Spatial analysis of carbon emission effect of financial development in Africa: the role of energy and socioeconomic factors

Abstract

The need to mitigate global warming has led policymakers and other stakeholders to see further understanding of the driving forces behind CO_2 emissions. Financial development (FD) has been identified among the most influential factors. However, the importance of FD has not been well explored in developing countries, especially in Africa. Several studies have explored the CO_2 emissions-effects of FD in the Africa but focused on the temporal aspect and overlooked the spatial dependence which has the potential to influence the estimated marginal effects. In so doing, they consider each country as an island which tends to suggest that there are no spatial spillover effects that could originate from countries' proximity. In this study, such inaccurate assumption is relaxed by deploying a Spatial Durbin Model (SDM) to explore the spatial dependence in the FD−CO_2 emissions nexus for 52 African countries between 1995 and 2017. Our results reveal a significant positive direct effect (0.020) of FD in a given country and a significant positive indirect effect (0.074). Thus, our estimated marginal effects show a positive and significant total effect (0.095), indicating that a 1% increase in FD will result in a net increase of CO_2 emissions of about 0.095%. This finding implies that FD contributes negatively to the surge of CO_2 emissions in Africa. While environmental Kuznets curve hypothesis is validated in the continent, renewable energy utilisation is found to posit significant environmental effect. This finding is crucial to policymakers as it stands as a reminder about the role of the neighborhood in designing and implementing environmentally friendly policies that aim at reducing pollution in Africa.

Keywords: Financial development; economic and natural resources; environmental quality; spatial analysis; Africa.

JEL codes: C31, C33, Q4, Q5, N27

1. Introduction

Considering that climate change is taking a dimension of increasing poverty, food insecurity, and displacement of people in Africa (World Meteorological Organization, 2021; Marco et al (2022), financing climate mitigation and adaption are along the paradigm of justice and socioeconomics. Because large-scale investments are crucial elements to achieving emission reduction objectives of the United Nations Framework Convention on Climate Change (UNFCCC), climate partners in the developed states are mostly saddled with the task of providing essential climate and environmental-related financial resources. Thus, as reported in 2019 by the Organization for Economic Co-operation and Development (OECD), more than 70 billion USD (United States Dollars) of climate finance was provided and deployed by the developed states toward climate actions in the developing economies (OECD, 2019). Although climate financing remained a major bottleneck in the African region, many countries are recording success in the experimentation of FD approach of innovative financing. For instance, Uganda is adopting a crowd-founding for clean energy while green bond financing is being experimented in Nigeria and the Green Climate Fund (GCF) of global multilateral mechanisms are being accessed by many other African countries such as Morocco and Zambia to address climate and environmental-related problems (United Nations Development Programme, 2019). In spite the aforementioned positive development in the deployment of financial mechanism to tackle climate challenge across the continent, the recent report of the United Nations Development Programme (UNDP) suggests that there is more uncovered ground. Specifically, the UNDP report implies that mobilization of domestic and international climate finance is a major problem in more than half of the African countries with only less than one quarter and one third of the continent's countries respectively having strategic financial plan and standby financial instruments (United Nations Development Programme, 2019).

Therefore, to offer a complimentary justification for the role of FD in carbon emission mitigation in Africa, the current study deploys the spatial econometric approach. Considering that this study is one of the sparse studies to employ spatial econometric analysis in examining FD-environmental quality nexus for the case of Africa, the investigation is also conducted within the framework of environmental Kuznets curve (EKC) hypothesis as part of the study's novelty. Moreover, simultaneous investigation is conducted to examine the role of trade openness, renewable energy consumption, population density and industrialization in carbon emission with spatial econometric framework. With this in mind, the current study is expected to close the existing gap in the literature of the determinants of carbon emission and EKC hypothesis in Africa. Importantly, unlike most studies on Africa that managed to cover selected countries, the current endeavour covered 52 African countries, with only 2 left out because of data limitation. Moving to other matters in this study, the sections are carefully presented in a particular content-specific order. In section 2, it presents an engaging section about the nexus of FD and environmental quality alongside the nexus of carbon emission and other examined determinants. The deployed empirical approaches and details of the utilized dataset are presented in section 3 while the results of the investigation are analyzed in section 4. Lastly, section 5 is reserved to outline the summary of the study with the incorporation of relevant policy and recommendation.

2. Literature review

Several empirical studies are centred on the impact of FD on CO_2 emissions. Nonetheless, the empirical debate is still far from being settled. On one hand, some studies (including Adams & Klobodu, 2018; Guo, 2021; Lee et al., 2015; Lv & Li, 2021; Musa et al., 2021; Odhiambo, 2020;) confirm that FD improves environmental quality. On the other hand, some evidence (including

Acheampong, 2019; Ali et al., 2019; Bui, 2020; Fang et al., 2020; Ganda, 2019; Mahmood, 2020); Zhang, 2011) suggests that FD may indeed worsen environmental pollution. In some cases, evidence is weak (Raheem et al., 2019) or inconclusive (Haas & Popov, 2019; Tsaurai, 2019). While findings are expected to different conclusions across countries and/or regions, we find it interesting that evidence is heterogeneous even within, highlighting the controversiality of the nexus.

The vagueness of the empirical examination is well reflected in the African context. For instance, Acheampong (2019) used several indicators of FD (domestic credit to the private sector by banks and domestic credit to the private sector, broad money, FDI, domestic credit to the private sector by financial sector, and liquid liabilities) to examine the direct and indirect effects of FD on CO_2 emissions for 46 sub-Saharan Africa countries between 2000 and 2015. Results from a system-generalized method of moments (GMM) estimation revealed a positive and significant effect for the first three FD proxies. It follows that FD increased environmental degradation. The remaining proxies were found to have no effect on CO_2 emissions. However, a similar GMM investigation by Odhiambo (2020) for 39 sub-Saharan African countries over the comparative period from 2004-2014 contradicted findings by Acheampong (2019). Odhiambo (2020) found that FD is associated with CO2 emissions reductions. Nonetheless, the favorable effect is conditional on inequality level thresholds, beyond which the effect becomes positive.

In another study, Adams and Klobodu (2018) used data on 26 African economies in the period 1985–2011 to investigate the impact of FD on CO2 emissions. After controlling for political regimes, a series of econometric approaches, including the Chow test, cross-country regressions, the Generalized Method of Moments (GMM), were used for analysis. Results suggested that FD significantly improves environmental quality. An investigation by Tsaurai (2019) suggests that the impact of FD on CO_2 emissions in Africa is sensitive to the proxy of FD. The study was done based on data for 12 West African countries from 2003-2014 and analyzed using the pooled OLS, fixed and random effects estimations. Three proxies of FD, (1) domestic credit provided by the financial sector as a ratio of GDP, (2) domestic credit to the private sector by banks as a ratio of GDP, and (3) broad money as a ratio of GDP, were used. It was documented that only domestic credit provided by the financial sector worsens environmental degradation.

We observe that the inconclusive evidence between FD and CO_2 emissions is not only for Africa but also characterizes findings in developed countries. A look at evidence from G-7 countries by Shahbaz et al. (2013) and Raheem et al. (2019) and OECD countries by Lee et al. (2015) and Ganda (2019) elaborates this. Unlike most studies based on static relationships, Shahbaz et al. (2013) provide evidence based on time-varying cointegration analysis for the G7 countries G-7 countries over the period 1870 to 2014. The study used money supply (M2) as a proxy for FD and applied the Bierens and Martins (2010) time-varying cointegration (TVC) test for analysis. The results indicated that the effect of FD is heterogeneous across countries. The relationship was M- shaped in the US, Japan; upturned M-shaped in Germany, and inverted N-shaped in the UK, Italy, and France. However, in another study on G-7 countries over the period 1990-2019, Raheem et al. (2019) found a weak impact of FD on CO_2 emissions. Turning to the OECD studies, Lee et al. (2015) use a panel fully modified ordinary least squares (FMOLS) and data from 25 OECD countries over the 1971–2007 period to show that FD reduces environmental pollution. However, Ganda (2019) shows from static and dynamic panel data models that domestic credit to private sector, the same measure of FD as in Lee et al. (2015), had a significant positive effect on CO_2 emissions.

