408 (103.96)	0.0523 (7.47)
UGANDA	1.41 (1.24, 1.65)	6.040 (69.11)	---
ZAMBIA	1.01 (0.85, 1.22)	8.093 (73.13)	---
ZIMBABWE	0.90 (0.70, 1.14)	8.435 (60.28)	---

In parenthesis in the third and fourth column, the t-values of the estimated coefficients.

Table 2: Estimated coefficients in an I(d) model with autocorrelated errors

Series	No terms	An intercept	A time trend
ALGERIA	1.07 (0.84, 1.44)	8.673 (55.30)	0.0582 (2.13)
ANGOLA	0.74 (0.20, 1.09)	6.334 (25.70)	0.0737 (5.20)
BENIN	0.37 (0.03, 1.04)	4.665 (45.42)	0.0720 (22.72)
BURKINA FASO	0.74 (0.33, 1.16)	3.882 (27.96)	0.0731 (9.16)
BURUNDI	2.10 (1.38, 2.37)	3.7418 (37.36)	---
CAMEROON	0.51 (0.21, 0.86)	7.704 (19.95)	0.0606 (6.08)
CENTR. AF. REP.	0.35 (-0.18, 1.13)	4.480 (49.66)	0.0234 (8.49)
CÔTE D'IVOIRE	1.06 (0.82, 1.38)	6.062 (33.79)	0.0606 (2.01)
CHAD	1.12 (0.16, 1.47)	3.984 (16.59)	---
COMOROS	0.10 (-0.17, 0.51)	2.517 (47.53)	0.0496 (31.05)
CONGO DEM. R.	1.08 (0.51, 1.61)	7.748 (44.43)	---
CONGO REP.	0.39 (-0.17, 1.19)	5.592 (27.43)	0.0400 (6.28)
CABO VERDE	0.00 (-0.35, 0.44)	2.889 (38.37)	0.0622 (26.60)
EGYPT	0.64 (0.04, 1.49)	9.659 (128.43)	0.0490 (14.64)
EQU. GUINEA	1.00 (0.78, 1.46)	3.088 (6.60)	---
ETHIOPIA	0.86 (0.37, 1.50)	5.815 (37.82)	0.0624 (4.89)
GABON	1.14 (0.77, 1.58)	4.843 (18.31)	---
GAMBIA	1.19 (0.95, 1.52)	2.816 (32.25)	0.0672 (2.85)
GHANA	0.43 (0.06, 0.88)	7.167 (89.43)	0.0406 (15.75)
GUINEA	0.73 (0.42, 1.13)	6.105 (95.20)	0.0305 (8.53)
GUINEA BISSAU	1.07 (0.70, 1.55)	2.818 (18.89)	0.0531 (2.05)
KENYA	0.26 (-0.51, 1.19)	7.770 (138.32)	0.0311 (18.57)
LIBERIA	1.03 (0.55, 1.35)	7.770 (22.20)	---
LIBYA	0.78 (0.40, 1.24)	5.088 (20.19)	0.0786 (3.68)
MADAGASCAR	0.43 (-0.27, 0.92)	6.682 (48.57)	0.0318 (7.85)
MALDIVAS	1.01 (-0.22, 1.65)	5.771 (69.90)	0.0271 (2.23)
MALI	0.48 (-0.04, 1.27)	4.863 (59.37)	0.0410 (14.80)
MAURITUANA	0.54 (0.03, 1.04)	5.261 (43.42)	0.0584 (13.11)
MOROCCO	1.06 (0.79, 1.47)	8.151 (113.05)	0.0513 (4.25)
MOZAMBIQUE	1.35 (1.03, 1.94)	7.473 (46.70)	---
NIGER	1.37 (1.13, 1.91)	3.100 (22.53)	0.1471 (2.11)
NIGERIA	0.91 (0.65, 1.24)	8.110 (35.13)	0.0607 (2.67)
RWANDA	1.18 (0.85, 1.58)	4.659 (22.29)	---
SOUTH AFRICA	0.97 (0.70, 1.38)	11.463 (245.65)	0.0298 (5.27)
SAO TOME	0.99 (0.60, 1.49)	2.353 (18.00)	0.0433 (2.54)
SENEGAL	0.14 (-0.18, 0.55)	6.751 (79.79)	0.0409 (16.14)
SEYCHELLES	1.03 (0.71, 1.64)	1.910 (7.51)	0.0822 (2.09)
SIERRA LEONE	0.19 (-0.50, 0.75)	6.004 (58.59)	0.0115 (3.77)
SOMALIA	1.28 (0.96, 1.68)	4.000 (19.97)	---
SUDAN	1.31 (0.86, 1.84)	7.189 (52.83)	---
TANZANIA	1.11 (0.80, 1.58)	6.9684 (47.91)	0.0498 (1.77)
TUNISIA	1.24 (1.03, 1.52)	7.401 (113.39)	0.0532 (2.52)
UGANDA	1.27 (0.73, 1.76)	6.034 (66.60)	---
ZAMBIA	1.19 (0.84, 1.49)	8.066 (74.54)	---
ZIMBABWE	1.11 (0.35, 1.64)	8.380 (59.99)	---

