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Evidence of supply security and sustainability challenges in Nigeria's power sector

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ABSTRACT

The increasing mismatch between the demand and supply of power in Nigeria raises concerns about the ability of this country to meet its vital energy security and sustainability targets in a demography-growing environment. This paper assesses how these three factors comove over the long run. While Nigeria provides an illustrative case, a multivariate framework including population dynamics, the demand for electricity, and CO_2 emissions from the power and heating sector is set with actual time-series data spanning the last five decades. Two independent estimation strategies are conducted: a time-series analysis (i.e., Least Squares with breaks regression) is complemented with Machine Learning experiments (i.e., ML Clustering method). In general, both methodologies' outputs stress the engine role of the population in driving the demand for power over the long run.

1. Introduction

The security of the power electricity supply has become unavoidable when dealing with strategic energy decisions worldwide. Defined as the "uninterrupted availability of energy sources at an affordable price" (IEA, 2017), this concept is relevant to many nations impacted by the recent conflict between Russia and Ukraine. In Africa, power supply challenges include chronic electricity shortages linked to underinvestment, lack of power infrastructure, and adequate technologies. Hence, finding optimal policies to meet growing sectoral (for domestic and industrial purposes) electricity demands in a more secure and less costly fashion without jeopardizing carbon targets are key policy direction for the future (Menyah and Wolde-Rufael, 2010; Intergovernmental Panel on Climate Change (IPCC), 2014; Li and Jiang, 2019). Within this trade-off lays the demographic channel: incoming economic and population expansions in Africa are expected to affect the power supply availability substantially, threaten the availability and affordability of resource inputs, and worsen already existing waste-related issues (Nepal and Paija, 2019b). From resource utilization to waste management, a low-carbon expansion of the electricity sector is also a concern and requires a much better understanding of how to consume, reuse, and recycle inputs in a circular way that would benefit greener energy production.

In most advanced economies, many utilities' primary role gradually shifted to "the management of energy supplied by independent power producers, rather than building and owning capacity themselves" (BNEF, 2017). Recent progress in digitalization enabled better coordination of supply and demands through adjusted prices and contributed to reducing the supply uncertainties related to power-based renewables volatility due to changing weather conditions and interconnected mini-grids. That is, such statements cannot entirely hold for Africa. Despite progress in rural electrification, more than 250 million people do not have access to electricity in the African continent; the gap was further widened by the COVID-19 outbreak, which drove more people into the poverty trap (Puig et al., 2021). In this context, electricity sectors are undergoing multi-faced challenges not limited to offering an affordable, secure energy supply but also enabling sustainable management of mineral resources to produce low-carbon energy plants and facilities. Indeed, renewable energy technologies, like any other innovative applications, are heavily resource-dependent and waste-enablers, which sets how potentially conflicting power access and climate mitigation policies can be for the power sector. Solid waste associated with economic activity cannot be disconnected from the global environmental concern, raising central questions about aligning these diverging targets. If unprocessed (i.e., left in landfills), waste liberates toxic

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Abbreviations

ACF	Auto-Correlation Function
ARDL	Auto-Regressive Distributed Lags
CAIT	Climate Analysis Indicators Tool
CNN-LSTM	Convolution Neural Network, Long Short-term Memory
CO_2	Carbon Dioxide
DFE	Dynamic Fixed Effects
DTW	Dynamic Time-Warping
ERT	Energy for Rural Transformation
FDI	Foreign Direct Investments
FMOLS	Fully Modified Ordinary Least Squares
GFCF	Gross Fixed Capital Formation
GHG	Greenhouse Gas
GMM	Generalized Method of Moments
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
ML	Machine Learning
MuSIASEM	Multi-Scale Integrated Analysis of Societal and Ecosystem Metabolism
NIPPS	National Integrated Power Projects
NIPR	Nigeria Industrial Revolution Plan
PACF	Partial Auto-Correlation Function
PMG	Pooled Mean Group
RETs	Renewable Energy Technologies
STIRPAT	Stochastic Impacts by Regression on Population, Affluence, and Technology
UNICEF	United Nations of International Children's Emergency Fund
VAR	Vector Auto-Regressive
VECM	Vector Error Correction Model
WDI	World Development Indicators

substances traveling into the soil and water. If processed (i.e., collected and burned up in treatment facilities), waste releases particles into the atmosphere that trigger our changing climate (Mele et al., 2022). Therefore, the nature and ways materials are extracted and combined into energy generation technologies codetermine the quality and sustainability of expanding electricity markets in search of reducing inflated power prices in Africa.

In this study, Nigeria provides an illustrative case because of its incomparable demographic, economic, and power demand features that call for urgent implementation of sustainability policies in the electricity sector. Moreover, given its endowment in coastal zones and agricultural lands, Nigeria's future cannot be delinked from global climate goals. First, with a population of 208.8 million in 2020, this country is the most populated in Africa and represents 15% of the continent's total population (Muftahu and Jamil, 2020). At the heart of this elevated trend stands a relevant natality rate, which has translated into a 2.6% annual growth rate of population (the fastest population growth rate of Africa's continent). However, a substantial share of the population remains impoverished (44% is under 15 years old), justifying the alarming nature of UN demographic projections (UNICEF, 2017). Circa 2050, Nigeria should have 400 million inhabitants (including 212 million in urban areas), whereas other forecasts extrapolate up to 864 million births by the end of the century (Ali et al., 2016; Cilluffo and Ruiz, 2019). While human development indexes and electricity use appear highly correlated in most regions of the world[1] (Akuru and Animalu, 2009; Akuru et al., 2017; Amaral et al., 2005; Alam et al., 2016; O'neill et al., 2010; World Bank, 2019; Lawal et al., 2020; Shahbaz et al., 2018; Soytas et al., 2022), Nigeria's high demographic trends highlight how limiting the extraction and consumption of resources in the present may constrain aggregate income and, thus, limit future employment perspectives, already in critical lack.[2] If the developing economy is identified as an energy-dependent one, lowering the power supply (through energy conservation policies) may contradict the well-established "growth hypothesis." Conversely, the expansion of urban activities has pushed up the forest and land degradation and impoverished soils, which in turn might affect the productive resource base of the economy (Ray and Ray, 2011). Therefore, designing effective regulatory measures over environmental common property resources and air quality is critical.

Second, Nigeria is undergoing drastic shifting across both economic and social vectors, including the development of agro-industrial sectors, deregulation of the financial sector, elaboration of a public system through customs and excise duties, and achievement of a higher education system (Ibanichuka et al., 2016; Isibor et al., 2017; Sulaiman and Abdul-Rahim, 2018). As it needs a more diversified economy, the country tempts to reduce its heavy dependence on crude oil exports, in conflict with most Sustainable Development Goals (SDGs) (Mesagan et al., 2018). Although its primary energy resources endowment allows for a limited import dependence, expanding the industrial and agricultural sectors will require energy, for which local health and environmental costs remain conditioned by the fossil or renewable inputs used throughout the domestic electricity production process.

Third, looking at information on Nigeria's energy balances and GHG emissions trends helps draw the nature of supply security and environmental challenges in this country. Above all, nearly 60% of the population remains out of grid-connected power and other standard electricity services (Akuru and Okoro, 2010). More precisely, the World Development Indicators (2023) reports that access to electricity in the urban areas reached 86% (% of the urban population) in 2020, which contrasts with rural electrification (eq. to 34% of the rural population) for the same year. Hence, current per capita electricity consumption reflects this energy gap, falling below a pretty low figure (100 kWh in 2010: one of the lowest worldwide). Between 1971 and 2018 period, the total consumption of energy rose from 31,906.8 to 140,902.8 kilotons of oil equivalent (ktoe), whereas the total power supply was itself multiplied 15 times (from 136.4 to 2262.7 ktoe) over the same period (IEA, 2020a, 2020b). Furthermore, the evolution of atmospheric carbon components is critical. Over the long historical time frame, Nigeria's annual carbon dioxide emissions from fossil fuels and industry (land use change being excluded) recorded a substantial increase from 18,320 tons in 1915, to 136.99 million tons in 2021, with an exponential rise over the 2000–2011 period (from 39.59 million tons to 129.57 million tons) (Our World in Data, 2023).

Nonetheless, given the population size of Nigeria, demographic-weighted figures show per capita footprint information displaying much smaller scales (from 0.01 tons to 0.64 tons per capita over the 1915–2021 period) (Our World in Data, 2023). Interestingly, the relative decline recorded after the 1980s matches the booming population rise that pushes down the total per capita ratio. On the other hand, its energy intensity, defined as the amount of energy consumed per unit of GDP (i.e., it captures how efficiently a country uses energy to produce a

[1] This was notably the case in China and India whose booming population has been identified as a non-negligible development-enabler in the past decades (Mazur, 1994; Mesagan et al., 2018). It also corroborates the 2014 review of the World Urbanization Prospects by the United Nations (UN) DESA's Population Division stating that China, India, and Nigeria will lead the world urbanization growth in the coming decades. Asia and Africa are expected to record 90% of the global urbanization growth in the future, cover 37% of world's urban population (India and Nigeria together) by mid-century (Ali et al., 2016).