We also observe the same trend in Nigeria, where evidence by Ali et al. (2019) and Musa et al. (2021) contradict. Both studies use credit to the private sector as a percentage of GDP and the ARDL econometric approaches over comparable periods 1971-2010 and 1981-2019, respectively. In Ali et al. (2019), FD was found to significantly positively impact CO_2 emissions. This depicts worsening environmental degradation due to better financial intermediation. In contrast, Musa et al. (2021) find that FD has a significant negative impact on CO2 emission. In other studies worth mentioning, Haas & Popov (2019) and Bui (2020) bring the effect of the financial structure and transmission mechanisms into perspectives, respectively. The study by Haas and Popov (2019) was carried out for a panel of industries and countries over the period 1990-2013. Estimations from 2SLS regression reveal that for certain levels of FD, environmental degradation is low in relatively equity-funded countries. Results from sector-level investigation disclosed that equity markets (1) transfer investment to fewer polluting sectors and (2) force carbon-intensive sectors to invest in greener technologies, thereby lowering CO_2 emissions.

According to Espoir & Sunge (2021) it is becoming a norm to include spatial dependence in analysing environmental pollution determinants. With regards to FD, Mahmood (2020) and Lv & Li (2021) considered spatial effects. The analysis by Lv & Li (2021) confirmed spatial correlation among CO_2 emissions in 97 economies between 2000 and 2014. The study found that FD from neighboring countries significantly reduces CO_2 emissions. Similarly, Mahmood (2020) also found spatial dependence in 21 North American countries over the period. In contrast to Lv & Li (2021), domestic and neighboring FD were found to escalate environmental degradation.

3. Methodological approach and data

3.1. Econometrics of spatial panel models

This study aims to investigate the impact of FD on CO_2 emissions across African countries by considering countries' spatial dependence. As we shall see later in the data sub-section, we employ cross-sectional – time-series data covering the year 1995 to 2017. The empirical literature recommends using classical/traditional econometric techniques (pooled Ordinary Least Square, Fixed and Random effects) to estimate panel data models. However, these econometric techniques, specifically the Ordinary Least Square (OLS), assume independence between observations (LeSage and Pace, 2009; Elhorst, 2014b). This assumption is strong and unrealistic if one considers Tobler's First Law of Geography. This law enounces that no region is isolated. This implies that data observed at a geographical scale often present a spatial interaction effect. In this case, modeling panel data using OLS technique could provide biased marginal effects. Spatial panel models could be the alternative as they incorporate the spatial dependence between observations (Anselin, 1988). The recent spatial econometric empirical literature (Espoir and Ngepah, 2020) points to three key classical model specifications: the Spatial Error Model (SEM), Spatial Autoregressive (SAR) model, and Spatial Durbin Model (SDM). Following Elhorst (2009), the three models can be specified as follows:

$$y_{,t}=\rho W y_{,t}+i_N \emptyset_t+X_t\beta+\delta+\varepsilon_t \tag{1}$$

$$y_t=i_N \emptyset_t+X_t\beta+\delta+u_t$$
$$u_t=\lambda W u_t+v_t \tag{2}$$

$$y_t=\rho W y_{,t}+i_N \emptyset_t+X_t\beta+W X_t\zeta+\delta+\varepsilon_t \tag{3}$$

where Eq. (1), (2), and (3) represent the SAR, SEM, and SDM. $t = 1, \dots, T$; ρ stands for the spatial autoregressive coefficient. This is the parameter that captures the existence of spatial spillover effects across panel units. The high/low the magnitude of ρ, the high/low the intensity of spatial autocorrelation among panel units. W is a row-normalised (in some cases W is a row-standardised) spatial weights matrix that defines the spatial structure of connections among adjacent and non-adjacent units. Specifically, W is a vector that is constituted by the following elements: $w_{i,j}$ is the spatial connection between unit i and j so that Wy_t (spatial lagged dependent variable) is the average value of the dependent variable of neighbouring countries in period $t;$ λ represents the spatial autoregressive parameter of the stochastic error term; $\lambda W u_t$ is the spatial lagged disturbances at period t; WX_t is a matrix of spatial lagged independent variables, and ζ is the associated vector parameters. Finally, δ is the traditional panel unit fixed effects parameter, and ε_t and v_t are the disturbances.

3.2. Spatial model results uncertainty

Spatial models' results uncertainty is a crucial issue that is highlighted in applied spatial econometric research (LeSage and Pace, 2014; Fu et al., 2014; Insee – Eurostat, 2018). This uncertainty is determined based on the instability or behaviour of the variables marginal effects when the definition of the spatial weight matrix (W) is changed. Originally, W was developed based on the concept of land or maritime geographical boundaries, according to which $W_{i,j}$= 1 when entity i and j are geographical neighbours, = 0 if otherwise (Cliff and Ord 1969; Getis 2009).

Furthermore, there exists different type of spatial connection structures between entities, countries or regions. All those connection structures can be presented into graphs based on the definition of neighbourhood. (For more details see – Eurostat, 2018). Speaking in terms of graph connections, only three types seem to have emerged in empirical application. These are: (1) neighbourhood based on geometric concepts (Delaunay's triangulation, the sphere-of-influence based graph, Gabriel's graph, and the graph of relative neighbours), (2) neighbourhood based on distance concepts (nearest neighbour, two nearest neighbours, neighbours at a minimum distance, and inverse distance), and (3) neighbourhood based on contiguity (Queen and Rook contiguity).

In this study, we have maintained three types of connections structures (inverse distance=W_1), inverse distance with cut-off=W_2, and Queen contiguity=W_3) among African countries:

1) Inverse distance=$\begin{cases} W_{i,j} = \frac{1}{dist_{i,j}} \text{ if countries i and j are neighbours , } \mathrm{dist_{i,j}} = 2000km \\ W_{i,j} = 0 \quad \text{ if otherwithse} \end{cases}$

2) Inverse distance with cut-off (W_2)=$\begin{cases} W_{i,j} = 1 \; if \frac{1}{dist_{i,j}} \leq distance\ cut\ off\ (1.280km) \\ W_{i,j} = 0 \; if \; \frac{1}{dist_{i,j}} > 1.28km \end{cases}$

3) Queen contiguity (W_3)=$\begin{cases} W_{i,j} = 1 \; if\ country\ j\ share\ the\ corner\ or\ edge\ with\ country\ i \\ W_{i,j} = 0\ otherwise \end{cases}$ (6)

where $\mathrm{dist_{i,j}}$ is the distance between the centroids of countries i and j. We have defined this distance to be equal to 2000km based on the average distance between the centroid of South Africa and Angola. The 1.28km is the lowest distance between centroids (distance cut off) so that no country is left without at least one neighbour. Given this, it can be noted that the spatial interaction effect of FD will increase when African countries are closer, which generally leads to use the inverse of the distance among weight matrices.

Figure 1 presents nine different connection networks across African countries. Particularly, we focus on three connection networks: Fig 1e (W_1 connection networks is less dense compared to W_2 and W_3 with an average of 1 link between countries); Fig 1g (W_2 type of neighbourhood with a highly dense neighbourhood structure of average 27 associations between countries); and Fig 1h (W_3 connection structure is slightly dense connection network compared to W_2 with an average of 3.93 links) as presented in Eq. (6). In Fig. 1e and 1h, we observe that the connection links are abundant in West and Southern Africa and all because the distance between the centroids is shorter than 1.28km (minimum expected distance).