In parenthesis in the third and fourth column, the t-values of the estimated coefficients.

Table 3: Classification of countries based on persistence

No autocorrelation			With autocorrelation		
d < 1	**d = 1**	**d > 1**	**d < 1**	**d = 1**	**d > 1**
Comoros (0.43)	Benin (0.71)	Niger (1.20)	C. Verde (0.00)	Benin (0.37)	Mozamb. (1.37)
Ghana (0.44)	S Leone (0.73)	Gabon (1.15)	Comoros (0.10)	Mauritania (0.54)	Niger (1.37)
Senegal (0.52)	Bk. Faso (0.77)	Uganda (1.41)	Senegal (0.14)	Egypt (0.64)	Burundi (2.10)
Angola (0.66)	C Verde (0.79)		S. Leone (0.19)	Guinea (0.73)	
Cameroon (0.67)	Mali (0.79)		Ghana (0.43)	Angola (0.74)	
Somalia (0.71)	Kenya (0.81)		Madagascar (0.43)	Bk Faso (0.74)	
Madagascar (0.71)	Maldives (0.82)		Cameroon (0.51)	Libya (0.78)	
Mauritania (0.74)	Egypt (0.83)			Ethiopia (0.86)	
Chad (0.77)	C. Af. R (0.83)			Nigeria (0.91)	
Morocco (0.80)	Congo R. (0.83)			S. Africa (0.97)	
Eq. Guinea (0.80)	Burundi (0.85)			Sao Tome (0.99)	
	Seychelles (0.86)			Eq. Guinea (1.00)	
	Tanzania (0.88)			Liberia (1.03)	
	Sao Tome (0.89)			Seychel. (1.03)	
	Zimbabwe (0.90)			Morocco (1.06)	
	Tunisia (0.91)			C. Ivory (1.06)	
	Sudan (0.93)			Algeria (1.07)	
	Guinea B. (0.94)			Guinea B. (1.07)	
	C d'Ivoire (0.97)			Congo DR (1.08)	
	Algeria (0.97)			Zimbabwe (1.11)	
	Gambia (1.01)			Tanzania (1.11)	
	Zambia (1.01)			Chad (1.12)	
	Guinea (1.02)			Gabon (1.14)	
	Ethiopia (1.02)			Rwanda (1.18)	
	S. Africa (1.04)			Zambia (1.19)	
	Nigeria (1.04)			Gambia (1.19)	
	Congo DR (1.07)			Tunisia (1.24)	
	Rwanda (1.08)			Uganda (1.27)	
	Liberia (1.16)			Somalia (1.28)	
	Mozambiq. (1.18)			Sudan (1.31)	
	Libya (1.25)				

Note: The categories are made based on the confidence intervals. In the case of autocorrelation, Kenya (0.26), Central African Rep. (0.35), Congo Rep. (0.39), Mali (0.48) and Maldives (1.01) are not included in any category since the confidence intervals are so wide that include both the I(0) and I(1) hypothesis.

