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Ecological footprint, electricity consumption, and economic growth in China: geopolitical risk and natural resources governance

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Abstract

This paper examines the relationship among ecological footprint (EF), electricity consumption, and GDP in China using annual data ranging from 1960 to 2019. However, factors like trade openness, urbanization, and life expectancy might increase EF as ecological distortions are mainly human-induced. This study explores the effect of these variables on the environment, which is captured by EF. Quantile Regression estimates indicate that electricity consumption and real GDP increase environmental degradation, while trade and urbanization reduce EF, allowing for a higher environmental quality. On the other hand, the spectral Granger-causality tests reveal that only urbanization and life expectancy affect environmental degradation over the whole frequency domain. In the current geopolitical scenario, relevant policy implications may be derived.

Abbreviations

AI	Artificial intelligence
AMG	Augmented mean group
ARCH	Auto-regressive conditional heteroskedasticity
ARDL	Auto-regressive distributed lags
BCSG	Breitung and Candelon (2006) Spectral Granger
BH	Bayer–Hanck

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BRICS   Brazil, Russia, India, China, and South Africa
CCR   Canonical cointegrating regression
CO_2 Carbon dioxide
Covid-19   Coronavirus disease 19
CUSUM   Cumulative sum
D2C   Causal direction from dependency
DHC   Dumitrescu–Hurlin causality
DK   Driscoll–Kraay
DOLS   Dynamic ordinary least squares
DW   Durbin–Watson
EF   Ecological footprint
EG-J   Engle–Granger and Johansen
EG-J-Ba-Bo   Engle–Granger, Johansen, Banerjee, and Boswijk
EJ   Elliott–Jansson
EM   Elliott–Müller
FDIs   Foreign direct investments
FE   Fixed effects
FGLS   Feasible generalized least squares
FMOLS   Fully modified ordinary least squares
GC   Granger causality
GCC   Gulf Cooperation Council
GDP   Gross domestic product
GHG   Greenhouse gas
GMM   Generalized method of moments
HAC   Heteroskedasticity and autocorrelation consistent
HQIC   Hannan–Quinn information criterion
ICT   Information and communications technology
JC   Johansen cointegration
LM   Lagrange multiplier
LSDVC   Least squares dummy variable corrected
LSTM   Long short term memory
MENA   Middle East and Northern Africa
MINT   Mexico, Indonesia, Nigeria, and Turkey
PCA   Principal component analysis
PCSE   Panel corrected standard errors
PM2.5   Particulate matter 2.5 microns
POLS   Pooled ordinary least squares
PPP   Public–private partnership
QR   Quantile regression
RE   Random effects
SBIC   Schwarz Bayesian information criterion
SEs   Standard errors
SER   Standard error of the regression
TYC   Toma-Yamamoto causality
UECM   Unrestricted error correction model
WB   World Bank

WDI   World development indicators
WN   White noise

1 Introduction

As the world struggles to get out of the Coronavirus disease 19 (Covid-19) pandemic and, at the same time, is facing an energy crisis exacerbated by the Russian invasion of Ukraine, the disaster due to climate change—a risk of unprecedented scale and complexity—is evident. The Earth's surface temperature (measured on the surface of global landmasses) has registered a sharp increase since 1980, and in 2020 there was a record temperature rise of 1.7 °C above the climatic average recorded between 1951 and 1980. Climate change affects many countries, particularly low-income and less resilient ones, due to the increasing impact on the environment and population. Its acceleration—fueled by constantly rising greenhouse gas (GHG) emissions—will also lead to an intensification of the severity and frequency of impacts due to climate change.

Climate risks can take many forms. Although the climatic risks most highlighted today are mainly severe droughts, floods, water stress, heat waves, uncontrolled fires, hurricanes, and typhoons, the rapid decline in biodiversity remains undiscovered, which however represents a particularly worrying aspect given the central role it plays in ecosystems and for humanity. Furthermore, in relation to Covid-19, scientific research has highlighted the high risk that climate change in the future will facilitate the emergence and spread of new pandemics (Carlson et al. 2022; Magazzino et al. 2022).