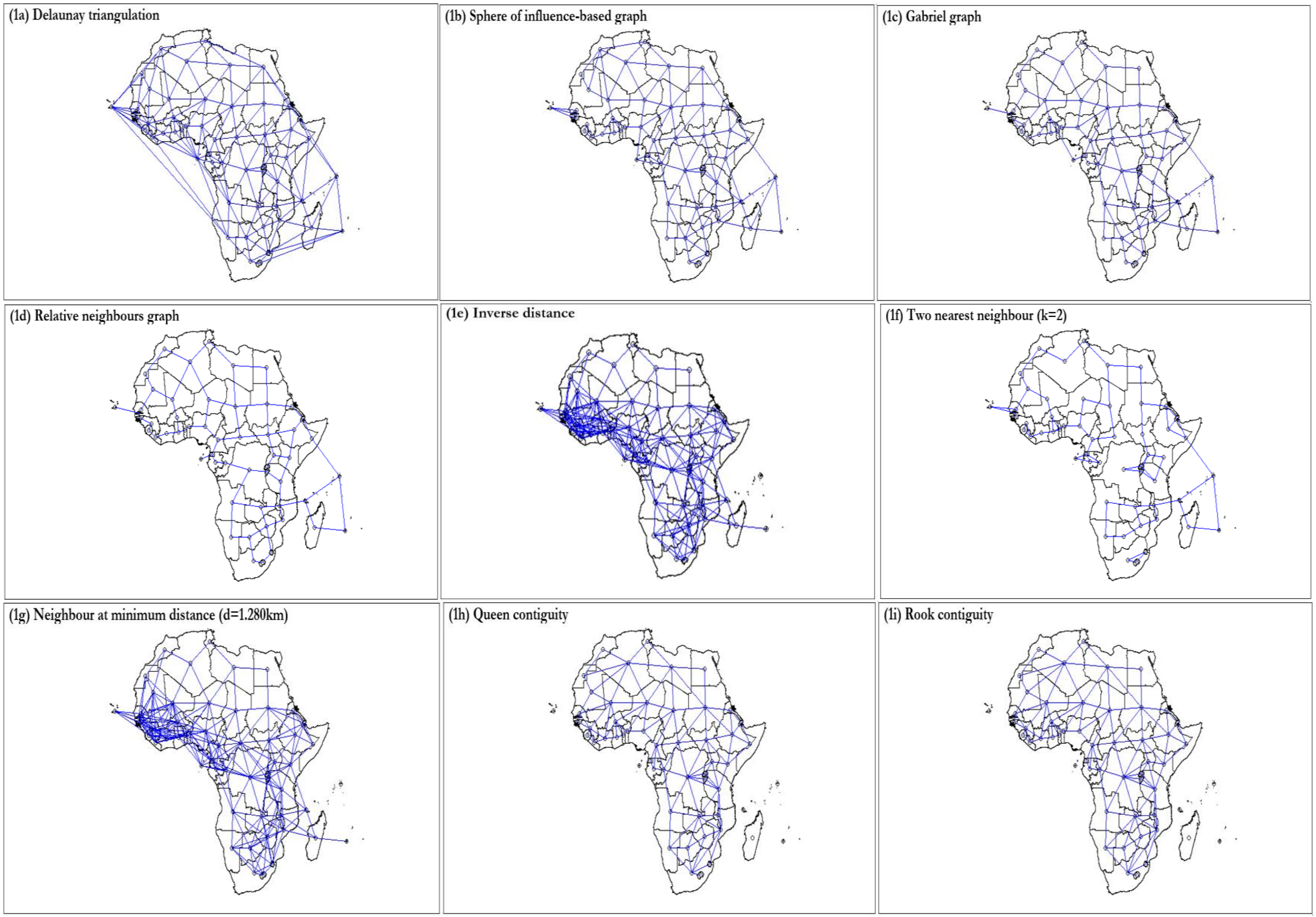

Figure 1: Different types of connection structures among African countries. Source: Authors' self-painting

3.3. Testing for spatial dependence

Before analysing panel data with spatial econometric techniques, it is compulsory to start by testing for the presence of spatial autocorrelation. One of the instruments proposed in literature is the Local and Global Moran's I test (Anselin, 1995). This test measures the degree of spatial clustering among the geographical units (countries). On the one hand, it is essential to indicate that the Local Moran's I test measures the similarity of countries to their neighbours while Global Moran's I calculate the average of all comparisons to offer inference about the spatial pattern of the variable. For the case at hand, we utilise the Global Moran's I as the first measure of spatial autocorrelation. The calculated values of this indicator range from −1 to 1. The value "1" implies perfect positive spatial autocorrelation, while "−1" means perfect negative spatial autocorrelation, and "0" suggests perfect spatial randomness (Fu et al., 2014). The Global Moran's I index is expressed as follows:

$$\text{Global Moran's } I_i = \frac{n}{SF} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{i,j}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{7}$$

where $W_{i,j}$ is the spatial weighting matrix and it shows the association between unit i and j, x_i is the value of the variable of interest (FD and $CO_2\ emissions$) and $\bar{x}$ is the mean value, $\bar{x}=\frac{1}{n}\sum_{i=1}^{n} x_i$. n is the number of countries in the sample, and SF is a standardization factor introduced to assign an equal weight to all the values of the spatial matrix, $SF=\sum_{i=1}^{n}\sum_{j=1}^{n} W_{i,j}\, x_i$.

While the Global Moran's I quantify to test the spatial dependence among adjacent units (countries), Harries (2006) shows that it is also important to identifying local spatial cluster patterns and spatial outliers using the Local Indicators of Spatial Association (LISA). According to Anselin (1995), the LISA measures the degree of spatial autocorrelation at each specific location by using local Moran's I. In general terms, the LISA is of a variable y_i, observed at location i is expressed as:

$$LISA_i = f(y_i, y_j) \tag{8}$$

where f is a function indicator, and the y_j are the values observed in the neighborhood J_i of location i. Thus, we employ this indicator as the second measure of spatial autocorrelation of CO_2 emissions among African countries.

3.4. Empirical model

To empirically investigate the spatial effects of FD on CO_2 emissions in Africa, our estimated model is specified in line with the existing literature in environmental economics (Radmehr et al., 2021; Abid, 2016; Yang and Chng, 2019; Fang et al., 2018), but also in relation to the recent finance-pollution empirical studies (Khezri et al., 2021; Lv and Li, 2021). To ensure that our results are compared with the existing findings on the FD−CO2 emissions nexus and the EKC hypothesis, we adopt the model specification as is in Lv and Li (2021), Abid (2016), and Espoir and Sunge (2021). Thus, we specified a SDM as it includes the spatial lag of the dependent and independent variables. The SDM functional form is written as follows:

$$\begin{aligned} CO_{2,it} = {} & \beta_0+\beta_1 FD_{i,t}+\beta_2 GDP_{i,t}+\beta_3 GDPSQ_{i,t}+\beta_4 TRADE_{i,t}+\beta_5 REC_{i,t}+\beta_6 POPD_{i,t}+\beta_7 IND_{i,t} \\ & +\rho W_{n,t} CO_{2,jt}+\theta_1 FD_{j,t}+\theta_2 W_{n,t} GDP_{j,t}+\theta_3 W_{n,t} GDPSQ_{j,t}+\theta_4 W_{n,t} TRADE_{j,t} \\ & +\theta_5 W_{n,t} REC_{j,t}+\theta_6 W_{n,t} POPD_{j,t}+\theta_7 W_{n,t} IND_{j,t}+\delta_i+\varepsilon_{i,t} \end{aligned}$$

$$\varepsilon_{i,t} = \lambda W \varepsilon_{j,t}+u_{i,t},\ u_{i,t}\sim i.i.d(0,\sigma^2) \tag{9}$$

where the β_s=1, 2, …, 7, are the parameters of the effects of the explanatory variables for all θ_s=1, 2, …, 7 (i.e parameters of the spatial part of the equation depicting the impact of the explanatory variables of a neighboring country on CO_2 emission in a given country), θ_s = Spatial Autocorrelation (SAC) coefficients, ρ = Spatial Autoregressive (SAR) parameter while country-specific effects and stochastic error term are respectively δ_i and $\varepsilon_{i,t}$.

3.5. Data

We collect data for the period spanning the years 1995–2017 for 52 African countries. CO_2 emissions is the dependent variable and is measured per head metric tonnes. The data for this variable is sourced from the World Bank database (http://www.worldbank.org/). Moreover, we extract data of nine financial structure indicators from the Financial Structure Database (FSD)[1] and apply the principal component analysis (PCA) method to build an index of FD for African countries. Those nine indicators are: the deposit money bank assets to (deposit money + Central) bank assets (dbacba), liquid liabilities to GDP (llgdp), Central bank assets to GDP (cbagdp), deposit money assets to GDP (dbagdp), private credit by deposit money banks to GDP (pcrdbgdp), private credit by deposit money banks and other financial institutions to GDP (pcrdbofgdp), Bank deposit to GDP (bdgdp), financial system deposit to GDP (fdgdp), and Bank credit to bank deposit (bcbd). The principlas component analysis (PCA) was computed for the variable FD index.