[2] Nigeria's unemployment rate rose from 3.10% to 43.1% over the 1970–2018 period (Raifu et al., 2020).

given amount of economic output), decreased from 1.30 kWh in 1984 to 0.46 kWh in 2018 (Our World in Data, 2023). Fig. 1 displays the total electricity generation by source from 1990 to 2020 in Nigeria (and shows the dominant place devoted to fossil fuels), whereas the total final energy consumption by source from 1990 to 2020 is shown in Fig. 2. Finally, Fig. 3 presents a chart of GHG emissions by the domestic sector for 2019.

Therefore, electricity rationing and blackouts are frequent for households and industries, thus slowing down the country's transition toward an industrial and productive path requiring fast-growing energy needs. As of 2021, industry (including construction) represented 31.4% of total GDP (i.e., 90.39 billion of constant 2015 US$), whereas services and agriculture covered 43.8% (i.e., 302.69 billion of constant 2015 US $) and 23% of GDP (i.e., 119.49 billion of constant 2015 US$), respectively (World Development Indicators, 2023). To cope with this demand, non-renewable installed capacities[3] to generate power (and notably coal fire plants) have been expanded, being cheaper, more efficient, and operationally flexible than renewables, which hindered the early deployment of a low-carbon energy sector. Accordingly, Nigeria's electricity sector is facing a double-edged challenge:

- Ensuring affordable power access to its growing population
- Allowing for the secure deployment of low-carbon energy sources.

To offer a comprehensive picture of this critique power segment and provide energy security and environmental sustainability insights, since no clear consensus has been reached, this paper examines the interrelationships between population, electricity demand, and environmental pollution dynamics in this topic, the power sector in Nigeria. Based on the literature, the population-GDP nexus has been subject to many applications (Kuznets, 1968; Becker et al., 1999; Dao, 2012; Shaari et al., 2013; Peterson, 2017; Abeywardhana, 2019; Kuhe, 2019; Magazzino et al., 2023). Some underlined that a poverty trap might emerge as population and income grow (Bloom and Canning, 2001), while others did not (Kraay and McKenzie, 2014). However, Casey and Galor (2017) showed that lower fertility could increase per capita income and lower carbon emissions. Second, both single-country (Amaral et al. (2005) for Brazil; Rehman and Deyuan (2018) for Pakistan; Imasiku and Ntagwirumugara (2020) for Rwanda), multi-country (Keho (2016) for 12 Sub-Saharan African countries) or global-scale (Sheffield, 1998) approaches were adopted to investigate this nexus for developing countries. However, while most of the existing papers relied on employment data to conduct their analysis (Shahbaz et al., 2013; Bhattacharya et al., 2016; Magazzino and Schneider, 2020), population driver remains overlooked by the energy and environmental literature, despite much stronger policy-relevant potentials for regions displaying fast demographic features (Schneider, 2022). Regarding the Nigerian case, very few seminal empirical applications exist (Aiyetan and Olomola, 2017; Mesagan et al., 2018), but they systematically relied on aggregate energy data, avoiding other fundamental sub-components, including the power sector. Third, the population-CO_2 emissions nexus has attracted extensive attention in the research domain, but mainly from a global perspective,[4] whereas only a few recent examinations considered the single Nigerian case even though limiting their inquiry to single country case study (Alege and Ogundipe, 2015; Sulaiman and Abdul-Rahim, 2018; Yahaya et al., 2020). Fourth and finally, most

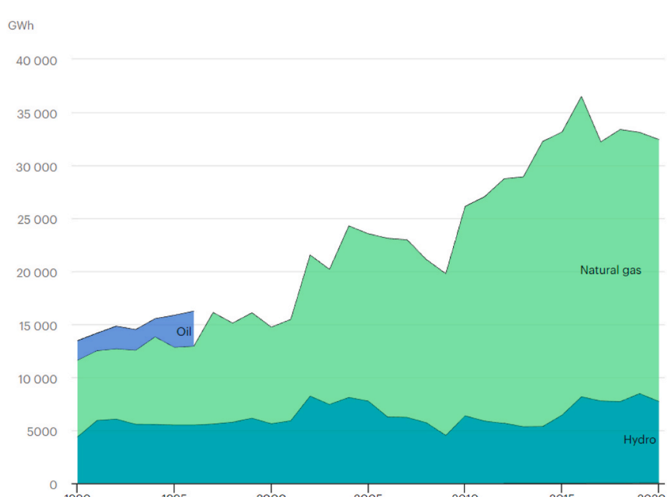

Fig. 1. Total electricity generation (GWh) by source (Nigeria, 1990–2020).
Source: International Energy Agency (2023).

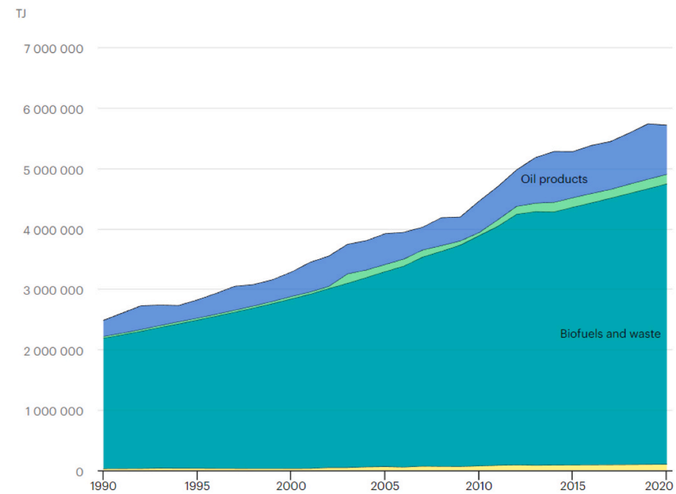

Fig. 2. Total final energy consumption (TJ) by source (Nigeria, 1990–2020).
Notes: the yellow area represents electricity consumption.
Source: International Energy Agency (2023).

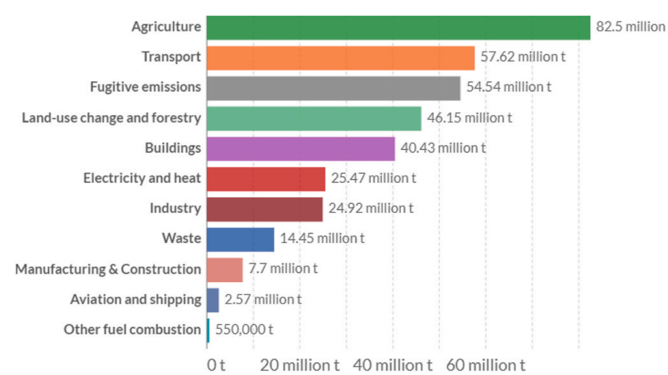

Fig. 3. GHG emissions (million tons) by sector (Nigeria, 2019).
Source: Our World in Data (2023) based on Climate Analysis Indicators Tool (CAIT).

[3] The proportion of electricity produced from oil, gas, and coal sources has risen from 16.6% to 81.8% over the 1971–2015 period, making the electricity and heating sector now responsible for more than 40% of the global CO_2 emissions (WDI, 2019).

[4] See O'neil et al. (2010) for 34 countries; Alam et al. (2016) for Brazil China, India, and Indonesia; Zoundi (2017) for 25 African countries; Dong et al. (2019) for 128 countries; Hashmi and Alam (2019) for 29 OECD countries; Weber and Sciubba (2019) for 22 EU countries; Nabi et al. (2020) for 98 countries.

previous assessments relied on econometric tools (Granger causality test, Auto-Regressive Distributed Lags (ARDL), and Vector Error-Correction Model (VECM)) that did not preclude conflicting conclusions. That is, the use of Machine Learning (ML) experiments remains incipient for such type of study, although AI-derived techniques recently demonstrated great potential in complementing standard time-series outputs (Mele and Magazzino, 2020; Magazzino et al., 2020a, 2020b, 2020c; Soytas et al., 2022).

Following previous empirical studies (Akpan and Akpan, 2012; Chindo et al., 2015; Rafindadi, 2016), we analyzed in a multivariate framework the relationship among population, electricity, and growth for a geopolitical oil-exporter relevant country.

In sum, this paper contributes to the literature in three distinct manners (both empirically and methodologically). First, this is the first empirical assessment of the long-run effect of population dynamics on demand for electricity, along with the CO_2 emissions from Nigeria's power and heating sector, using actual time-series data spanning the past five decades. Second, this study contrasts with previous ones as it conducts two independent estimation strategies thought to ensure more robust outcomes: a time-series analysis (i.e., unit root and cointegration tests, Least Squares with breaks regression, spectral Granger causality tests) complemented with ML robustness checks (i.e., ML clustering method). Third and finally, this research displays a last competitive edge as it uses the concept of energy security as a reading grid to interpret the results and generate policy implications for Nigeria's electricity sector.

The rest of the paper is organized as follows. Section 2 presents the relevant literature. Section 3 describes the data and the empirical approach. Section 4 displays and discusses the empirical findings. Section 5 gives concluding remarks and policy implications.

2. Literature review

This Section presents the literature grouped into the following subsections: population-electricity (2.1.), population-growth (2.2), and population-environment (2.3) links.