In the long-term, climate change will significantly affect the global economy and country risks. At the country level, vulnerability caused by affected domestic production, rapidly rising food and commodity prices, public finances under pressure (lower government revenues and higher spending to finance adaptation costs and damage resulting from natural disasters), and growth of external debt will have particular repercussions on the effects of climate change (Mele et al. 2021).

The risk of political violence is induced by various factors, including the availability of weapons, ethnic and religious tensions, economic inequality, institutional resilience, and a high level of distrust of the authorities. Climate change is increasingly affecting many of the factors that contribute to political violence (Theisen 2017). Extreme weather events can undermine economic livelihoods (for example, destruction of crops, machinery, and buildings, reduced quality of grazing land) and increase poverty and economic inequality between those affected by extreme weather events and those who are not. Across all regions, poverty and economic inequality have a significant impact on political violence. Desertification has also been regularly correlated with an increase in political violence. Furthermore, the relationship between political violence and inequality becomes even stronger in the face of a rapid deterioration of the situation (such as in the aftermath of a natural disaster). The impact will be more severe in low-income countries, but it will also affect middle-income countries, specifically due to economic inequality.

Furthermore, climate change can also cause political unrest (due to higher inflation of food prices and food insecurity) or induce scarcity of resources such as water. The risks of conflict and social instability will also be fueled by internal and external mass migratory flows of historical significance, triggered by climate change (Sofuoğlu and Ay 2020).

Climate-related conflict risks will also come in the form of geopolitical risks. China is already leading the race towards achieving food security and internal stability, while Russia and other emerging powers such as India, Turkey, and Saudi Arabia are already very active, particularly in Africa (Magazzino 2016).

China is also driven by an interest in the resources of the South China Sea: gas and oil. Moreover, with production costs on the rise, Chinese energy producers are already putting pressure on the government to let consumers bear the costs. In the recent past, the government allowed power producers to raise electricity rates by just 10% to account for a sudden rise in operating costs.

This paper contributes to the literature in different ways. First, to the best of our knowledge, this is the first study that applies Quantile Regression (QR) to analyze the ecological footprint (EF) in China. Second, we conduct causality analyses through the Spectral Granger Causality tests, a recent time-series methodology in the frequency domain. Third, we implement innovative stationarity and unit root tests as well as cointegration tests to inspect the time-series properties of the selected variables. Fourth, our empirical findings shed light on the inextricable link among environmental degradation, economic development, urbanization, and trade and the geopolitical consequences on the Asian continent. Finally, this paper extends the literature on the Environmental Kuznets Curve (EKC), using EF as a proxy for the quality of the environment.

The remainder of the paper proceeds as follows. An overview of the scientific literature on the relationship among EF, economic growth, and energy—with a specific focus on China—is offered in Sect. 2. Section 3 illustrates the methodology used, the estimated model, and the data. In Sect. 4 the empirical findings are presented and discussed. Finally, Sect. 5 concludes, suggesting some relevant policy implications.

2 Overview of the literature

The literature on the environmental quality in China is increasingly conspicuous, since the country is among the main world economies and, at the same time, one of the biggest polluters.

Several studies analyzed the determinants of EF. Ahmed et al. (2022) investigated the relationship among democracy, environmental regulations, economic growth, and EF for G-7 economies from 1985 to 2017. The results clarify that economic growth increases EF; on the contrary, democracy and environmental regulations enhance environmental quality. Alola et al. (2022) analyzed the dynamics of EF in the 1971–2016 time span, showing that economic growth has a positive effect on EF. Ahmed et al. (2021) studied the nexus among EF, economic globalization, economic growth, and financial development in Japan. The long-run estimates suggest that economic globalization and financial development deteriorate the environment. Sharma et al. (2021)