4. Empirical results and discussion

4.1: Exploratory spatial data analysis

Given the aim of this study, we start our empirical analysis by performing exploratory spatial data analysis (ESDA) of the two variables of key interest (CO_2 emissions and FD index). Figure 2(a) shows the spatial distribution of the average CO_2 emissions covering 1995–2017. As can be seen, only three countries (South Africa, Libya, and Equatorial Guinea) are found to have the highest stock of CO_2 emissions. In this category, the average stock of CO_2 emissions for the covering 1995–2017 is between the interval of 6.45-8.05 metric tons per capita. Moreover, Gabon has an average stock of CO_2 emissions between 4.84-6.44 and is the only country that forms the second-highest category with an average value of emissions on the continent. The level of emissions is too high in these countries (of the two categories) because they are among the main producers of nonrenewable energy from fossil fuels, natural gas, and coal. Lastly, the remaining African countries have low average stock of CO_2 emissions from 1995 to 2017. Their average stock of CO_2 emissions is between the interval of 0.00001-3.22 metric tons per capita. In looking at this Figure (2b), it is clearly seen that, the countries with the highest FD index are located in Southern and Northern Africa (South Africa, Lesotho, Namibia, Egypt, Libya, and Morocco). There are also some few exceptions in East and Western Africa where countries such as Liberia and Eritrea are found to have high FD index. Additionally, it is also observed that the majority of African countries have low FD index, which suggest that countries with high (low) CO_2 emissions values are surrounded by countries with high (low) FD values.

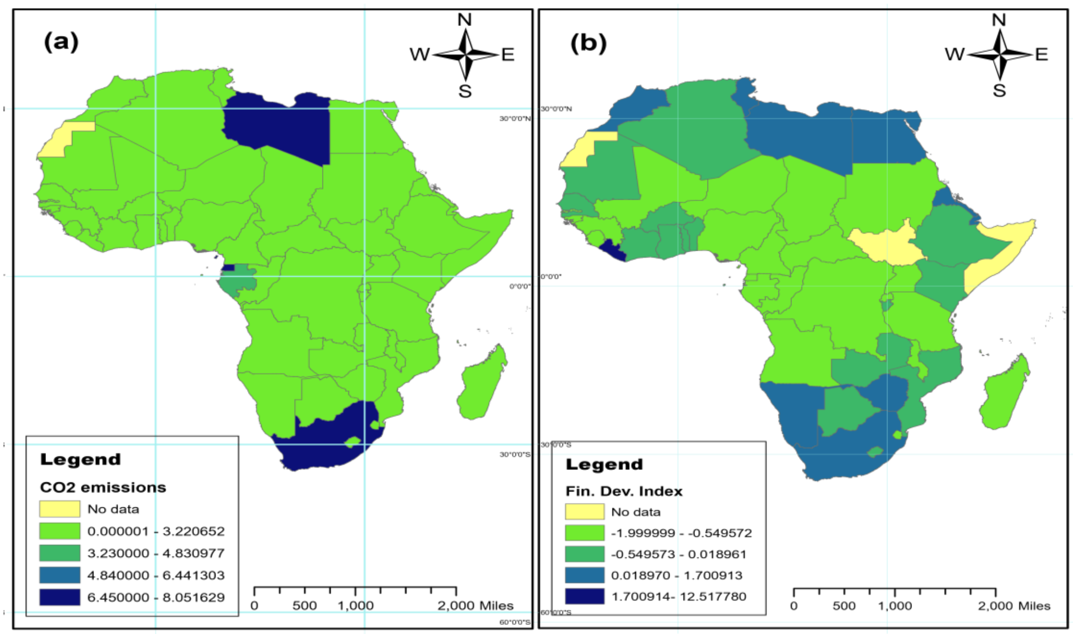

Figure 2: Spatial distribution map of (a) CO2 emissions and (b) FD index across African countries. Source: data is from the World Development Indicators.

However, the Global Moran's I test is limited in effectiveness when the Moran's I index tend to a value of 0, thus showing non-spatial autocorrelation. For this reason, we further assess the presence of spatial dependence in the data by presenting in Fig. 3 the Moran's I scatter plots (left-hand side) and LISA maps (right-hand side) for the year 1995, 2005, and 2017. We also report the mean values of the Global Moran's I in Figure 3. Starting with the scatter plots on the left-hand side, we aim at visualising the quadrants in which most African countries are situated and see whether the fitted blue line is different from zero. For most countries as shown in Figure 3, there is positive spatial dependence in CO_2 emissions for all the three selected years 1995, 2005, and 2017. We also report the results of the LISA cluster maps emission of CO_2 on the right-hand side of Figure 3. We observe a slightly different picture across the years. In 1995, A large low–low spatial cluster is observed in the western and eastern part of the continent, while a high-high spatial autocorrelation is seen in the southern and northern part of the continent.

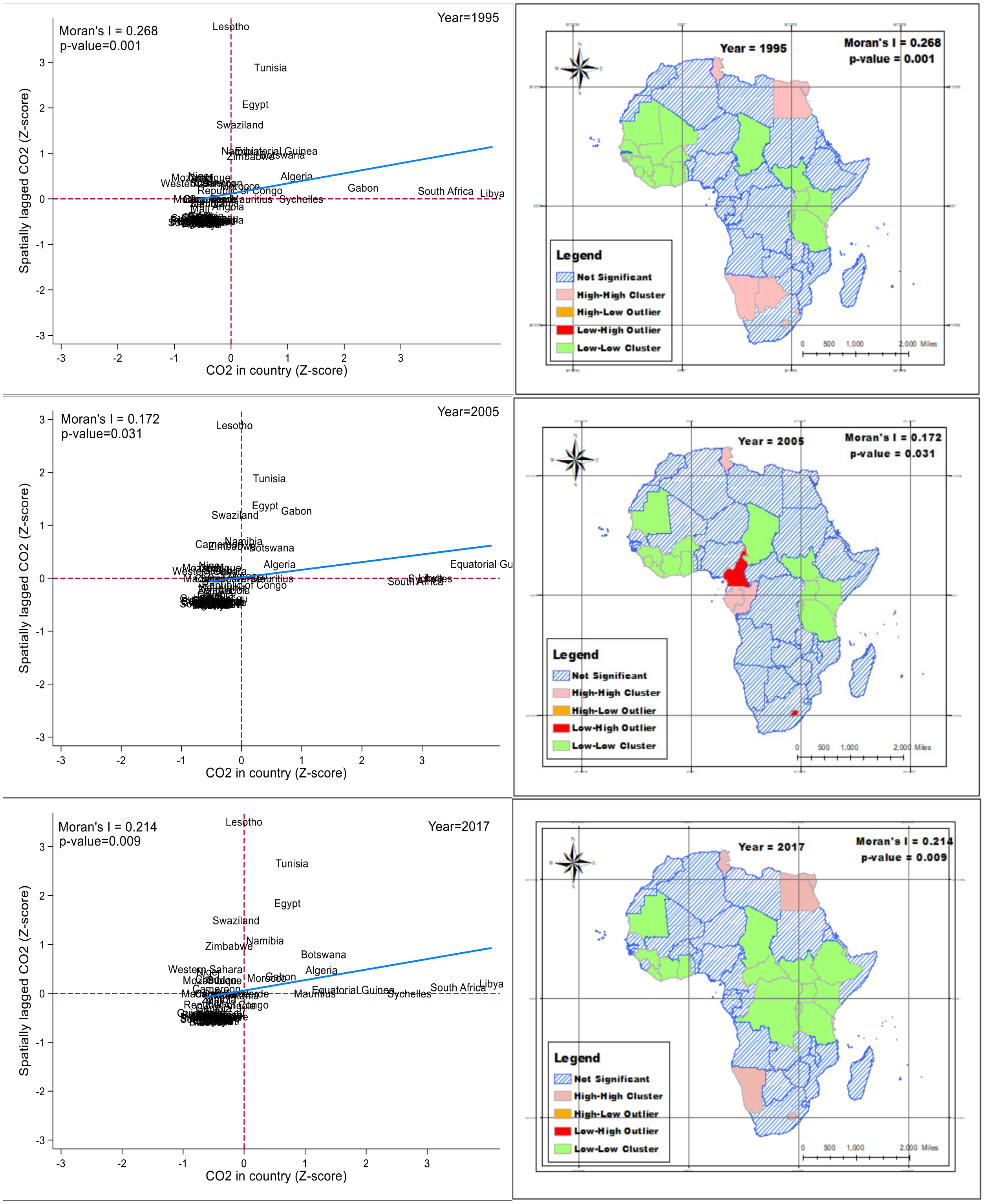

Figure 3: Global Moran's I scatter plot (left-side) and spatial clusters and spatial outliers map (right-side) of CO_2 emissions for selected years across African countries.