Table 4: Classification of countries based on time trend coefficients

No autocorrelation		With autocorrelation	
No trend	**With a linear trend**	**No trend**	**With a linear trend**
Congo DR	C. African Rep (0.232)	Burundi	Sierra Leone (0.115)
Gabon	Maldives (0.258)	Chand	Central Af. Rep (0.234)
Liberia	South Africa (0.298)	Congo DR	Maldives (0.271)
Libya	Kenya (0.323)	Equatorial Guinea	South Africa (0.298)
Mozambique	Guinea (0.334)	Gabon	Guinea (0.305)
Rwanda	Madagascar (0.349)	Liberia	Kenya (0.311)
Sierra Leone	Somalia (0.368)	Mozambique	Madagascar (0.318)
Uganda	Ghana (0.406)	Rwanda	Congo Rep. (0.400)
Zambia	Burundi (0.415)	Somalia	Ghana (0.406)
Zimbabwe	Senegal (0.425)	Sudan	Senegal (0.409)
	Mali (0.431)	Uganda	Mali (0.410)
	Chad (0.432)	Zambia	Sao Tome (0.433)
	Sao Tome (0.440)	Zimbabwe	Egypt (0.490)
	Sudan (0.443)		Comoros (0.496)
	Congo Rep. (0.459)		Tanzania (0.498)
	Tanzania (0.472)		Egypt (0.490)
	Equat. Guinea (0.480)		Morocco (0.513)
	Guinea Bissau (0.481)		Guinea Bissau (0.531)
	Comoros (0.507)		Tunisia (0.532)
	Tunisia (0.523)		Algeria (0.582)
	Morocco (0.532)		Mauritania (0.606)
	Cote Ivory (0.580)		Côte d'Ivoire (0.606)
	Mauritania (0.585)		Nigeria (0.607)
	Algeria (0.587)		Cabo Verde (0.622)
	Cabo Verde (0.601)		Ethiopia (0.624)
	Cameroon (0.609)		Gambia (0.672)
	Gambia (0.618)		Benin (0.720)
	Nigeria (0.627)		Burkina Faso (0.732)
	Ethiopia (0.651)		Angola (0.737)
	Benin (0.701)		Libya (0.786)
	Angola (0.728)		Seychelles (0.822)
	Burkina Faso (0.734)		Niger (1.471)
	Seychelles (0.829)		
	Niger (0.998)		
	Equat. Guinea (1.046)		

RESULTS FOR EMISSIONS PER CAPITA

Table 5: Estimated coefficients in an I(d) model with white noise errors

Series: Ems. p. cap.	No terms	An intercept	A time trend
ALGERIA	0.94 (0.81, 1.13)	-0.624 (-3.98)	0.0354 (2.07)
ANGOLA	0.71 (0.56, 0.91)	-2.189 (-8.79)	0.0434 (3.30)
BENIN	0.68 (0.44, 1.02)	-2.891 (-19.37)	0.0432 (5.91)
BURKINA FASO	0.81 (0.61, 1.08)	-4.619 (-31.88)	0.0499 (4.87)
BURUNDI	0.83 (0.69, 1.01)	-4.154 (-29.71)	---
CAMEROON	0.67 (0.53, 0.91)	-2.910 (-8.61)	0.0332 (2.06)
CENTR. AF. REP.	0.82 (0.57, 1.14)	-2.841 (-19.41)	---
COTE D'IVOIRE	0.94 (0.78, 1.16)	-2.005 (-11.28)	---
CHAD	0.74 (0.61, 0.92)	-3.880 (-16.39)	---
COMOROS	0.54 (0.35, 0.83)	-2.805 (-21.69)	0.0245 (5.15)
CONGO DEM. R.	1.07 (0.92, 1.30)	-1.877 (-10.76)	---
CONGO REP.	0.82 (0.57, 1.13)	-1.463 (-4.78)	---
CABO VERDE	0.79 (0.48, 1.31)	-2.303 (-7.62)	0.0427 (2.12)
EGYPT	0.83 (0.61, 1.10)	-0.523 (-6.28)	0.0254 (4.04)
EQU. GUINEA	0.78 (0.63, 0.98)	-2.589 (-5.73)	0.0778 (2.67)
ETHIOPIA	1.03 (0.76, 1.30)	-4.147 (-26.70)	---
GABON	1.16 (1.02, 1.37)	-1.368 (-5.19)	---
GAMBIA	1.05 (0.93, 1.22)	-3.032 (-33.21)	0.0310 (2.10)
GHANA	0.44 (0.28, 0.66)	-1.614 (-19.71)	0.0144 (5.46)
GUINEA	1.03 (0.43, 1.70)	-2.161 (-32.50)	---
GUINEA BISSAU	0.96 (0.79, 1.17)	-3.518 (-23.14)	0.0299 (1.68)
KENYA	0.83 (0.63, 1.12)	-1.212 (-11.00)	---
LIBERIA	1.13 (0.97, 1.39)	-1.948 (-8.57)	---
LIBYA	1.24 (0.95, 1.63)	-0.851 (-2.52)	---
MADAGASCAR	0.71 (0.49, 0.99)	-2.492 (-14.98)	---
MALDIVES	0.86 (0.69, 1.09)	-2.489 (-29.89)	---
MALI	0.83 (0.62, 1.13)	-3.773 (-34.85)	0.0219 (2.69)
MAURITUANA	0.74 (0.55, 0.99)	-2.967 (-8.90)	0.0472 (2.46)
MOROCCO	0.73 (0.60, 0.92)	-1.267 (-18.73)	0.0346 (9.16)
MOZAMBIQUE	1.17 (0.97, 1.47)	-1.364 (-8.15)	---
NIGER	1.20 (1.07, 1.37)	-4.916 (-33.99)	0.0677 (1.67)
NIGERIA	1.05 (0.88, 1.30)	-2.605 (-11.31)	---
RWANDA	1.05 (0.90, 1.26)	-3.315 (-15.63)	---
SOUTH AFRICA	0.97 (0.78, 1.24)	1.747 (38.53)	---
SAO TOME	0.87 (0.72, 1.09)	-1.800 (-14.04)	0.0232 (2.11)
SENEGAL	0.41 (0.15, 0.87)	-1.426 (-5.13)	0.0163 (1.85)
SEYCHELLES	0.95 (0.79, 1.17)	-1.888 (-7.47)	0.0694 (2.36)
SIERRA LEONE	0.67 (0.45, 1.11)	-1.517 (-7.13)	---
SOMALIA	0.67 (0.56, 0.81)	-3.297 (-15.11)	---
SUDAN	0.93 (0.80, 1.11)	-2.030 (-13.77)	---
TANZANIA	0.87 (0.76, 1.00)	-0.907 (-13.10)	0.0341 (5.73)
TUNISIA	0.88 (0.73, 1.06)	-2.491 (-17.87)	---
UGANDA	1.40 (1.23, 1.64)	-2.764 (-31.73)	---
ZAMBIA	1.00 (0.86, 1.20)	---	---
ZIMBABWE	0.85 (0.71, 1.07)	---	---