explored the long- and short-run effects of per capita income, renewable energy, life expectancy, and population density on EF in eight developing countries of South Asia in 1990–2015 years. The empirical results highlight an N-shaped association between per capita income and EF. Moreover, the increased use of renewable energy significantly reduced EF in the area, while an increase in population density led to a raise in pollution emissions. Balsalobre-Lorente et al. (2018) analyzed the EKC in five European countries over the period 1985–2016. The findings show an N-shaped relationship between economic growth and carbon dioxide (CO_2) emissions. In addition, renewable electricity consumption, natural resources, and energy innovation reduce pollution, while trade openness deteriorates the environment. Khoshnevis Yazdi and Shakouri (2017) inspected the relationship among economic growth, renewable energy consumption, energy consumption, financial development, and trade openness between 1979 and 2014 for Iran, finding a unidirectional causal flow from renewable energy consumption to economic growth.

In the last decades, a growing amount of papers have been devoted to analyzing the environmental effects of production and consumption or empirically testing the EKC hypothesis for China. A group of research implemented a time-series approach. Jiang et al. (2021) examined the impact of electricity production and consumption on CO_2 emissions for the 1985–2018 years, showing that electricity series significantly contribute to environmental pollution both in the short- and long-run. Pata and Caglar (2021) examined the effects of income, human capital, globalization, renewable energy consumption, and trade openness on EF during the 1980–2016 years. The findings reveal that the EKC hypothesis does not hold for the country. Ahmed et al (2020) studied the effect of natural resources abundance, human capital, and urbanization on EF for the years 1970–2016. The results show that natural resource rent increases EF in the long-run; however, urbanization and economic growth contribute to environmental degradation, while human capital improves environmental quality. Shahbaz et al. (2020) studied the relationship between public–private partnership investment in the energy sector and carbon emissions. The empirical findings show that public–private partnerships investment in energy negatively affects environmental quality raising carbon emissions. Udemba et al. (2020) explored the interaction among pollutant emissions, Foreign Direct Investments (FDIs), energy consumption, tourism arrival, and economic growth between 1995 and 2016. The econometric findings highlight a positive relationship between pollutant emissions with all other variables except economic growth. Xia and Wang (2020) investigated the relationship among economic growth, fossil energy, carbon emissions, hydropower, industrial development, and energy endowment to test the EKC hypothesis between 1965 and 2016, concluding in favour of the existence of EKC. Yilanci and Pata (2020) test the validity of the EKC hypothesis over the period 1965–2016. The results demonstrate that energy consumption and ecological complexity increase EF in both the short- and long-run. Gokmenoglu et al. (2019) analyzed data between 1971 and 2014 finding empirical support for the EKC hypothesis. Dong et al. (2018) tested the EKC for CO_2 emissions in the years 1965–2016, confirming its existence. Zhang and Zhang (2018) explored how Gross Domestic Product (GDP), trade structure, exchange rate, and FDI inflows affected carbon emissions from 1982 to 2016 finding results in line with EKC hypothesis. He et al. (2017) inspected the effect of urbanization on CO_2 emissions in provinces

between 1995 and 2013. The empirical findings did not confirm the existence of the EKC between income and CO_2 emissions. Riti et al. (2017) analyzed the nexus among CO_2 emissions, economic growth, and energy consumption over the period 1970–2015 supporting the EKC hypothesis. Saboori et al. (2017) explored the link among oil consumption, economic growth, and CO_2 emissions in the 1980–2013 years. The results give evidence of the existence of a long-run relationship between oil consumption and economic growth. Li and Yang (2016) examined the dynamic impact of non-fossil energy consumption on CO_2 emissions over the 1965–2014 period. The results suggest consumption of non-fossil energy plays a vital role in curbing CO_2 emissions only in the long-run. Lin and Moubarak (2014) assessed the relationship between renewable energy consumption and economic growth for 1977–2011 time span. The results highlight a bi-directional long-run causality between renewable energy consumption and economic growth. Wang et al. (2011) explored the causal relationships among CO_2 emissions, energy consumption, and real economic output for 28 provinces in the 1995–2007 period. The results clarify that emissions should not decrease in the long-run, since this might negatively affect the country's economic growth. Jalil and Mahmud (2009) evaluated the long-run relationship among CO_2 emissions, energy consumption, income, and foreign trade in the 1975–2005 period, supporting the EKC relationship.