Source: Data is sourced from World Development Indicators.

4.2: Specification testing and results of spatial panel model

We start the analysis of spatial panel models by testing the appropriate specification between spatial econometric models and the traditional panel data models. To this end, we consider four classical panel data models: the pooled OLS (Model 1), individual fixed effects (Model 2), time fixed effects (Model 3), and two-way (TW) fixed effects (FE) i.e TWFE (Model 4)[2]. The diagnostic tests revealed that the consistent model is a panel specification with fixed effects[3]. For the spatial dimension, we obtain a χ^2= 117.50, p-value=0.000, and df=54), and for the temporal dimension, we obtain a χ^2= 109.86, p-value=0.000, and df=53).

After we have tested and chosen the appropriate traditional panel data model for our data (Model 4: TWFE), we now follow by determining which is the most suitable spatial specification between SAR, SEM, and SDM. To this end, we employ four versions of the Lagrange multiplier (LM) test (Breusch and Pagan, 1980): LM spatial lag and Robust LM spatial lag (two tests of endogenous spatially lagged dependent variables, LM spatial error, and Robust LM spatial error (two tests of the error dependence). We use the inverse distance spatial weights matrix (W1) to conduct these four tests and the results are reported in Table 1.

[2] The TWFE model means time and individual fixed effects

[3] We did not present the results of these regressions here, but we can make them available upon request.

Table 1: Traditional panel models estimation results

Models variables	Model (1) Pooled OLS	Model 2 Individual FE	Model 3 Time-FE	Model 4 TW-FE
FD	0.0006	-0.008	0.002	-0.004
	(0.006)	(0.009)	(0.005)	(0.009)
GDP	0.00001***	0.00006***	0.0001***	0.00009***
	(0.00001)	(0.00001)	(0.00001)	(0.00002)
GDPSQ	-3.45e-09***	4.51e-10	-4.15e-09***	-1.06e-09
	(7.23e-10)	(8.82e-10)	(6.76e-10)	(9.38e-10)
TRADE	-0.0007**	0.0001	-0.0006**	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
REC	-0.001***	-0.006***	-0.001***	-0.007***
	(0.0004)	(0.0012)	(0.0004)	(0.0012)
POPD	-0.012	-0.078*	-0.003	0.118**
	(0.008)	(0.043)	(0.0079)	(0.053)
IND	0.002***	0.0002	0.002***	0.0017
	(0.0008)	(0.0010)	(0.0008)	(0.001)
CONSTANT	0.227***	1.131***	0.913***	0.862***
	(0.049)	(0.158)	(0.065)	(0.183)
AIC	1377.207	634.0403	1180.517	557.762
SIC	1418.350	775.1829	1334.802	712.047
R-squared	0.954	0.953	0.962	0.657
Adj. R-squared	0.954	0.953	0.961	0640
LM spatial lag	0.005	8.637***	1.075	4.731**
	(0.940)	(0.003)	(0.299)	(0.029)
Robust LM spatial lag	20.158***	80.206***	0.007	20.378***
	(7.132e-06)	(2.2e-16)	(0.929)	(6.356e-06)
LM spatial error	156.14***	27.572***	12.506***	1.730
	(2.2e-16)	(1.513e-07)	(0.0004)	(0.188)
Robust LM spatial error	176.3***	99.142***	11.439***	17.376***
	(2.2e-16)	(2.2e-16)	(0.0007)	(3.066e-05)
Obs= NxT	1265	1265	1265	1265

Note: ***, **, and * are respectively p<0.01, p<0.05, and p<0.1. The values reported in bracket are standard errors.

For the chosen model (Model 4: TWFE), the results show that the LM spatial lag statistic is statistically significant, while the LM spatial error statistic is insignificant. These results seem to indicate spatial autoregressive than the presence of spatial autocorrelation of the disturbances. In this case, Anselin et al. (1996) propose to conduct the robust versions of these tests to determine the true data generating process (DGP). Thus, we perform the Robust LM spatial lag and Robust LM spatial error tests. The results of these two tests (for Model 4) show that the statistics are statistically significant, indicating the presence of spatial autocorrelation and spatial dependence of the errors. According to LeSage and Pace (2009), Eq. (8) can be used to test if the SDM can be reduced to a SAR model (H_0: θ_s=0) or a SEM (H_0: $\theta_s+\rho\beta$=0). The results are reported in Table 5. Then, two LR and Wald tests (LR-lag=76.80, p-value = 0.000, df=7; LR-error = 97.41, p-value= 0.000, df=7, and Wald-lag= 20.30, p-value=0.000; Wald-error=0.03, p-value= 0.862, respectively) are conducted. Thus, the LR and the Wald-lag statistics reject the null hypotheses and conclude that the SDM is the preferred model. For this reason, we estimate the SDM with TWFE using three spatial weight matrices (W1, W2, and W3) as specified in Eq. (6). Specifically, we use the three spatial weight matrices in our regressions to show the robustness of the estimated results of the variable of our key interest (FD). Table 2 presents the results of the SDM with TWFE. As can be seen from this table, the inverse distance spatial matrix specification has the lowest value of AIC and SIC, and the highest log likelihood value. This indicate that the W1 specification is the most appropriate compared to W2 and W3. Focusing on the results of W1, we observe that the variable WFD (ρ=0.106) is positive and statistically significant.

Table 2: Results of SDM with TWFE for different spatial weight (W) matrix specifications

Estimated model Variables	SDM-FE W_1=inverse distance	SDM-FE W_2=inverse distance with cut off	SDM-FE W_3=queen contiguity
FD	0.021*	0.023*	0.017
	(0.012)	(0.0123)	(0.0125)
GDP	0.0003***	0.0003***	0.0003***
	(0.00002)	(0.00002)	(0.00002)
GDPSQ	-3.83e-09***	-3.28e-09***	-3.21e-09***
	(1.27e-09)	(1.26e-09)	(1.27e-09)
TRADE	0.0013***	0.0012***	0.0014***
	(0.0004)	(0.0004)	(0.0004)
REC	-0.014***	-0.014***	-0.011***
	(0.0017)	(0.0016)	(0.0017)
POPD	0.114	0.124*	0.055
	(0.0714)	(0.072)	(0.073)
IND	0.003*	0.003**	0.001
	(0.0014)	(0.0014)	(0.0014)
YEAR	0.017**	0.007	-0.008*
	(0.0079)	(0.0057)	(0.0046)
WFD	0.106*	0.127**	0.042*
	(0.0550)	(0.0638)	(0.0246)
WGDP	-0.0001	-0.0001	0.00004
	(0.0001)	(0.0001)	(0.00005)
WGDPSQ	-1.30e-08*	-9.86e-09*	-6.88e-09***
	(6.84e-09)	(5.74e-09)	(2.81e-09)
WTRADE	0.0009	0.002	-0.0007
	(0.0031)	(0.0023)	(0.0009)
WREC	0.013	0.007	0.011***
	(0.0122)	(0.0094)	(0.0038)
WPOPD	-0.768**	-0.756***	-0.149
	(0.351)	(0.265)	(0.1334)
WIND	0.046***	0.035***	0.002
	(0.0104)	(0.0087)	(0.0022)
WCO_2	-0.289***	-0.264***	-0.044
	(0.1233)	(0.1053)	(0.0477)
Obs= NxT	1265	1265	1265
Pseudo R^2	0.327	0.409	0.683
Log likelihood	-612.415	-614.283	-633.297
AIC	1254.831	1258.567	1296.595
SIC	1331.973	1335.709	1373.738
LR test spatial lag	76.80 [0.0000]		
Wald test spatial lag	20.30 [0.0000]		
LR test spatial error	97.41 [0.0000]		
Wald test spatial error	0.03 [0.8620]		

Note: ***, **, and * are respectively $p<0.01$, $p<0.05$, and $p<0.1$. The values in square bracket are p-value and those in bracket are standard errors.