2.1. Population-electricity

A strand of the literature examined the relationships between energy consumption and economic growth (Odhiambo, 2009; Apergis and Payne, 2009; Ozturk and Acaravci, 2010; Gozgor et al., 2018; Shahbaz et al., 2018), and a subset of it considered the electricity component (Shiu and Lam, 2004; Altinay and Karagol, 2005; Shahbaz and Lean, 2012; Osman et al., 2016; Lawal et al., 2020) in either bivariate or a multivariate framework for a single country or a multi-country setting (Nepal and Paija, 2019a). Furthermore, various studies focused on the population-energy nexus for various cases. In addition, Sheffield (1998) analyzed the population growth rate and energy consumption correlations with global insights. Focusing on the ten major regions of the world (North America, Latin America, Europe OECD, Former Soviet Union, and Central and Eastern Europe, China, Pacific OECD, East Asia, South Asia, Africa, and the Middle East), the author provided an estimated growth of the energy demand. Overall, this study highlighted that the growing population expansion worldwide requires a massive utilization of energy resources. Amaral et al. (2005) adopted an innovative approach and estimated the population-energy consumption nexus using the Defense Meteorological Satellite Program (DMSP) with night-time satellite data for the case of Brazil. They studied 749 municipals in Amazonia, concluding that the population is linearly correlated with power consumption. Shaari et al. (2013) investigated the relationship between population, energy consumption, and economic growth in Malaysia. Empirical results confirmed a long-term relationship between population, energy consumption, and economic growth in this country. Keho (2016) explored the drivers of energy consumption for 12 Sub-Saharan African countries, collecting data from 1970 to 2011. Results provided evidence that energy consumption is cointegrated with population and real GDP per capita, Foreign Direct Investments (FDI), and urbanization.

Moreover, the study of the long-run determinants of total energy consumption confirmed the leading role of population and per capita income for the whole sample. Rehman and Deyuan (2018) examined the link between economic growth, electricity access, energy use, and population growth in Pakistan using yearly data covering 1990–2016. Applying an ARDL bounds testing approach to cointegration, results indicated that the electricity access to the total population, energy use, population growth, and urban population growth significantly impact the economy's growth.

Furthermore, population and energy use appear closely related. Lizunkov et al. (2018) presented the forecast for world energy consumption, considering population growth through 2030. The estimated trends of primary energy consumption per capita are fundamentally different when comparing countries with rapid population growth (i.e., most developed economies) to others (i.e., developing countries). Furthermore, they highlighted that some developing countries could not sufficiently increase their per capita energy consumption to meet the outstripping population growth. Hence, the energy poverty concern remains, and massive energy supply expansion is suggested. More recently, Imasiku and Ntagwirumugara (2020) analyzed how the population growth in Rwanda exerts energy-water-food-land pressures. Although policymakers promoted these sectors, they omitted integrating population growth and land usage within the forecasting, posing a critical concern if left unattended.

The authors recommended using the Multi-Scale Integrated Analysis of Societal and Ecosystem Metabolism (MuSIASEM) method to design appropriate transition policies in Rwanda. On a more neighbouring topic, He et al. (2023) investigated how city centrality, population density, and electricity efficiency interact. They employed continuous night light data and LandScan population data to construct a monocentric index to measure whether a city tends to be a monocentric or polycentric spatial structure and estimated the impact of such structure on energy and power efficiency by using a two-way fixed effects model. Results showed that increasing the urban mono-centricity index would significantly reduce urban energy intensity. Jain et al. (2023) investigated the climate sensitivity of electricity consumption and peak demand in six energy-intensive Indian states across heterogeneous climate zones using a non-parametric approach known as multivariate adaptive regression splines and suggested that the highest temperature sensitivity of cooling electricity consumption peaks. All in all, Park and Yun (2022) offered evidence on the social determinants of residential electricity consumption in Korea, whereas Wang et al. (2023) applied a Convolution Neural Network, Long Short-Term Memory (CNN-LSTM) model with multimodal information to forecast power demand in China.

2.2. Population-economic growth

Population growth is said to play a crucial role in the development process of a country. The relationship between population and economic growth is controversial. A well-known theory regarding the population-development nexus comes from Malthus (1797), who argued that the stationary level of world per capita income at the end of the 18th century was related to the elevated population growth rate. The Malthusian income determination model postulates that a higher population may depress per capita incomes since it reduces marginal productivity. Subsequently, establishing the foundations of the theory of economic growth, the neo-classical models (notably (Solow, 1956; Swan, 1956) enlarged the knowledge of the role of population growth and supported the inclusion of capital formation determinants. Later, Kuznets (1968) provided a seminal contribution to the literature on this topic, analyzing how much high population growth impedes GDP growth. Related findings emphasized that technological and economic factors may allow for sufficient economic gains in most developing countries under a significant population rise. Becker et al. (1999) sketched out a few features of past research on population and growth, providing important implications for the effects of population dynamics on economic growth. Upon them, they questioned the well-established Malthusian theory and stated that, with a few exceptions, a greater population does not necessarily lower per capita incomes through diminishing returns. Although positive and negative effects of population on productivity are found, larger populations may boost specialization and favour investments in knowledge. Bloom and Canning (2001) estimated the statistical relationship between the youth-age and old-age population shares and economic growth in Asian countries. Regression analysis indicated that an increase in old-age shares might not significantly impact the economy's growth in the long run. Inversely, an increase in youth-age shares negatively affects the long-run economic performance. Dao (2012) investigated the population-economic growth nexus and took the demographic transition in 43 developing countries as an illustrative case. Results highlighted that per capita GDP growth is linearly dependent upon population growth. Kraay and McKenzie (2014) investigated the various underlying poverty trap mechanisms that have notably been used to explain the poverty concerns of highly populated developing economies. Through various approaches ("big-push" theories of development, hunger-based traps, and occupational poverty trap), they concluded that these are rare and largely limited to remote or disadvantaged areas. Hence, relying on non-traditional policy (i.e., migration) is recommended. Looking at the feedback growth-population channel, Aiyetan and Olomola (2017) showed a unidirectional causality flow from economic growth to population growth in Nigeria. Performing a global-scale assessment, Casey and Galor (2017) provided evidence that lower fertility can increase per capita income and lower carbon emissions. This finding contrasts with a strand of the literature and suggests that population policies could be part of the approach to combating global climate change. Peterson (2017) collected historical data to link population growth and overall economic growth over the past 200 years. Empirical insights showed that low population growth in high-income countries would likely create social and economic issues. Conversely, higher population growth in low-income countries may slow their development. In addition, important income inequality concerns may emerge under limited migration. More recently, Abeywardhana (2019) looked at the impact of the aging population on economic growth in South Asia, assessing whether employment targets would be sufficient to compensate for the negative impact of the demographic burden expected in the region. An important finding is that GDP remains highly sensitive to demographic change. Hence, a degreasing working-age population may adversely affect the region's growth. Kuhe (2019) investigated the empirical relationship between population growth and economic growth in Nigeria. Based on data from 1960 to 2015, Engle-Granger residual-based cointegration test, Fully Modified Ordinary Least Squares (FMOLS), Vector Auto-Regressive (VAR), and Granger causality test are applied. Although evidence of cointegrating relationships among variables is provided, no significant causal relationship between population growth and economic growth in Nigeria is established. For the Gulf Cooperation Council (GCC) countries, Al Bannay and Takizawa (2022) proposed an empirical framework to capture the decoupling potential of water production, power generation, GDP and population. Rennert et al. (2022) advanced research on the social cost of carbon and the long-term probabilistic projections of population, GDP, and emissions. Related work by Mason and Lee (2022) proposed a reading grid highlighting six potential scenarios through which population will affect the global economy by mid-century. Overall, Fariss et al. (2022) offered newly updated estimates on the historical GDP-population nexus using data series spanning 500 years and provided inclusive knowledge on this long-debated topic.

2.3. Population-environment

A seminal assessment has been conducted by O'Neil et al. (2010), who conducted a comprehensive analysis of the implications of demographic change for global carbon dioxide emissions. An energy-economic growth model that accounts for a range of demographic dynamics is employed to do so. Based on information collected from 34 countries, they showed that slowing population growth could provide 16–29% of the emissions reductions suggested to be necessary by 2050 to avoid dangerous climate change. Tightly linked to this issue, Ray and Ray (2011) studied the effect of population growth on India's land, forest, water, and energy resources. Findings revealed that rapid population growth is central to decreasing per capita agricultural land, forest, and water resources. Furthermore, population pressure was established as a leading contributor to land degradation and soil erosion.

A range of studies has assessed population-environmental pollution through multi-country approaches. Upon the most recent contributions, Alam et al. (2016) examined the impacts of population, income, and energy consumption on CO_2 emissions in Brazil, China, India, and Indonesia. They used data for 1971–2012 and performed an ARDL analysis considering linear and non-linear assumptions for time-series data. While a significant relationship between CO_2 emissions and population growth is found for India and Brazil, an insignificant one is found for China and Indonesia in both the short and long runs. Zoundi (2017) explored the viability of the Environmental Kuznets Curve (EKC) for 25 selected African countries and incorporated population growth and renewable energy consumption in a multivariate framework. Generalized Method of Moments (GMM), Dynamic Fixed Effects (DFE), and Pooled Mean Group (PMG) results highlighted that population growth does not affect CO_2 emissions in Africa. This finding contradicts Dong et al. (2019) who used the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model and the Dumitrescu and Hurlin (2012) panel causality test on a panel dataset of 128 countries covering 1990–2014. For the global panel, a unidirectional causality is found running from population size to CO_2 emissions. This finding indicates that the population may be an effective pollution driver, and adequate policies should be designed to address the climate issue. This result aligns with those of Hashmi and Alam (2019), who extended the analysis on evaluating factors influencing carbon emissions for 29 OECD countries.