In parenthesis in the third and fourth column, the t-values of the estimated coefficients.

Table 6: Estimated coefficients in an I(d) model with autocorrelated errors

Series: Ems. p. cap.	No terms	An intercept	A time trend
ALGERIA	**1.03 (0.70, 1.46)**	-0.587 (-3.79)	---
ANGOLA	**0.83 (0.22, 1.17)**	-2.278 (-8.74)	0.0447 (2.28)
BENIN	**0.31 (0.02, 0.98)**	-3.062 (-33.97)	0.0447 (16.49)
BURKINA FASO	**0.81 (0.48, 1.17)**	-4.619 (-31.90)	0.0499 (4.88)
BURUNDI	**1.65 (1.18, 2.22)**	-4.208 (-38.61)	---
CAMEROON	**0.50 (0.20, 0.87)**	-2.794 (-9.88)	0.0328 (3.34)
CENTR. AF. REP.	**0.33 (-0.28, 1.12)**	-2.789 (-44.53)	---
CÔTE D'IVOIRE	**1.05 (0.37, 1.45)**	-2.038 (-11.48)	---
CHAD	**1.11 (0.71, 1.48)**	-4.015 (-16.72)	---
COMOROS	**0.14 (-0.19, 0.55)**	-2.661 (-44.72)	0.0228 (12.78)
CONGO DEM. R.	**1.08 (0.75, 1.58)**	-1.877 (-10.77)	---
CONGO REP.	**0.43 (-0.17, 1.20)**	-1.320 (-6.07)	0.0120 (1.71)
CABO VERDE	**0.00 (-0.39, 0.43)**	-2.439 (-32.37)	0.0451 (19.27)
EGYPT	**0.61 (-0.20, 1.50)**	-0.517 (-7.04)	0.0264 (8.63)
EQU. GUINEA	**0.98 (0.71, 1.45)**	-2.531 (-5.30)	---
ETHIOPIA	**0.89 (-0.34, 1.52)**	-4.166 (-26.82)	0.0353 (2.47)
GABON	**1.15 (0.84, 1.53)**	-1.365 (-5.13)	---
GAMBIA	**1.29 (1.00, 1.71)**	-3.041 (-34.67)	---
GHANA	**0.44 (0.03, 0.87)**	-1.615 (-19.78)	0.0144 (5.46)
GUINEA	**0.74 (0.35, 1.14)**	-2.029 (-31.10)	0.0090 (2.40)
GUINEA BISSAU	**1.09 (0.30, 1.67)**	-3.567 (-23.84)	---
KENYA	**0.45 (-0.04, 1.23)**	-1.7256 (-23.26)	---
LIBERIA	**1.00 (0.70, 1.31)**	-1.913 (-8.38)	---
LIBYA	**0.73 (0.30, 1.24)**	-0.505 (-1.56)	0.0501 (2.77)
MADAGASCAR	**0.30 (-0.01, 0.97)**	-2.332 (-21.56)	---
MALDIVES	**1.07 (0.51, 1.72)**	-2.508 (-29.75)	---
MALI	**0.61 (0.14, 1.32)**	-1.823 (-15.98)	0.0240 (5.05)
MAURITUANA	**0.53 (0.16, 0.88)**	1.998 (9.93)	0.0437 (4.39)
MOROCCO	**0.93 (0.59, 1.45)**	-1.257 (-17.65)	0.0334 (4.46)
MOZAMBIQUE	**1.31 (1.01, 1.89)**	-1.386 (-8.56)	---
NIGER	**1.37 (1.13, 1.76)**	-4.997 (-36.30)	0.1156 (1.66)
NIGERIA	**0.91 (0.37, 1.28)**	-2.540 (-11.10)	---
RWANDA	**1.13 (0.78, 1.56)**	-3.314 (-15.81)	---
SOUTH AFRICA	**0.84 (0.53, 1.33)**	1.745 (38.81)	0.0083 (2.39)
SAO TOME	**0.94 (0.59, 1.46)**	-1.763 (-13.77)	---