It indicates the existence of positive spatial spillover effects of CO_2 emissions across African countries. In other words, this coefficient means that the spatial distribution of CO_2 emissions across African countries is not random. The coefficient of FD in local country is positive and statistically significant at the 10% level, while that of neighbouring country is also positive and statistically significant at the 10% level. The sign of the coefficient of GDP in the local country is positive and significant at the 1% level, whereas GDPSQ is negative and statistically significant as well. In the neighbouring country, GDP is negative and insignificant, while GDPSQ is positive and statistically significant. The variable TRADE shows a positive and significant effect in local country, while in neighbouring country it shows a positive but not significant effect. Moreover, REC presents a negative and significant effect in local country, whereas in adjacent country, the variable shows an insignificant positive impact. POPD exhibits a positive and insignificant effect on CO_2 emissions in local country and a negative significant effect in adjacent country. Finally, the variable IND presents a significant positive impact on CO_2 emissions in local country, while in neighbouring country, the impact is also positive and statistically significant. According to Elhorst (2014b), the coefficients of the spatial lagged explanatory variables (WGDP, WGDPSQ, WTRADE, WREC, WPOPD, and WIND) are the local effects. However, when ρ and θ are jointly equal to zero, the local and global effects cannot be separated. Thus, (in)direct effects is reported as the average of (column sums of the off-diagonal elements of the matrix) diagonal elements of the matrix as is in Eq. (8) according to LeSage and Pace (2009).

Another element to be mentioned here is the interpretation of the estimated coefficients of spatial panel models. For example, in the traditional panel models, the estimated coefficients (see Table 1) are directly interpreted as elasticities/marginal effects. On the contrary, the estimated coefficients in the SDM (see Table 2) do not directly represent the variables' elasticities. To correctly interpret the coefficients of the SDM-FE, specifically the SDM-FE (W1) model, we calculate the (in)direct and total impact of each explanatory variable according to the specification in Eq. (8). The results of this calculation are presented in Table 3. As can be seen from Table 3, the coefficients of the SDM-FE (W1) model differ from those reported in Table 4. The difference is probably due to the feedback impacts across neighbouring countries, as the effects pass from one neighbouring country to another and back again (Elhorst, 2014a).

In Table 3, the direct effect of FD (0.020) is positive and significant at the 10% level, whereas the indirect effect (0.074) is also positive and significant at the 10% level. Altogether, the total effect of FD in the local country when considering the effect originating from neighbouring countries' FD is positive (0.095) and significant at 10%. This coefficient indicates that a 1% increase in FD increases emissions on average by 0.095% across African countries. This finding is in line with other recent studies that have reported positive effects of FD on CO_2 emissions in Africa. For example, Acheampong (2019) uses the system-generalised method of moments technique to study the impact of FD on CO_2 emissions across 46 sub-Saharan African (SSA) countries over the period 2000–2015. This author found that FD increase carbon emissions. Other studies such as Shahbaz et al. (2016); Al-Mulali et al., (2015a, 2015b); Maji et al., (2017) have confirmed the positive impact of the bank-based FD on CO_2 emissions. Although there is enough support from this strand of previous literature suggesting environmental degradation through FD activities, our result is inconsistent with another strand of literature indicating that FD improves environmental quality by reducing CO_2 emissions (Abbasi and Riaz, 2016; Al-Mulali et al., 2015a, 2015b; Maji et al., 2017; Shahbaz et al., 2018; Shahbaz et al., 2013b). In the specific case of the African continent for instance, Odhiambo (2020) investigates the dynamic relationship between FD, and CO_2 emissions using data of 39 SSA countries during the period 2004–2014. This author reported that FD unconditionally reduces CO2 emissions in SSA countries.

Table 3: Cumulative marginal long-run effects results for the different specifications of spatial W

Effects / Variables	Direct effects			Spillover effects			Total effects		
Weight matrix	W_1	W_2	W_3	W_1	W_2	W_3	W_1	W_2	W_3
FD	0.020*	0.022*	0.017	0.074*	0.083*	0.036*	0.095*	0.106***	0.053**
	(0.0123)	(0.0123)	(0.0125)	(0.044)	(0.0445)	(0.0212)	(0.0578)	(0.0461)	(0.0246)
GDP	0.0003***	0.0003***	0.0003***	-0.0001	-0.0001	0.00002	0.00013**	0.0001**	0.0003***
	(0.00002)	(0.00002)	(0.00002)	(0.00009)	(0.00007)	(0.00004)	(0.00007)	(0.00007)	(0.00004)
GDPSQ	-3.72e-09***	-3.18e-09***	-3.15e-09***	-8.83e-09*	-6.21e-09	-5.80e-09***	-1.25e-08***	-9.39e-09***	-8.95e-09***
	(1.27e-09)	(1.27e-09)	(1.28e-09)	(5.16e-09)	(4.00e-09)	(2.45e-09)	(5.24e-09)	(4.09e-09)	(2.57e-09)
TRADE	0.001***	0.001***	0.001***	0.0003	0.001	-0.0007	0.0016	0.002	0.0007
	(0.0004)	(0.0004)	(0.0004)	(0.002)	(0.0016)	(0.0008)	(0.0022)	(0.0016)	(0.0008)
REC	-0.014***	-0.014***	-0.011***	0.013	0.007	0.010***	-0.001	-0.007	-0.001
	(0.0016)	(0.0016)	(0.0017)	(0.0089)	(0.0063)	(0.0032)	(0.0093)	(0.0066)	(0.0040)
POPD	0.121*	0.134*	0.057	-0.594***	-0.545***	-0.131	-0.473*	-0.411***	-0.073
	(0.072)	(0.0731)	(0.0731)	(0.254)	(0.1802)	(0.1152)	(0.2435)	(0.1700)	(0.1224)
IND	0.002*	0.002*	0.001	0.034***	0.023***	0.002	0.036***	0.026***	0.0037*
	(0.0014)	(0.0014)	(0.0014)	(0.007)	(0.0059)	(0.0019)	(0.0073)	(0.0059)	(0.0022)

Note: ***, **, and * are respectively p<0.01, p<0.05, and p<0.1. The values reported in bracket are standard errors.

A genuine explanation for the significant positive total effect of FD on CO_2 emissions is that most African countries financial sectors are weak in facilitating or attracting green technologies transfer to promote environmental sustainability. While some studies point to the financial system of most African countries that are less or poorly liberalised (Acheampong, 2019), other studies emphasis the financial infrastructure in most African countries that remains light with a contribution to growth, poverty reduction, and environmental improvement that is minimal (Gakunu, 2007). Generally, mixed and inconclusive findings concerning the nexus between FD aspects and environmental degradation vis-à-vis carbon emissions have largely been documented in the literature (Ekwueme et al., 2021; Nwani et al., 2022; Zoaka et al., 2022). In other words, one could strongly argue that the poor financial system across African countries is an important factor limiting financial institutions and markets to support green technologies development projects. As can be observed in Table 3, indirect effects of FD causes ~78% of total effects. This indicates the importance of considering country interdependence relations for FD policy designed and implemented to determine pollution in Africa.

Turning to the examination of the EKC hypothesis theory based on the coefficients of GDP and GDPSQ, the result shows the following: (1) for GDP, the direct effects (0.0003) are positive and statistically significant at the 5% level, whereas the indirect effects (-0.0001) are negative and insignificant, (2) for GDPSQ, the direct effects (-3.72e-09) are negative and statistically significant at the 1% level, while the indirect effects (-8.83e-09) are negative and significant at the 10% level. Overall, the results in Table 3 show that the total effects for GDP (0.00013) are positive and significant at the 5% level, whereas the total effects for GDPSQ (-1.25e-08) are negative and significant at the 1% level. This result implies that economic prosperity hampers environmental quality in a given local country but the local and neighbouring environmental quality improves after a threshold level of economic growth (i.e EKC is valid). The results on the economic development variables (GDP and GDPSQ) are in line with the results of the recent studies by Lv and Li (2021) and Espoir and Sunge (2021) that validated the evidence of the EKC hypothesis across the 97 countries and 48 African countries respectively.