Another great amount of empirical studies used a panel data approach. Li et al. (2021) evaluated the impact of natural gas consumption on $PM_{2.5}$ emissions by studying the EKC hypothesis through the relationship between economic growth and $PM_{2.5}$ emissions in 30 provinces from 1998 to 2016. The estimates reveal an inverse relationship between $PM_{2.5}$ emissions and natural gas consumption both at the national and regional level. Chen et al. (2019) studied the effects of economic growth, renewable energy consumption, and non-renewable energy consumption on CO_2 emissions, testing the EKC hypothesis using a provincial panel dataset in the period 1995–2012. The empirical results suggest that the inverted U-shaped curve is not supported. Dong et al. (2017) investigated the nexus among per capita CO_2 emissions, GDP, natural gas, and renewable energy consumption between 1985 and 2016, providing strong evidence in favour of the EKC hypothesis. Li et al. (2016) studied a panel of 28 provinces between 1996 and 2012 to analyze the impact of economic development, energy consumption, trade openness, and urbanization on CO_2, waste of water, and waste of solid emissions. The empirical evidence is in line with the EKC hypothesis for all three major pollutant emissions. Wang et al. (2016a, b) inspected the spatiotemporal variations in CO_2 emissions, studying a panel of 30 provinces in the years 1995–2012, finding higher emissions in the eastern regions. Hao et al. (2015) used a panel of 29 provinces over the period 1995–2012 to forecast the national coal consumption, detecting an inverted U-shaped EKC between coal consumption and GDP per capita. Ren et al. (2014) evaluated the impact of FDI, trade openness, exports, imports, and per capita income on CO_2 emissions using data for the period 2000–2010. The results suggest the existence of an inverted-U EKC between the industrial sector's per capita income and CO_2 emissions. Wang et al. (2014) analyzed the relationship among urbanization, energy consumption, and CO_2 emissions in 30 provinces for the 1995–2011 period. The empirical findings suggest that CO_2 emissions in the country present serious regional imbalances.

Another branch of literature applied spatial econometrics techniques to these data. Wang et al. (2021) studying data on 30 provinces from 2009 to 2017 found that energy economic security improved in the country. Song et al. (2020) analyzed data for 104 cities between 2009 and 2016, showing that an increase in the abundance of land resource assets generates an increase in urban GDP per capita. Wang and Ye (2017) tested the EKC hypothesis with city-level data, evidencing an increasing relationship between GDP and emissions. Zhou et al. (2017) analyzed the nexus between sulphur dioxide (SO_2) emissions and income using provincial panel data from 2004 to 2014 evidencing an inverse N-trajectory of the relationship between the variables. Kang et al. (2016) analyzed the EKC hypothesis for CO_2 emissions in the years 1997–2012, finding an inverted-N trajectory between the variables.

More recently, AI algorithms have been designed and applied to this topic. Magazzino et al. (2021) investigated the causal relationship among solar and wind energy production, coal consumption, economic growth, and CO_2 emissions over the period 1990–2017 concluding that China presents a promising path to sustainability. Mele and Magazzino (2020) analyzed the relationship among the iron and steel industries, air pollution, and economic growth using monthly time series from 2000 to 2017. The empirical results show that the relationship between economic growth and steel production is very strong in the first stage.

Finally, Chen et al. (2017), using water quality data between 2007 and 2015, classified seven typical bays in southeast China based on their environmental quality status, through a Principal Component Analysis (PCA).