SENEGAL	**-0.30 (-0.57, 0.09)**	-1.388 (-31.21)	0.0154 (9.99)
SEYCHELLES	**1.00 (0.64, 1.58)**	-1.886 (-7.46)	0.0687 (1.96)
SIERRA LEONE	**0.09 (-0.52, 0.69)**	-1.692 (-21.48)	0.0091 (-3.83)
SOMALIA	**1.11 (0.82, 1.58)**	-3.507 (-15.01)	---
SUDAN	**1.32 (0.94, 1.87)**	-2.065 (-15.16)	---
TANZANIA	**1.12 (0.70, 1.52)**	-2.487 (-18.04)	---
TUNISIA	**1.18 (0.55, 1.49)**	-0.919 (-14.19)	0.0350 (2.06)
UGANDA	**1.26 (0.91, 1.73)**	-2.770 (-30.58)	---
ZAMBIA	**1.16 (0.87, 1.47)**	---	---
ZIMBABWE	**0.95 (0.58, 1.52)**	---	---

In parenthesis in the third and fourth column, the t-values of the estimated coefficients.

Table 7: Classification of countries based on persistence

No autocorrelation			With autocorrelation*		
d < 1	**d = 1**	**d > 1**	**d < 1**	**d = 1**	**d > 1**
Senegal (0.41)	S. Leone (0.67)	Gabon (1.16)	Senegal (-0.30)	Mali (0.61)	Gambia (1.29)
Ghana (0.44)	Benin (0.68)	Niger (1.20)	C. Verde (0.00)	Libya (0.73)	Mozamb (1.31)
Comoros (0.54)	C. Verde (0.79)	Uganda (1.40)	S. Leone (0.09)	Guinea (0.74)	Sudan (1.32)
Cameroon (0.67)	Burk. Faso (0.81)		Comoros (0.14)	Burk Faso (0.81)	Niger (1.37)
Somalia (0.67)	C. Af. Rep. (0.82)		Madag. (0.30)	Angola (0.83)	Burundi (1.65)
Angola (0.71)	Congo Rep (0.82)		Benin (0.31)	S. Africa (0.84)	
Madag. (0.71)	Burundi (0.83)		Ghana (0.44)	Nigeria (0.91)	
Chad (0.74)	Kenya (0.83)		Cameroon (0.50)	Morocco (0.93)	
Morocco (0.73)	Egypt (0.83)		Mauritania (0.53)	Sao Tome (0.94)	
Mauritania (0.74)	Mali (0.83)			Zimbabwe (0.95)	
Eq. Guinea (0.78)	Zimbabwe (0.85)			Eq. Guinea (0.98)	
	Maldives (0.86)			Seychelles (1.00)	
	Sao Tome (0.87)			Liberia (1.00)	
	Tanzania (0.87)			Algeria (1.03)	
	Tunisia (0.88)			C. d'Ivoire (1.05)	
	Sudan (0.93)			Maldives (1.07)	
	Algeria (0.94)			Congo DR. (1.08)	
	C. d'Ìvoire (0.94)			Guinea B (1.09)	
	Seychelles (0.95)			Chad (1.11)	
	Guinea B. (0.96)			Somalia (1.11)	
	South Af. (0.97)			Tanzania (1.12)	
	Zambia (1.00)			Rwanda (1.13)	
	Guinea (1.03)			Gabon (1.15)	
	Ethiopia (1.03)			Zambia (1.16)	
	Gambia (1.05)			Tunisia (1.18)	
	Nigeria (1.05)			Uganda (1.26)	
	Rwanda (1.05)				
	Cong D.R. (1.07)				
	Liberia (1.13)				
	Mozambiq (1.17)				
	Libya (1.24)				