Another interesting result is that of openness to international trade (TRADE). The direct effects of TRADE on CO_2 emissions (0.001) are positively significant at the 1% level, while the indirect effects (0.0003) are positive but insignificant. The total effects of TRADE are (0.0016) positive but statistically insignificant. This finding suggests that the effects of international trade in all neighbouring countries is minimal in relation to environmental degradation in Africa. This finding is in line with the result reported by Espoir and Sunge (2021) that reveals an insignificant spatial total effect of TRADE on CO_2 emissions in Africa. REC shows negatively significant direct effects (-0.014), positively insignificant spillover effects (0.013), and thus negatively insignificant negative effects (-0.001). This finding is not surprising given that, in low-income countries like those of Africa, energy consumption is known to be relatively low, henceforth unable to produce significant effects on carbon emissions. The result for REC variable in this study agrees with Acheampong (2019) but contrary to Shahbaz et al. (2015b) which finds that energy utilisation spur CO_2 emission in low-income countries. Moreover, Espoir and Sunge (2021) find for the case of Africa that REC is a significant driver of environmental pollution as it decreases CO_2 emissions. The direct effects of POPD (0.121) are positive and significant at the 10% level, while the spillover effects (-0.594) are negative and highly significant at the 1% level. This implies that population density causes an increase in the pollutant emissions of a given country, while its causes a decrease in pollutant emissions in the neighboring countries. Specifically, the positive effects in local country can be interpreted as the contribution of an increased population size to a higher energy consumption, therefore spurring the generation of pollutant emissions (Lv and Li, 2021). Moreover, the total effects of POPD are (-0.473) negative and significant at the 10% level. This finding is inconsistent with our initial prediction. One of the plausible reasons for the total negative effects of POPD is that African population are constantly immigrating from rural to urban areas. In this regard, the UN-DESA (2014) reports that the African population living in urban areas rose from about 27% in 1950 to 40% in 2015 and are projected to reach 60% by 2050. With the danger related to climate global warming, most of the urban areas and cities are aware or have more knowledge about the impact of human footprints on the environment degradation than in rural areas. This helps to reduce the positive effects of POPD on pollution in Africa.

5. Conclusion and Policy Implications

Climate change is one of the biggest challenges of the 21st century. Humans continuously influence the climate and the world's temperature by burning fossil fuels, doing extensive farming activities, and cutting down forests. Several studies have shown that 2011-2020 was the warmest decade recorded, with global average temperature reaching 1.1°C above pre-industrial levels in 2019. It is also shown that Human-induced global warming is currently increasing at 0.2°C per decade. However, to keep global warming below 1.5°C in the 21st century, the aspirational objective of the Paris Agreement on climate, the world must halve annual greenhouse gas emissions, particularly carbon dioxide emissions (CO_2 emissions) in the next eight years (Emissions Gap Report, 2021). To do so, it necessitates to study and understand the key drivers of greenhouse gas and carbon dioxide emissions. Several developing countries, including those of Africa have elaborated and adopted the Nationally Determined Contributions (NDCs) that contain more ambitious commitments to reduce emissions. In most of those NDCs, it well highlighted that the emissions reduction objective can only be implemented with increased financial resources and other support such as technological and capacity-building support.

Against this backdrop, the current study applies a spatial econometric approach to investigate the finance-pollution nexus across African countries. Specifically, the study aims at investigating the direct and indirect effect (spatial spillover effect) of FD on CO_2 emissions across the 55 African countries during the period spanning the year 1995–2017. To avoid bias associated with the omission of variable bias, we control for the impact of economic development (GDP per capita), renewable energy consumption, trade openness, population density, and industrialisation. While several previous studies exhibit high tendency of producing biased estimates due to multicollinearity when employing various measures of FD to investigate the finance-pollution nexus. composite FD index was constructed by using a PCA to investigate the finance-pollution nexus across the African countries.

Importantly, the investigation which is based on Environmental Kuznets Curve (EKC) hypothesis affirms the validity of EKC hypothesis. Although the magnitude of the coefficients of GDP and GDPSQ is small, the revelation generally suggests an increase of pollution with economic growth in the early stage of development and a decrease in the last stage of development. Additionally, our results show that industrialisation (IND) produces a positive and statistically significant total effect on CO_2 emissions. Meanwhile, population density (POPD) produces a negative significant total effect on CO_2 emissions. However, authors note that the limitations in the current study could be improved upon especially from the perspective using more dated dataset and comparing related empirical approaches such as the SAR and SEM models with the SDM model.

5.1 Policy relevance

Therefore, formulation of policy recommendations is made based on the findings. First, given the positive (in)direct effects of FD on carbon emission, policymakers across the continent should make efforts to harmonise pollution abatement strategy through equitable financial resources allocations. More priority should be devoted to investment in environmentally friendly projects and related research and development (R&D. Investing in local content development by expanding R&D and innovations capabilities across the continent is a vital approach to pollution and environmental degradation abatement afterward. This, in addition to robust policy that promotes green technology transfer should aid to improve the continent's environmental sustainability and green growth. Additionally, implementation of environmental stringent conditions should indirectly propel industries or firms to invest in environmental sustainability projects while also exploring the best lower cost financial approach. Although the investigation confirms the presence of an inverted-U-shaped EKC relationship for the full sample, it is important to mention that this result may not be the case for several African countries. Thus, this is a crucial observation and it is expected that several African countries will continue to experience environmental pollution due to economic growth for a long period. In this regard, implementation of stricter environmental and energy legislation, such as increasing the market entry threshold for high energy-consuming businesses could further assist to restrict the increased environmental hazard that is associated with economic development.

References

Abid, M., 2016. Impact of economic, financial, and institutional factors on CO_2 emissions: evidence from Sub-Saharan Africa economies. Util. Pol. 41, 85–94.

Acheampong, A.O., 2019. Modelling for insight: Does financial development improve environmental quality? *Energy Economics*, *83*, 156–179. https://doi.org/10.1016/j.eneco.2019.06.025

Adams, S., Klobodu, M., 2018. Renewable and non-renewable energy, regime type and economic growth. *Renewable Energy*, *125*, 755–767. https://doi.org/doi.org/10.1016/j.renene.2018.02.135

Ali, H.S., Law, S.H., Lin, W.L., Yusop, Z., Chin, L., Bare, U.A.A., 2019. Financial development and carbon dioxide emissions in Nigeria: evidence from the ARDL bounds approach. *GeoJournal*, *84*(3), 641–655. https://doi.org/10.1007/s10708-018-9880-5

Akaike, H., 1974. A new look at the statistical model identification. IEEE Trans. Autom. Control 19 (6), 716–723.

Anselin, L., 1988. Spatial Econometrics: Methods and Models. Kluwer Academic Publishers, Dordrecht.

Anselin, L., 1995. Local indicators of spatial association-LISA. Geogr. Anal. 2, 93–105.

Anselin, L., Bera, A.K., Florax, R., Yoon, M.J., 1996. Simple diagnostic tests for spatial dependence, Regional Science and Urban Economics, 26, (1), 77-104

Bui, D.T., 2020. Transmission channels between financial development and CO2 emissions: A global perspective. *Heliyon*, *6*(11), e05509. https://doi.org/10.1016/j.heliyon.2020.e05509.

Breusch, T.S., Pagan, A.R., 1980. The Lagrange multiplier test and its applications to model specification in econometrics. Rev. Econ. Stud. 47 (1), 239–253.

Cliff, A.D., Ord, J.K., 1969. The problem of spatial autocorrelation. In A. J. Scott (Ed.), London papers in regional science, studies in regional science (Vol. 1, pp. 25–55). London: Pion.