Candelon and Hasse (2023), using Sweden as a case study over the period 1964–2021, showed that the carbon tax Granger causes carbon emissions reduction in the long-run. Troster et al. (2018) analyzed the causal relationship among renewable energy consumption, oil prices, and economic activity in the US from July 1989 to July 2016 through a Granger-causality in quantiles analysis, highlighting evidence of bi-directional causality between changes in renewable energy consumption and economic growth at the lowest tail of the distribution; furthermore, changes in renewable energy consumption lead economic growth at the highest tail of the distribution.

Table 1 provides a concise summary of the relevant literature on this topic.

3 Methodology, model, and data

The empirical analysis starts with the inspection of the stationarity properties of the series. We performed some unit root and stationarity tests. Elliott and Jansson (2003) derived a family of tests for a unit root with maximal power against a point alternative when an arbitrary number of stationary covariates are modelled with the potentially integrated series, showing that these tests have excellent properties in small samples. In addition, we performed the efficient test for general persistence in time variation in regression coefficients proposed by Elliott and Müller (2006). For robustness purposes, the results are also compared with those from standard stationarity tests (Leybourne 1995; Elliott et al. 1996; Kapetanios et al. 2003; Kapetanios and Shin 2008). Kapetanios et al. (2003) developed a nonlinear test to allow the structural change to be determined internally.

Table 1 Summary of existing literature on EF and environmental degradation in China

Author(s)	Study period	Empirical strategy
Ahmed et al. (2020)	1970–2016	TS: ARDL
Chen et al. (2017)	2007–2015	PCA
Chen et al. (2019)	1995–2012	PD: cointegration, FMOLS, DOLS, GC
Dong et al. (2017)	1985–2016	PD: cointegration, GC, AMG
Dong et al. (2018)	1965–2016	TS: ARDL, GC
Hao et al. (2015)	1995–2012	PD: FE, GMM, LSDVC
Gokmenoglu et al. (2019)	1971–2014	TS: ARDL, VECM
He et al. (2017)	1995–2013	PD: FE, FGLS, PCSE, DK, STIRPAT
Jalil and Mahmud (2009)	1975–2005	TS: ARDL
Jiang et al. (2021)	1985–2018	TS: ARDL
Kang et al. (2016)	1997–2012	Spatial models
Li and Yang (2016)	1965–2014	TS: ARDL, GC
Li et al. (2016)	1996–2012	PD: GMM, ARDL
Li et al. (2021)	1998–2016	PD: cointegration, FMOLS, DHC
Lin and Moubarak (2014)	1977–2011	TS: ARDL, GC
Lu (2017)	1990–2012	PD: cointegration, GC
Magazzino et al. (2021)	1990–2017	AI: D2C
Mele and Magazzino (2020)	2000–2017	AI: LSTM
Pata and Caglar (2021)	1980–2016	TS: Augmented ARDL, FMOLS, DOLS, CCR, TYC
Ren et al. (2014)	2000–2010	PD: RE, GMM, POLSC
Riti et al. (2017)	1970–2015	TS: ARDL, FMOLS, DOLS, GC
Saboori et al. (2017)	1980–2013	TS: JC, GC
Shahbaz et al. (2020)	1984–2018	TS: Bootstrap ARDL
Song et al. (2020)	2009–2016	Spatial models
Udemba et al. (2020)	1995–2016	TS: ARDL, GC
Wang et al. (2011)	1995–2007	PD: cointegration, GC
Wang et al. (2014)	1995–2011	PD: cointegration, GC
Wang et al. (2016a, b)	1995–2012	PD: cointegration, GC
Wang et al. (2021)	2009–2017	Spatial models
Wang and Ye (2017)		Spatial models
Xia and Wang (2020)	1965–2016	TS: ARDL, VECM, GC
Yilanci and Pata (2020)	1965–2016	TS: Bootstrap Fourier ARDL
Zhang and Zhang (2018)	1982–2016	TS: ARDL, GC
Zhou et al. (2017)	2004–2014	Spatial models