Note: The categories are made based on the confidence intervals. In the case of autocorrelation, Egypt (0.61), Kenya (0.45), Congo Rep. (0.43), Ethiopia (0.89) and Central African Rep. (0.33) are not included in any category since the confidence intervals are so wide that include both the I(0) and I(1) hypothesis.

Table 8: Classification of countries based on time trend coefficients

No autocorrelation		With autocorrelation	
No trend	**With a linear trend**	**No trend**	**With a linear trend**
Burundi	Ghana (0.0144)	Algeria	South Africa (0.0083)
Central Af. Rep.	Senegal (0.0163)	Burundi	Guinea (0.0090)
Côte d'Ivoire	Mali (0.0219)	Central Af. Rep.	Sierra Leone (0.0091)
Chad	Sao Tome (0.0232)	Côte de Ivoire	Congo Rep. (0.0120)
Congo Dem. Rep.	Comoros (0.0245)	Chad	Ghana (0.0144)
Congo Republic	Egypt (0.0254)	Congo Dem. Rep.	Senegal (0.0154)
Ethiopia	Guinea B (0.0299)	Equatorial Guinea	Comoros (0.0228)
Gabon	Gambia (0.0310)	Gabon	Mali (0.0240)
Guinea	Cameroon (0.0332)	Gambia	Egypt (0.0264)
Kenya	Tanzania (0.0341)	Guinea Bissau	Cameroon (0.0328)
Liberia	Morocco (0.0346)	Kenya	Morocco (0.0334)
Libya	Cameroon (0.0332)	Liberia	Tunisia (0.0350)
Madagascar	Algeria (0.0354)	Madagascar	Ethiopia (0.0353)
Maldives	Cabo Verde (0.0427)	Maldives	Mauritania (0.0437)
Mozambique	Benin (0.0432)	Mozambique	Angola (0.0447)
Nigeria	Angola (0.0434)	Nigeria	Benin (0.0447)
Rwanda	Mauritania (0.0472)	Rwanda	Burkina Faso (0.0449)
South Africa	Burkina Faso (0.0499)	Sao Tome	Cabo Verde (0.0451)
Sierra Leone	Niger (0.0677)	Somalia	Libya (0.0501)
Somalia	Seychelles (0.0694)	Sudan	Seychelles (0.0687)
Sudan	Equatorial G. (0.0778)	Tanzania	Niger (0.1156)
Tunisia		Uganda	
Uganda		Zambia	
Zambia		Zimbabwe	
Zimbabwe			

Table 9: Percentile distribution of African countries. % China FDI Stock / GDP. 2014.