Ekwueme, D. C., Zoaka, J. D., & Alola, A. A. (2021). Carbon emission effect of renewable energy utilization, fiscal development, and foreign direct investment in South Africa. Environmental Science and Pollution Research, 28(31), 41821-41833.

Espoir, D.K., Nicholas, N., 2020. The effects of inequality on total factor productivity across districts in South Africa: A spatial econometric analysis. In: GeoJournal, vol. 2. Springer Netherlands. https://doi.org/10.1007/s10708-020-10215-2.

Espoir, D.K., Sunge, R., 2021. Co2 emissions and economic development in Africa: Evidence from a dynamic spatial panel model. *Journal of Environmental Management*, *300*. https://doi.org/https://doi.org/10.1016/j.jenvman.2021.113617

Elhorst, J.P., 2009. Spatial panel data models. In: Fischer, M.M., Getis, A. (Eds.), Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications. Springer Science & Business Media.

Elhorst, J.P., 2014a. Linear spatial dependence models for cross-section data. Spatial Econometrics. Springer, pp. 5–36.

Elhorst, J.P., 2014b. Spatial Econometrics: from Cross-Sectional Data to Spatial Panels. Springer.

Fang, Z., Huang, B., Yang, Z., 2018. Environmental Kuznets Curve : evidence from cities in the people ' S republic of. In: Asian Development Bank Institute, 882.

Fang, Z., Gao, X., Sun, C., 2020. Do financial development, urbanization and trade affect environmental quality? Evidence from China. *Journal of Cleaner Production*, *259*, 120892. https://doi.org/10.1016/j.jclepro.2020.120892.

FSD (2021). database is accessible at: https://www.worldbank.org/en/publication/gfdr/data/financial-structure-database

Fu, W.J., Jiang, P.K., Zhou, G.M., Zhao, K.L., 2014. Using Moran's I and GIS to study the spatial pattern of forest litter carbon density in a subtropical region of southeastern China. Biogeosciences, 11, 2401–2409.

Ganda, F., 2019. The environmental impacts of financial development in OECD countries: a panel GMM approach. *Environmental Science and Pollution Research*, *26*(7), 6758–6772. https://doi.org/10.1007/s11356-019-04143-z

Getis, A., 2009. Spatial weights matrices. Geographical Analysis, 41, 404–410

Guo, Y., 2021. Financial Development and Carbon Emissions: Analyzing the Role of Financial Risk, Renewable Energy Electricity, and Human Capital for China. *Discrete Dynamics in Nature and Society*, *2021*. https://doi.org/10.1155/2021/1025669

Haas, R. De., Popov, A., 2019. Finance and carbon emissions. In *European Central Bank* (No. 2318; Vol. 85, Issue 6).

Hausman, J.A., 1978. Specification tests in econometrics. Econometrica. J. Econ. Soc. 1251–1271.

Harries, K., 2006. Extreme spatial variations in crime density in Baltimore County, MD, Geoforum, 37, 404-406.

Chang, H.-Y., Wang, W., Yu, J., 2021. Revisiting the environmental Kuznets curve in China: A spatial dynamic panel data approach. Energy Economics. https://doi.org/10.1016/j.eneco.2021.105600.

Insee - Eurostat., 2018. Handbook of Spatial Analysis: Theory and Application with R. https://www.insee.fr/en/information/3635545

Jiang, C., Ma, X., 2019. The impact of financial development on carbon emissions: A global perspective. *Sustainability (Switzerland)*, *11*(19). https://doi.org/10.3390/su11195241

Khezri, M., Karimi, M.S., Khan, Y.A., Abbas, S.Z., 2021. The spillover of financial development on CO2 emission: A spatial econometric analysis of Asia-Pacific countries. Renewable and Sustainable Energy Reviews, 145. https://doi.org/10.1016/j.rser.2021.111110.

Kwakwa, P.A., 2019. Energy consumption, financial development, and carbon dioxide emissions.

Journal of Energy and Development, *45*(1), 175–196.
Lee, J.M., Chen, K.H., Cho, C.H. 2015. The relationship between CO2 emissions and financial development. *Singapore Economic Review*, *60*(5), 1–21. https://doi.org/10.1142/S0217590815501179
LeSage, J.P., Pace, R.K., 2009. An introduction to spatial econometrics. Rev. Econ. Ind. 123, 19–44.
LeSage, .J.P., Pace, R.K., 2014. The Biggest Myth in Spatial Econometrics. Econometrics, 2, 217-249; doi:10.3390/econometrics2040217.
Lv, Z., Li, S., 2021. How financial development affects CO2 emissions: a spatial econometric analysis. Journal of Environmental Management, 277, 111397.
Marco, R., Llano, C., & Pérez-Balsalobre, S. (2022). Economic complexity, environmental quality and income equality: A new trilemma for regions?. Applied Geography, 139, 102646.
Musa, K.S., Chindo, S., Maijama'a, R., 2021. Financial Market Development and Co2 Emissions Nexus in Nigeria: an Application of Ardl Approach. *Journal of Developing Economies*, *6*(1), 91. https://doi.org/10.20473/jde.v6i1.22448
Nwani, C., Alola, A. A., Omoke, C. P., Adeleye, B. N., & Bekun, F. V. (2022). Responding to the environmental effects of remittances and trade liberalization in net-importing economies: the role of renewable energy in Sub-Saharan Africa. Economic Change and Restructuring, 55(4), 2631-2661.
Odhiambo, N.M., 2020. Financial development, income inequality and carbon emissions in sub-Saharan African countries: A panel data analysis. *Energy Exploration and Exploitation*, *38*(5), 1914–1931. https://doi.org/10.1177/0144598720941999
OECD, 2019. Climate finance for developing countries reached USD 71 billion in 2017. https://www.oecd.org/environment/climate-finance-for-developing-countries-reached-usd-71-billion-in-2017.htm. (Accessed 23 October 2021).
Radmehr, R., Henneberry, S.R., Shayanmehr, S., 2021. Renewable energy consumption, CO2 emissions, and economic growth nexus: a simultaneity spatial modeling analysis of EU countries. Struct. Change Econ. Dynam. 57, 13–27. https://doi.org/10.1016/j.strueco.2021.01.006
Raheem, D. I., Tiwari, K. A., Balsalobre-lorente, D., 2019. *The role of ICT and financial development on CO2 emissions and economic growth* (WP/19/058).
Sadorsky, P., 2010. The impact of financial development on energy consumption in emerging economies. *Energy Policy*, *38*(5), 2528–2535. https://doi.org/10.1016/j.enpol.2009.12.048
Shahbaz, M., Muhammad, Q., Hye, A., Kumar, A., Carlos, N., 2013. Economic growth , energy consumption , fi nancial development , international trade and CO 2 emissions in Indonesia. *Renewable and Sustainable Energy Reviews*, *25*, 109–121. https://doi.org/10.1016/j.rser.2013.04.009
Schwarz, G., 1978. Estimating the dimension of a model. Ann. Stat. 6 (2), 461–464.
Tsaurai, K., 2019. The impact of financial development on carbon emissions in Africa. *International Journal of Energy Economics and Policy*, *9*(3), 144–153. https://doi.org/10.32479/ijeep.7073
United Nations Development Programme., 2019. https://www.africa.undp.org/content/rba/en/home/blog/2019/how-africa-can-improve mobilization-of-climate-finance-for-susta.html. (Accessed 23 October 2021).
World Meteorological Organization, 2021. Climate change triggers mounting food insecurity, poverty and displacement in Africa. https://public.wmo.int/en/media/press-release/climate-change-triggers-mounting-food-insecurity-poverty-and-displacement-africa. (Accessed 23 October 2021).
Yang, Z., Chng, R., 2019. Environmental Degradation and Economics Growth : Testing the Environmental Kuznets Curve Hypothesis (EKC) in Six ASEAN Countries.
Zhang, Y. J., 2011. The impact of financial development on carbon emissions: An empirical analysis in China. *Energy Policy*, *39*(4), 2197–2203. https://doi.org/10.1016/j.enpol.2011.02.026.

Zoaka, J. D., Ekwueme, D. C., Güngör, H., & Alola, A. A. (2022). Will financial development and clean energy utilization rejuvenate the environment in BRICS economies?. Business Strategy and the Environment, 31(5), 2156-2170.