Moreover, the authors showed that a 1% increase in population is associated with a 1.5% rise in CO_2 emissions (in the DFE model), while real GDP per capita growth is found to increase CO_2 emissions by 0.49%. Accordingly, population and GDP emerge as two CO_2 driving forces in the OECD. This evidence corroborates the findings from Liddle and Lung (2010), Wang et al. (2013), and Uddin et al. (2016), who indicated that population remains the most influential variable on CO_2 emissions. Weber and Sciubba (2019) compiled a dataset of 1062 regions within 22 EU countries and assessed the population growth-CO_2 emissions-urban land use relationship with data from 1990 to 2006. Results from panel data regressions, spatial econometric models, and Propensity Score Matching (PSM) confirmed that regional population considerably affects CO_2 emissions and urban-land use in Europe, although more pronounced in the Western states. Recently, Nabi et al. (2020) explored the dynamic linkages between population growth, price level, poverty headcount ratio, and carbon emissions for 98 countries in 2011. Results of the cross-sectional regression underlined the positive effect of poverty rates on CO_2 emissions, while a U-shaped curve between economic growth and environmental pollution is registered. Hence, this indicates that addressing the inequality issue should be at the forefront of development policies, as the emergence of a poverty trap may seriously hinder the sustainability perspectives of the country. Looking at the feedback channel, Ta et al. (2022) estimated and projected population and GDP exposure to extreme precipitation events on Loess Plateau under the 1.5 °C global warming level.

Finally, a few recent examinations considered the Nigerian case. Isola and Ejumedia (2012) inspected the effect of population and oil production on CO_2 emissions in Nigeria. Results of the ECM confirmed that population growth, oil production, and per capita income are positively related to CO_2 emissions in this economy. Alege and Ogundipe

(2015) tested the relationship between economic growth and environmental quality in Nigeria, controlling for population density and using data covering 1970–2011. They showed that as population density intensifies, the marginal impact of GDP on emissions decreases, indicating that the pressure for cleaner environments allows for establishing an inverted U-shaped curve among economic and environmental indicators. Sulaiman and Abdul-Rahim (2018) assessed the nexus between population growth and CO_2 emissions through an ARDL model covering various periods (1971–2000, 1971–2005, and 1971–2010) in Nigeria. While energy consumption and economic growth drive CO_2 emissions, the population is not a significant determinant of CO_2 emissions in all three periods in the long run. Lastly, Yahaya et al. (2020) analyzed the role of population growth, energy use, GDP, financial progress, and trade on environmental degradation in Nigeria. Employing an ARDL technique from 1980 to 2014, a long-run association is discovered among the variables. In addition, short-run results indicated that population density, energy consumption, and financial progress increase CO_2 emissions. However, output growth reduces environmental pollution in Nigeria. Based on the long-run estimations, population growth is emphasized to accelerate environmental degradation.

3. Materials and methods

3.1. Data collection

To implement our model, we collected data on Nigeria for the following core variables: population (total), total electricity consumption (kilo tons of oil equivalent), per capita GDP (constant LCU), Gross Fixed Capital Formation (GFCF, constant LCU), CO_2 emissions from fuel combustion (restricted to electricity and heat production, thousand tons). Accordingly, total electricity consumption is used as a proxy for electricity demand. As made in Nepal and Paija (2019a, 2019b), GFCF is a closed proxy value for capital stock. CO_2 emissions series is used as a proxy for environmental pollution. The data series cover the 1971–2019 period. Population, per capita GDP, and GFCF data are taken from the World Development Indicators database (WDI, 2019).[5] Data on electricity consumption are taken from the OECD Environment Statistics database (2020).[6] CO_2 emissions from electricity and heat production are taken from the IEA CO_2 emissions from fuel combustion Statistics (IEA, 2020a, 2020b).[7] Data definitions, data sources, and variable definitions are summarized in Table 1, while exploratory data analyses and scatterplot matrices are given in Table A and Figure A, respectively (in the Appendix).

3.2. Methodology

In this paper, the behaviour of the log-periodogram regression estimation introduced by Geweke/Porter-Hudak (Geweke and Porter-Hudak, 1983) is considered for various slowly decaying trends in the data. The GPH method uses non-parametric methods – a spectral regression estimator – to evaluate the long memory (fractional integration) parameter *d* of a time series without explicit specification of the "short memory" Auto-Regressive Moving Average (ARMA) parameters of the series. Furthermore, we apply the Bayer and Hanck (Bayer and Hanck, 2013) combined cointegration approach to examine the long-run relationship among the variables. This test combines the results of previous cointegration approaches (Engle and Granger, 1987; Johansen, 1991; Boswijk, 1994; Banerjee et al., 1998) and provides Fisher *F* statistics for more conclusive and reliable empirical findings. Then, the Gregory and Hansen (1996) residual-based test for cointegration is employed to test for structural breaks in the cointegrating relationship.

Table 1
Data description.

Indicator	Acronym	Measure	Source
Population	POP	Total population	World Development Indicators (WDI, 2019)
Electricity consumption	EPC	Kilo tons of oil equivalent (ktoe)	OECD Environment Statistics (2020)
CO_2 emissions from fuel combustion (electricity and heating production)	CO2	Thousand tons	IEA CO_2 Emissions from Fuel Combustion Statistics (2020)
Per capita GDP	RGDP	Constant LCU	World Development Indicators (WDI, 2019)
Gross Fixed Capital Formation	K	Constant LCU	World Development Indicators (WDI, 2019)

Source: authors' elaborations.

Afterward, we run the Least Squares with breaks regression to estimate the model. The standard linear regression model assumes that the model's parameters do not vary across observations. Nevertheless, structural change can significantly alter the estimation's results. Consequently, in this paper, linear regression models subject to structural change are performed. The regime breakpoints are estimated according to Bai (1997), Bai and Perron (2003), and related techniques.

Finally, this study employs the Breitung and Candelon (2006) Spectral Granger (BCSG) causality test. Such a test is superior to standard causality tests because it can predict the target variables at precise time frequencies. Hence, the technique enables us to identify the historical changes to implement the policy intervention. However, the methodology is limited to a finite time horizon and cannot predict infinite time models.

Afterward, we use some ML tools for robustness checks. In Artificial Intelligence (AI) context, ML lets computers find patterns in data and make decisions based on this information (Aguiar-Pérez et al., 2023). Typically, unsupervised learning consists of grouping datasets into homogeneous clusters based on their characteristics. When clustering time-series, we attempt to find relevant clusters of the series that are maximally similar in their clusters (or groups of series) and, simultaneously, maximally different between the different series clustered together.

In this respect, we consider an unsupervised learning approach to analyze the selected time series. To this extent, we select different algorithms to classify the series. So, we start by considering different algorithms used in economic applications and use them to classify the selected time series. Then, we choose the PVclust algorithm to evaluate the uncertainty.

Following Montero and Vilar (2015) from two real-value processes:

$$X = \{x_t, t \in \mathbb{Z}\} \tag{1}$$

$$Y = \{y_t, t \in \mathbb{Z}\} \tag{2}$$

as time series composed of real-value data points. In this way, we get in the clustering process two realizations as sequences of *T* observations represented as vectors of length *T*. So, we can write:

$$X_T = (x_1, \dots, x_T)' \tag{3}$$

and, at the same time, a second realization:

$$Y_T = (y_1, \dots, y_T)' \tag{4}$$

Alternative clustering methodologies are used to categorize the time

[5] Data on Population, per capita GDP, and GFCF are available at: https://databank.worldbank.org/source/world-development-indicators.

[6] Data on electricity consumption are available at: https://data.oecd.org/environment.htm.

[7] Data on CO_2 emissions from fuel combustion (electricity and heating production) are available at: <u>https://www.oecd-ilibrary.org/energy/data/iea-co2-emissions-from-fuel-combustion-statistics/co2-emissions-by-product-and-flow_data-00430-en.</u>.

series as groups with some specific similarities. We consider different clustering approaches (methods and algorithms) to check the results obtained. Thus, we use the Euclidean distance (Liao, 2005; Berthold and Höppner, 2016):

$$D_E(x_T, y_T) = \sqrt{\sum_{t=1}^{T} (x_t - y_t)^2} \tag{5}$$

Another relevant measure to classify the time series is Fréchet's distance (Fréchet, 1906). When comparing two curves, Fréchet's distance takes into account the point locations and orderings along the curves to calculate the similarity between them:

$$D_F(x_T, y_T) = \min_{r \in N} \left(\max_{i=1,\dots,n} \left| x_{a_i} - y_{c_i} \right| \right) \tag{6}$$

In order to use this approach, we need to set all the possible sequences of n pairs. It is important to note that we are explicitly preserving the order of the different observations. Thus, the distance between them can be calculated based on the observed pairs of two time series.

Given N as all sequences of n different pairs which are considering all the data:

$$r = \left(\left(x_{a_1}, y_{c_1}\right), \dots, \left(x_{a_n}, y_{c_n}\right) \right) \tag{7}$$

and given as indices within a time series that represent specific points in time:

$$a_i, c_j \in \{1, \dots, T\} \tag{8}$$

with $a_1 = c_1 = 1$ and $a_n = c_n = T$, where we also have $a_{i+1} = a_i$ or a_{i+1} and $c_{i+1} = c_i$ or c_{i+1} for $i \in \{1, .., n-1\}$ (Montero and Vilar, 2015). Fréchet's distance differs from other dissimilarity measures because it considers the order of observations in a time series; this approach evaluates the structure and orderings of the time series and the observations across time.