Percent. (0-22) Africa Compared **Very Low China FDI/GDP**	Tunisia (0.031) Burkina Faso (0.071) Gambia, The (0.101) Morocco (0.104) Sao Tome & Principe (0.109) South Sudan (0.138)	Cote d'Ivoire (0.182) Egypt (0.215) Libya (0.265) Comoros (0.395) Nigeria (0.409)
Percent. (23-40) Africa Compared **Low China FDI/GDP**	Lesotho (0.424) Burundi (0.498) Cameroon (0.509) Benin (0.521) Senegal (0.658)	Cape Verde (0.816) Angola (0.833) Equatorial Guinea (0.957) Gabon (0.992) Algeria (1.147)
Percent. (43-60) Africa Compared **Medium China FDI/GDP**	Rwanda (1.381) Kenya (1.389) Botswana (1.613) Ethiopia (1.645) South Africa (1.697)	Uganda (1.701) Tanzania (1.772) Djibouti (1.809) Mauritania (1.872) Ghana (1.971)
Percent. (63-80) Africa Compared **High China FDI/GDP**	Sudan (2.127) Mali (2.390) Niger (2.407) Madagascar (2.816) Chad (2.906)	Sierra Leone (2.946) Togo (2.969) Centr. Afr. Rep. (3.016) Mozambique (3.691) Malawi (4.260)
Percent. (83-100) Africa Compared **Very High China FDI/GDP**	Mauritius (4.528) Guinea (4.774) Congo Dem. Rep. (6.039) Guinea Bissau (6.343) Congo Rep. (6.974)	Liberia (7.304) Namibia (7.679) Zambia (8.368) Seychelles (8.518) Zimbabwe (8.697)

*Note: No available FDI data for Maldives and Somalia.

Table 10: FDI/GDP and CO_2 emissions persistence with no autocorrelation

FDI/GDP	d < 1	d = 1	d > 1
Very Low	Morocco Comoros	Tunisia Burkina Faso Gambia Sao Tome C. d'Ivoire Egypt Libya Nigeria	
Low	Senegal Angola Cameroon Eq. Guinea	Burundi Benin C. Verde Algeria	Gabon
Medium	Ghana Mauritania	Rwanda Kenya Ethiopia South Africa Tanzania	Uganda
High	Madagascar Chad	Sudan Mali Sierra Leone Central Af. Republic Mozambique	Niger
Very High		Guinea Congo Dem. Rep. Guinea Bissau Congo Rep. Liberia Zambia Seychelles Zimbabwe	

*Note: No available FDI data for Maldives and Somalia.

Table 11: FDI/GDP and CO_2 persistence with autocorrelation

FDI/GDP	d < 1	d = 1	d > 1
Very Low	Comoros	Tunisia Burkina Faso Gambia Morocco Sao Tome & Principe C. C. d'Ivoire Egypt Libya Nigeria	
Low	Senegal Cameroon C. Verde	Benin Burundi Algeria Angola Gabon	Burundi
Medium	Ghana	Rwanda Ethiopia South Africa Uganda Tanzania Mauritania	
High	Madagascar Sierra Leone	Sudan Cent. Af. Rep.	Mozambique Niger
Very High		Guinea Congo DR Guinea Bissau Liberia Zambia Seychelles Zimbabwe	

Note: In the case of autocorrelation, Kenya (0.26), Central African Rep. (0.35), Congo Rep. (0.39), Mali (0.48) and Maldives (1.01) are not included in any category since the confidence intervals are so wide that include both the I(0) and I(1) hypothesis. No available FDI data for Maldives and Somalia.

Table 12: FDI/GDP and CO_2 per capita emission persistence with no autocorrelation

FDI/GDP	d < 1	d = 1	d > 1
Very Low	Morocco Comoros	Tunisia Burkina Faso Gambia Sao Tome & Principe C. d'Ivoire Egypt Libya Nigeria	
Low	Cameroon Senegal Angola Eq. Guinea	Burundi Benin Cape Verde Algeria	Gabon
Medium	Mauritania Ghana	Rwanda Kenya Ethiopia South Africa Tanzania	Uganda
High	Madagascar Chad	Sudan Mali Sierra Leone Cent. Af. Rep. Mozambique	Niger
Very high		Guinea Congo DR Guinea B. Congo Rep. Liberia Zambia Seychelles Zimbabwe	

*Note: No available FDI data for Maldives and Somalia.

Table 13: FDI/GDP and CO_2 per capita emission persistence with autocorrelation

FDI/GDP	d < 1	d = 1	d > 1
Very Low	Comoros	Tunisia Burkina Faso Morocco Sao Tome & Principe Côte d’Ivoire Libya Nigeria	Gambia
Low	Cameroon Benin Senegal C. Verde	Angola Eq. Guinea Algeria Gabon	Burundi
Medium	Mauritania Ghana	Rwanda South Africa Uganda Tanzania	
High	Madagascar Sierra Leone	Mali Chad	Sudan Niger Mozambique
Very high		Guinea Congo DR Guinea B Liberia Zambia Seychelles Zimbabwe	

Note: In the case of autocorrelation, Egypt (0.61), Kenya (0.45), Congo Rep. (0.43), Ethiopia (0.89) and Central African Rep. (0.33) are not included in any category since the confidence intervals are so wide that include both the I(0) and I(1) hypothesis. No available FDI data for Maldives and Somalia.