Dynamic Time Warping (DTW) distance is another approach that accounts for the order of the time series (Sankoff and Kruskal, 1983; Berndt and Clifford, 1994). This distance can consider time series of various lengths and shapes. In many real-world applications, the size and structure of time-series data might change due to variable sample rates, measurement errors, or other causes. Furthermore, the DTW distance aligns the two time series by reducing the distance between them, allowing for more exact grouping findings on the clustering. Therefore, we have:

$$D_{DTW}(x_T, y_T) = \min_{r \in N} \left(\sum_{i=1,\dots,n} \left| X_{a_i} - Y_{c_i} \right| \right) \tag{9}$$

Another dissimilarity criterion is based on Pearson's correlation (Liao, 2005; Berthold and Höppner, 2016). Pearson's correlation coefficient is a straightforward dissimilarity measure for analyzing the similarity between two time series. This approach can analyze the linear relationship between two series by calculating the correlation coefficient. In this sense, the dissimilarity criterion can be written as follows:

$$COR\ (X_T, Y_T) = \frac{\sum_{t=1}^{T} (x_t - \overline{y}_T)(y_t - \overline{y}_T)}{S_x S_y} \tag{10}$$

where we consider as $\overline{x}_T$ and $\overline{y}_T$ the mean of their realization process. In the case of x_T, we have:

$$\overline{x}_T = \frac{1}{N} \sum_{t=1}^{T} x_t \tag{11}$$

and

$$S_x = \sqrt{\sum_{t=1}^{T} (x_T - \overline{x}_T)^2} \tag{12}$$

Another relevant problem in time-series cluster analysis is evaluating uncertainty about obtained clusters. With the Pvclust algorithm (Suzuki and Shimodaira, 2006), considering the clustering performed, running a bootstrap analysis to assess the associated uncertainty is possible. It is recognized that uncertainty assessment is of paramount importance and can be used to evaluate the different clusters obtained.

Auto-Correlation Function (ACF) distance (Galeano and Pena, 2000; Montero and Vilar, 2015) may be used to classify the time series taking into account their temporal structure (i.e., temporal dependence). Let us consider the autocorrelation vectors estimated from the time series X_T and Y_T:

$$\widehat{\rho}_{X_T} = \left(\widehat{\rho}_{1,x_T}, \dots, \widehat{\rho}_{L,x_T} \right)' \tag{13}$$

and also

$$\widehat{\rho}_{Y_T} = \left(\widehat{\rho}_{1,y_T}, \dots, \widehat{\rho}_{L,y_T} \right)' \tag{14}$$

Then, we take the Euclidean distance used to construct the distance D_{ACF} between two relevant processes. In addition, a distance from the Partial Auto-Correlation Function (PACF) D_{PACF} is simple to obtain.

Finally, looking at the alternative models, a specific distance might be derived based on the models' differences. Therefore, Piccolo's distance D_P is calculated considering the parameter estimations of the ARMA models for the time series X_T and Y_T.

Validation of clusters requires examining the groups generated by the clustering method. We validate each obtained cluster by considering a silhouette plot and maximizing the average silhouette width, determining if the number of clusters is correct. Thus, we determine the exact number of clusters for each methodology.

Finally, for each variable, we compute the different methods in which the single variable falls in the same cluster. The final measure determines the level of concordance of the different time series in the same clusters obtained by the different procedures considered and allows us to understand the level of concordance of the economic time series.

4. Empirical findings

The Geweke and Porter-Hudak (1983) test is performed to check the stationarity properties of the variables. The results are given in Table 2.

The GPH test, applied to our series, generates estimates of the long memory parameter, with a power = 0.50, that cannot reject the null hypothesis at the 5% significance level using the z test for CO_2 emissions and capital formation. On the contrary, real GDP seems non-stationary, while the test statistic varies over the power spectrum for electric power consumption. A range of power values (from 0.40 to 0.60) is also calculated to evaluate the robustness of the GPH estimate.

Moreover, we check for the (eventual) presence of a long-run relationship among the selected series, applying the Bayer and Hanck (2013) procedure (see Table 3). The first model, which in the deterministic specification does not allow either a constant or a trend, gives a test statistic = 7.8259 (with a 5% Critical Value = 10.640), based on Engle and Granger (1987) and Johansen (1991) tests, and a test statistic = 12.4445 (with a 5% Critical Value = 20.237), based on Engle-Granger, Johansen, Boswijk (1994), and Banerjee et al. (1998) tests. We can assume that a cointegrating relation does not emerge from these findings. The second model includes an unrestricted constant, with a test statistic = 7.6406 (with a 5% Critical Value = 10.637), based on Engle and Granger and Johansen tests, and a test statistic = 10.8322 (with a 5% Critical Value = 20.486), based on all four tests. Again, we cannot find any support for a long-run relationship. Finally, the last model includes both a linear and a quadratic trend, with a test statistic = 6.6008 (with a

Table 2
Results for Geweke/Porter-Hudak test.

Power	Estimated d	Standard Error	z	P-Value
EPC				
0.40	0.7836	0.4624	1.2641	0.206
0.45	0.8741	0.3190	1.7172*	0.086
0.50	0.7649	0.2063	1.9717**	0.049
0.55	0.8181	0.1764	2.3317**	0.020
0.60	1.0288	0.1873	3.4374***	0.001
CO2				
0.40	0.2386	0.4824	0.3849	0.700
0.45	0.5624	0.4207	1.1048	0.269
0.50	0.5710	0.2716	1.4718	0.141
0.55	0.5334	0.2266	1.5203	0.128
0.60	0.6571	0.1832	2.1955**	0.028
RGDP				
0.40	1.0458	0.8544	1.6871*	0.092
0.45	1.2635	0.6008	2.4823**	0.013
0.50	1.5816	0.3948	4.0770***	0.000
0.55	1.6473	0.3309	4.6951***	0.000
0.60	1.4188	0.3054	4.7406***	0.000
K				
0.40	0.2477	0.1261	0.3982	0.690
0.45	0.1491	0.1181	0.2914	0.771
0.50	0.2919	0.1498	0.6624	0.508
0.55	0.3497	0.1289	0.8940	0.371
0.60	0.4503	0.1076	1.3807	0.167

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 3
Results for Bayer-Hanck tests.

Test	Test Statistic	P-Value
Model 1		
Engle-Granger	−1.0155	0.9653
Johansen	26.6715**	0.0207
Banerjee-Dolado-Mestre	−1.9143	0.4399
Boswijk	9.5161	0.2258
Model 2		
Engle-Granger	−1.4198	0.9657
Johansen	30.1068**	0.0227
Banerjee-Dolado-Mestre	−2.1224	0.5687
Boswijk	9.9955	0.3565
Model 3		
Engle-Granger	−1.3618	0.9911
Johansen	32.0739**	0.0372
Banerjee-Dolado-Mestre	−1.9167	0.8185
Boswijk	3.8434	0.9648

Notes: Model 1: do not include a trend or a constant in the model; Model 2: include an unrestricted constant in the model; Model 3: Include a linear trend in the cointegrating equations and a quadratic trend in the undifferenced data. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

5% Critical Value = 10.711), based on Engle and Granger and Johansen tests, and a test statistic = 7.0730 (with a 5% Critical Value = 20.788), based on all tests. Here, the evidence of a lack of cointegration is clear, and the null hypothesis cannot be rejected at any significance level.

For robustness purposes, the Gregory and Hansen (1996) cointegration technique is also performed, allowing for potential structural breaks in the data.

The results based on the Gregory and Hansen cointegration procedure suggest that the calculated statistic is smaller than the 5% Critical Value reported by Gregory and Hansen (1996) in all four deterministic specifications. This test confirms that we cannot reject the null hypothesis of no cointegration in favour of the existence of at least one cointegration relationship in the presence of a structural break. Regarding the structural breaks, the results indicate their occurrence between 1979 and 1986, coinciding with the two oil shocks (see Table 4).

Given the possible structural breaks in the data, the Least Squares with breaks regression is estimated. The Heteroskedasticity and

Table 4
Results for Gregory-Hansen cointegration tests.

	Constant	Constant and trend	Constant and slope	Constant, slope and trend
Test Statistic	−2.71	−4.09	−3.13	−4.68
Critical Values	−5.77	−6.05	−6.51	−6.89
	−5.28	−5.57	−6.00	−6.32
	−5.02	−5.33	−5.75	−6.16
Date	1979	1981	1984	1986

Notes: Z_t statistics are reported. 1%, 5%, and 10% Critical Values are reported.

Autocorrelation-Consistent (Newey-West) Standard Errors with the Bartlett kernel is selected, allowing error distributions to differ across breaks and setting a trimming percentage of 15 and a significance level of 0.05.

The Bai and Perron test results suggest splitting the sample period into four sub-periods: 1981–1990, 1991–2001, 2002–2007, and 2008–2018. The estimation results highlight that electricity consumption, real GDP, and capital formation significantly affect CO_2 emissions in the first and third sub-periods. However, only real GDP has exhibited a significant coefficient in recent years.

The empirical findings evidence a positive effect of electricity consumption on emissions in Nigeria, which is also documented in Akpan and Akpan (2012). The positive association between aggregate income and CO_2 emissions in Nigeria is in line with previous empirical results by Akpan and Akpan (2012), Ayadi (2014), Lin et al. (2015), Rafindadi (2016), Sulaiman and Abdul-Rahim (2018), and Maduka et al. (2022). Finally, Mesagan (2015) shows capital formation's influence.

As regards the diagnostic tests, the Breusch-Godfrey serial correlation LM test does not reject the null hypothesis (*F*-statistic = 1.5650, P-Value = 0.2336), which confirms that the estimated model does not suffer from autocorrelation problems. In addition, the Breusch-Pagan-Godfrey heteroskedasticity test does not soundly reject the null hypothesis of homoskedasticity (*F*-statistic = 0.3417, P-Value = 0.9818). The correlogram of residuals clarifies how the residuals series is unaffected by the auto-correlation problem (Figure B in the Appendix). Results from CUSUM plots show that all the data series are within the 95% confidence band, confirming the estimated models' stability. Besides, we analyzed the stability tests to confirm the goodness fit of the model (Figure C in the Appendix).

In Fig. 4, the main results of the BCSG test are shown. The relationships among the variables are assessed over the time-frequency domain. Each figure displays the Wald statistics over all frequencies $\omega \in (0; \pi)$. The test statistics for the Granger non-causality from electricity consumption to CO_2 emissions are significant at the 10% level for frequencies with $\omega < 1.54$ (Fig. 4a). The opposite causal flow (from *CO2* to *EPC*) is not rejected at a 5% and a 10% level for all frequencies (Fig. 4b). Real GDP is found to significantly affect emissions for frequencies ≤ 0.43 and ≥ 1.26, at a 5% level; for frequencies in the range $\omega \in (0.44; 0.99)$ and (1.12; 1.25) at a 10% level in the range (Fig. 4c). On the other hand, CO_2 emissions seem to cause real GDP since the null hypothesis of no causality is rejected for $\omega \geq 0.45$ at a 5% level and a 10% level for all frequencies (Fig. 4d). Finally, for the last couple of variables, the capital formation causes emissions at a 5% level for $\omega < 1.62$ and $\omega > 2.42$ (Fig. 4e), while CO_2 emissions do not affect *K*, given the fact that the calculated test statistic is always lower than the Critical Values (Fig. 4f). Therefore, to summarize the causality findings, we discovered: a) a unidirectional causal flow from electricity consumption to CO_2 emissions; b) a bidirectional causal flow between CO_2 emissions and real GDP; c) a unidirectional causal flow from capital formation to CO_2 emissions.

Furthermore, generally speaking, the test results according to Geweke-type conditioning are qualitatively similar.

For the clustering analysis, the different results show some specific similarities in the behaviour of the electricity and CO_2 emissions series.

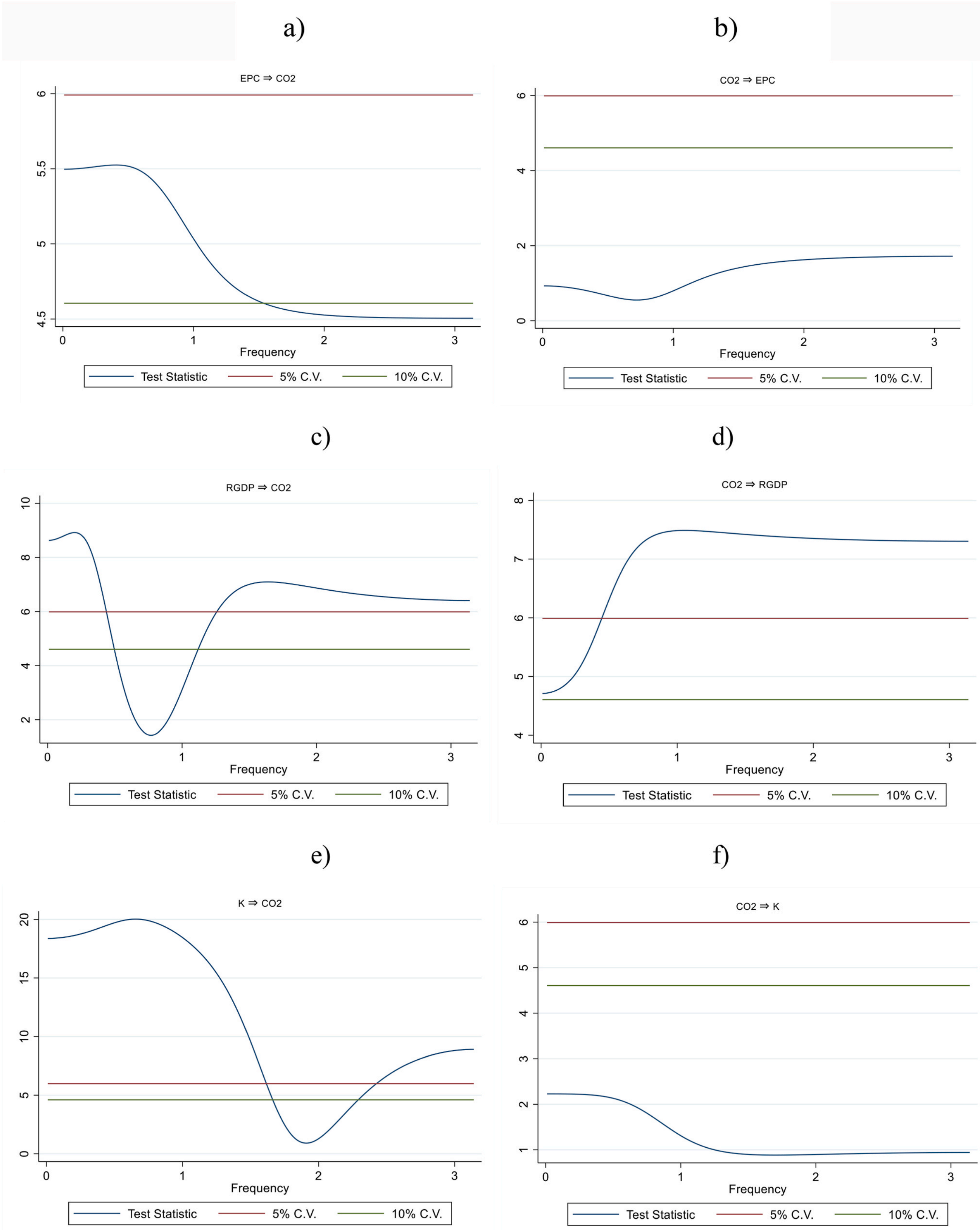

Fig. 4. Breitung-Candelon Spectral Granger causality test results
Source: authors' elaborations in STATA, Notes: Confidence level on *y-axis*. Hosoya-type conditioning was used. The following relationships are empirically tested: EPC → CO2: innovation in electricity consumption causes CO_2 emissions. CO2 → EPC: innovation in CO_2 emissions causes electricity consumption. RGDP → CO2: innovation in real GDP causes CO_2 emissions. CO2 → RGDP: innovation in CO_2 emissions causes real GDP. K → CO2: innovation in capital formation causes CO_2 emissions. CO2 → K: innovation in CO_2 emissions causes capital formation.

Considering the different approaches and methodologies, we can observe relevant similarities in this respect. We found a general association by observing the different dendrograms between the time series (Fig. 5).

However, a different result is obtained considering correlation distance and ACF and PACF distance, in which the different time series related to CO_2 emissions and electricity reacts to the same shocks and seem to have a specific strong relationship with each other. In this case, also considering the case of Piccolo's distance, the relationship seems confirmed. The different dendrograms show multiple relationships among the variables (Fig. 6).

The relationship between CO_2 and electricity is also significant, looking at the correlation distance and the PVclust algorithm, which found a statistically significant relationship (Fig. 7).

In the short run, these relationships clearly show a significance (between CO_2 emissions and electricity). However, in the long run, many confounding factors can impact emissions. We identify a clear and significant relationship in the short run by observing some relevant distances (particularly ACF and PACF). In this respect, the results confirm our previous analyses (see Table 5).

From these first exploratory analyses, we go to the cluster validation (the results are shown in Table 6). In order to validate the different clusters, we analyze different partitions to optimize the average silhouette width of the obtained clusters. This measure shows us the optimality of the partition obtained in each clustering.

Then we compare the different clusters obtained and analyze the level of concordance from the clusters for each time series (Table 7). We can observe a maximum concordance between CO_2 emissions and electricity; a lower concordance is found for *RGDP* and *K*. The result is consistent with the fact that we can observe a stronger relationship between CO_2 emissions and electricity in the short run.

5. Conclusions and policy recommendations

Given the pace at which the Nigerian population is growing, the concern for the increase in electricity demand, energy insecurity, and environmental pollution equally grows. This paper assesses how these three factors coevolve over the long run. While Nigeria is taken as an illustrative case, a multivariate framework including population dynamics, the demand for electricity, and CO_2 emissions from the power and heating sector is set using yearly time series spanning the last five decades. Two independent estimation strategies are conducted: a time-series analysis (i.e., stationarity tests, cointegration tests, Least Squares with breaks regression, spectral Granger causality tests) is complemented with ML experiments (i.e., ML Clustering method). In general, both methodologies' outputs stress the engine role of the population in driving the demand for power over the long run. Also, yearly recorded carbon levels keep exhibiting a strict dependence on trends in electricity generation, thus highlighting how such a segment of the economy is far from being decarbonized. On the other hand, while economic, energy, and environmental factors seem to comove over time, reasonable assumptions suggest that material use dependency is likely to rise further in the present and future periods. Causality findings reveal a unidirectional causal flow from electricity consumption to CO_2 emissions, a bidirectional causal flow between CO_2 emissions and real GDP, and a unidirectional causal flow from capital formation to CO_2 emissions. Based on these findings, some implications for energy policy can be proposed.