Figure 1: China's FDI stock and CO_2 emissions per GDP

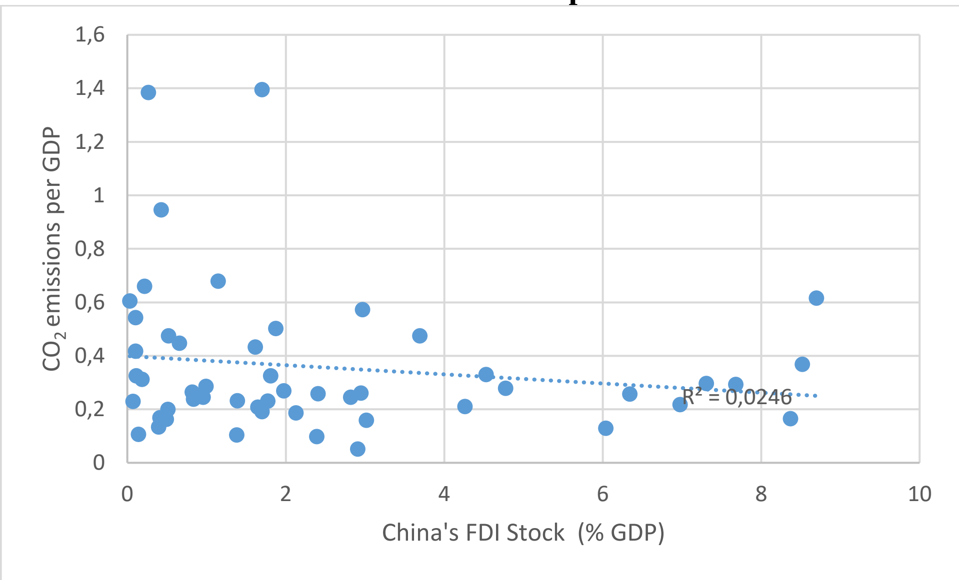


Figure 2: China's FDI stock and persistence of emissions per GDP ("d" values no autocorr.)

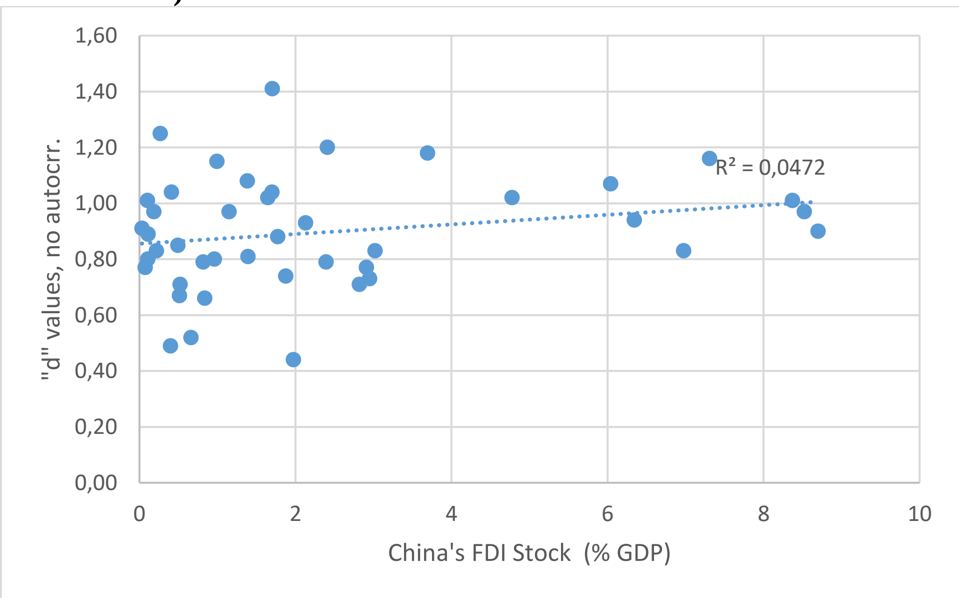


Figure 3: China's FDI stock and persistence of emissions per GDP ("d" values autocorr.)