First, as recent demographic forecasts suggest that global material use will double by 2060 (Gardiner and Hajek, 2020), minimizing the absolute waste volume generated through consumption and production patterns is complicated by the growing technological needs of the power sector. Therefore, not much is left but to incentivize sustainable post-consumption practices maximizing waste value-extraction, material recovery (including composting and incineration with waste-to-energy processes), and recycling, limiting landfilling for materials encompassing highly polluting chemicals (Magazzino and Falcone, 2022). However, additional policy suggestions can be offered to develop Nigeria's power sectors without jeopardizing its climate targets. In the past, several reform initiatives have indeed been conducted in Nigeria (e.g., the National Electric Power Policy (2002), the National Energy Policy (2003), and the Electric Power Sector Reform (ESPR) Act (2005)). The government should expand the national grid, as initiated through 10 National Integrated Power Projects (NIPPs), totalling an installed capacity of 5455 MW.

Notwithstanding, as shown by our results, the pivotal role of fossil

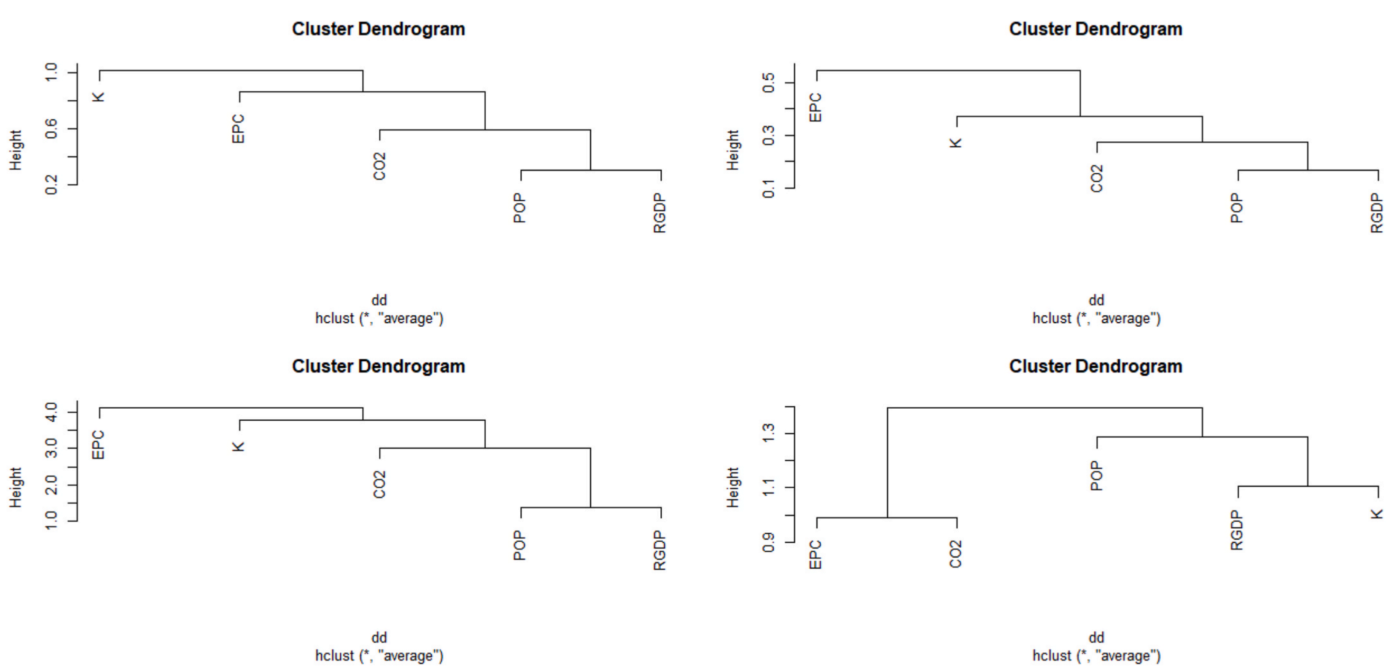

Fig. 5. Comparative clustering (Euclidean, Frechet, DTW, and correlation-based distance)
Source: authors' elaborations in R.

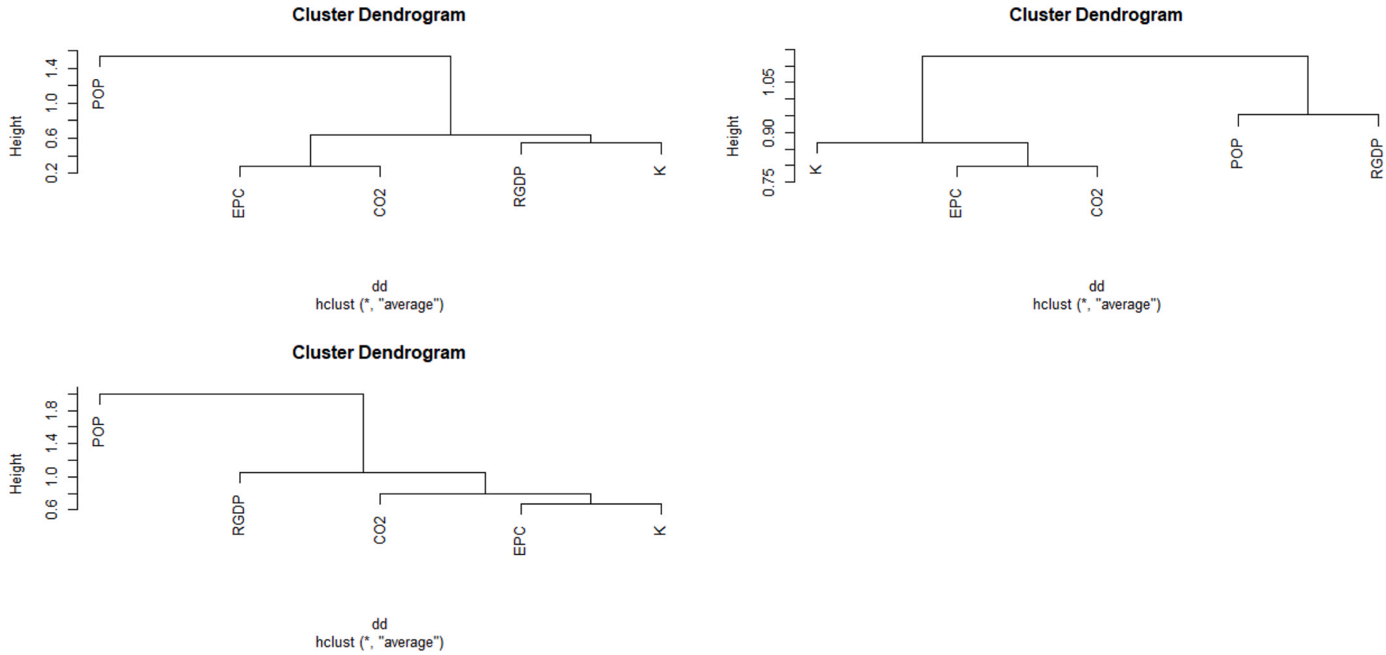

Fig. 6. Comparative clustering (ACF, PACF, and Piccolo distance)
Source: authors' elaborations in R.

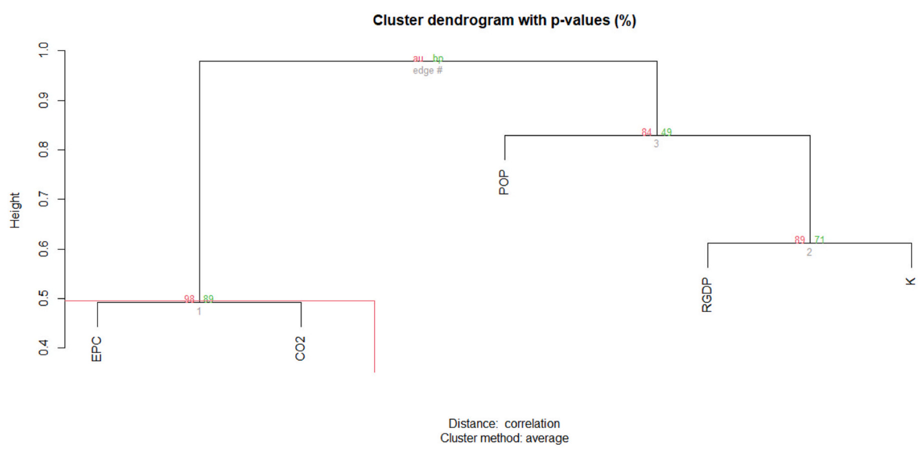

Fig. 7. PVclust Algorithm
Source: authors' elaborations in R.

Table 5
Results of Least Squares with breaks regression.

Variable	1981–1990	1991–2001	2002–2007	2008–2018
EPC	0.2013*** (0.0608)	0.2003* (0.1124)	0.9495*** (0.1264)	0.4604 (0.3500)
RGDP	0.9131*** (0.1710)	0.4998 (0.3057)	0.9630*** (0.1074)	0.9173*** (0.1504)
K	0.2766*** (0.0469)	0.3309*** (0.0558)	0.9308*** (0.1225)	0.1818 (0.2515)
Constant	3.5401* (1.9209)	22.0629*** (4.9011)	11.1821*** (1.1949)	24.5221*** (6.2020)
R-squared	0.9389	Adjusted *R*-squared	0.8972	
SER	0.0487	Log-Likelihood	71.3318	
F	22.5361 (0.0000)	AIC	−2.9122	
SBIC	−2.2227	HQIC	−2.6669	
DW	2.0222			

Notes: Weights: Inverse Standard Deviation. Break type: Bai-Perron tests of 1 to *M* globally determined breaks. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

fuels prevents low-carbon sources from taking centre stage in the power generation process. While renewable energy may guarantee sustainable development without imperilling the security of supply, we call for further expanding Nigeria's power-based solar strategy, although major obstacles related to technological gaps and fixed capital costs must be addressed first. Furthermore, training a skilled workforce capable of expanding low-carbon applications throughout the country, its operation, utilization, and integration with consistent standards and

Table 6
Memberships of the different clusters computed to validate the different results.

Variables	Euclidean	Frechet	DTW	Correlation	ACF	PACF	Piccolo
POP	1	1	1	1	1	1	1
EPC	1	2	2	2	2	2	2
REGDP	1	1	1	1	2	2	1
K	2	1	3	1	2	2	2
CO2	1	1	4	2	2	2	2

Table 7
Concordance levels between the different variables on different clusters.

Variables	POP	EPC	RGDP	K	CO2
POP	1	0.14	0.71	0.29	0.29
EPC	0.14	1	0.43	0.43	0.71
RGDP	0.71	0.43	1	0.57	0.57
K	0.29	0.43	0.57	1	0.57
CO2	0.29	0.71	0.57	0.57	1

procedures is unavoidable. In line with Monyei et al. (2018), we suggest reinforcing the Technical and Vocational Education (TVET) plan, a sub-component of the Nigeria Industrial Revolution Plan (NIPR), as a way to further match industrial skills to minimum international standards in the renewable electricity sector. Finally, our results may hold global relevance to other developing countries since there exist implications for most power generation sectors throughout the African continent. However, in general, our conclusions align with those of Puig et al. (2021), highlighting that an optimal combination of supply-side incentives (risk-guarantee schemes and blending instruments) and demand-side subsidies (direct or indirect payments to secure electricity access to the poorest households in Africa) might ensure a significant expansion of affordable and secure power through African grids. The cost of electrification, especially in off-grid communities and rural areas, is high because of the capital-intensive nature of such projects in Africa. For instance, Kenya endorsed a tax exemption on all imported LED-lighting products and solar application components to incentivize the domestic assembly of solar PV technologies within the country, whereas, in the context of the national Energy for Rural Transformation (ERT) program, a 45% subsidy on solar equipment has been implemented for targeted rural areas. Also, Ethiopia recently applied an inland tax duty and surtax exemption on solar technology components to reduce the mean cost borne by producers at each stage of the supply chain. As for Nigeria, subsidizing Renewable Energy Technologies (RETs) would push down prices and thus strengthen low-carbon energy deployment across the most financially constrained counties. Naturally, given the persisting low energy access in some rural regions of the continent, a partnership between African and other multilateral lending institutions is favoured, as promoted by the African Single Electricity Market (launched in February 2021). Besides offering large-scale policy direction, such an integrated approach presents the advantage of harmonizing regulatory and technical aspects of electricity generation, transmission, and distribution across the continent, with benefits for technology and knowledge transfers.

However, this paper is not without caveats, and future studies should aim at filling them. For instance, the empirical potential of combined time-series analyses and ML methodologies. If data availability allows that, drawing insights with plant-level information may help to identify other potential drivers hidden by the broad aggregation of heterogeneous units.

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The author read and approved the final manuscript.

Declaration of competing interest

The authors declare that they have no competing interests.

Data availability

Data will be made available on request.

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Appendix

Table A
Descriptive statistics.

Variable	Mean	Median	SD	Skewness	Kurtosis	Range	IQR	10-Trim
EPC	−11.8401	−11.8153	0.4297	−0.8037	3.0431	1.6680	0.6013	−11.78
CO2	−9.8917	−9.7781	0.4805	−1.6540	5.2231	2.1867	0.3305	−9.797
RGDP	12.5029	12.5601	0.2223	−0.0235	1.4606	0.6433	0.4428	12.50
K	11.1273	11.0967	0.2919	2.2927	8.7320	1.4502	0.2513	11.07

Notes: SD: Standard Deviation; IQR: Inter-Quartile Range; 10-Trim: 10% trimmed mean.

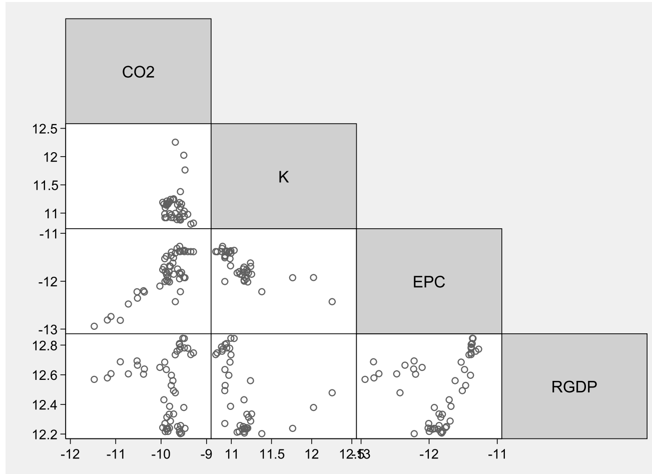
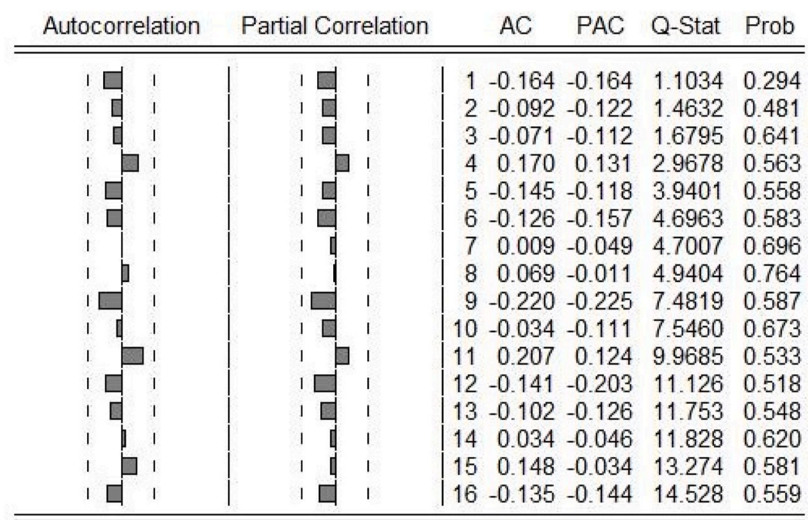


Fig. A. Scatterplot matrices.Source: authors' elaborations in STATA



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.164	-0.164	1.1034	0.294
		2	-0.092	-0.122	1.4632	0.481
		3	-0.071	-0.112	1.6795	0.641
		4	0.170	0.131	2.9678	0.563
		5	-0.145	-0.118	3.9401	0.558
		6	-0.126	-0.157	4.6963	0.583
		7	0.009	-0.049	4.7007	0.696
		8	0.069	-0.011	4.9404	0.764
		9	-0.220	-0.225	7.4819	0.587
		10	-0.034	-0.111	7.5460	0.673
		11	0.207	0.124	9.9685	0.533
		12	-0.141	-0.203	11.126	0.518
		13	-0.102	-0.126	11.753	0.548
		14	0.034	-0.046	11.828	0.620
		15	0.148	-0.034	13.274	0.581
		16	-0.135	-0.144	14.528	0.559

Fig. B. Correlogram of residuals.Source: authors' elaborations in EVIEWS

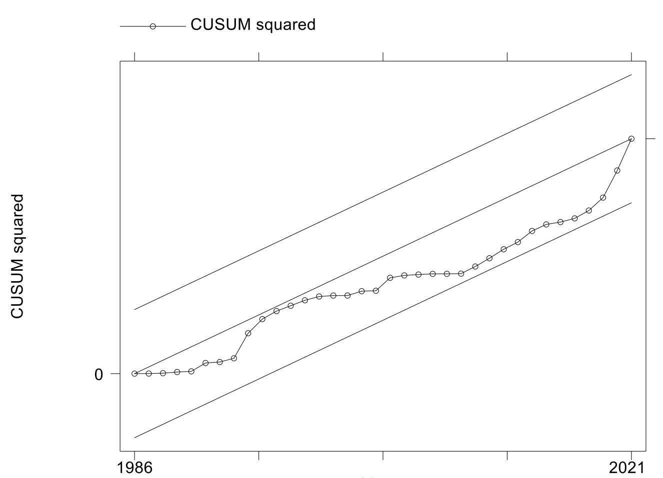


Fig. C. CUSUM test graph.Source: authors' elaborations in STATA

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