AI Artificial intelligence, *AMG* Augmented mean group, *ARDL* Auto-regressive distributed lags, *CCR* canonical cointegrating regression, *D2C* Causal direction from dependency, *DHC* Dumitrescu–Hurlin causality, *DK* Driscoll–Kraay, *DOLS* Dynamic ordinary least squares, *FE* Fixed effects, *FGLS* feasible generalized least squares, *FMOLS* fully modified ordinary least squares, *GC* Granger causality, *GMM* generalized method of moments, *JC* Johansen cointegration, *LSDVC* least squares dummy variable corrected, *LSTM* Long short term memory; *PCA* principal component analysis, *PCSE* Panel corrected standard errors, *POLS* pooled ordinary least squares, *RE* random effects, *TYC* Toma-Yamamoto causality
Source: author's elaborations

Furthermore, to examine the long-run relationship among the variables, we apply the Bayer and Hanck (2013) combined cointegration approach. 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. Bayer and Hanck (2013) highlighted that this represents a more parsimonious method, which helps in overcoming the bias of the previous approaches in determining the cointegrating properties of the time-series. For robustness purposes, we also applied the Auto-Regressive Distributed Lags (ARDL) bounds testing approach, a cointegration method developed by Pesaran et al. (2001) to test for the presence of a long-run relationship. This recent method presents several advantages compared to the classical cointegration tests. Firstly, the approach is used without considering the order of integration of the series. Secondly, an Unrestricted Error Correction Model (UECM) can be derived from the ARDL test through a simple linear transformation, having both short- and long-run dynamics. Thirdly, it provides consistent results in small samples. ARDL bound testing procedure has several advantages as compared to traditional cointegration methods. In contrast to the conventional cointegration tests, which require the same lag length for all dependent and independent variables, the ARDL cointegration can be estimated using different lag lengths. Thus, the ARDL cointegration model is suitable in the case of level-stationary or first difference-stationary variables as well as for small sample sizes, and it is also applicable for the analysis of the ARDL model.

In order to estimate the effect of the independent variables on the dependent one, we first run a QR with bootstrapped Standard Errors (SEs), retaining the assumption of independent errors but relaxing the assumption of identically distributed errors. Moreover, to take into account the presence of a long-run relationship, three different estimators are used (Fully Modified Ordinary Least Squares, FMOLS; Dynamic Ordinary Least Squares, DOLS; Canonical Cointegrating Regressions, CCR), as sensitivity tests.

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. To perform this test, we used the command "bgcausality" (Tastan 2015). However, Breitung and Schreiber (2018) showed that tests of Granger non-causality can also be specified in terms of frequency bands or intervals instead of single frequencies. In addition, Troster (2018) proposed a consistent parametric test of Granger-causality in quantiles.

This study improves the empirical literature on the determinants of EF, following the theoretical framework in Sharma et al. (2021), Balsalobre-Lorente et al. (2018), Khoshnevis Yazdi and Shakouri (2017), Van den Bergh and Verbruggen (1999). Urbanization increases the purchasing power of urban inhabitants which may turn the demand to clean energy consumption that might reduce EF (Danish and Wang 2019).

Thus, the following model is estimated to investigate the impacts of the selected variables on EF in China:

Table 2 Variables' description

Variable	Abbreviations	Measurement units	Data source
1. Ecological footprint	EFP	Global hectares per capita	Global Footprint Network
2. Electric power consumption	EPC	kWh per capita	World Development Indicators
3. Life expectancy at birth	LE	Years	World Development Indicators
4. Trade openness	Trade	% of GDP	World Development Indicators
5. GDP per capita	RGDP	Constant 2010 US$	World Development Indicators
6. Urban population	Urban	% of the total population	World Development Indicators

1. https://data.footprintnetwork.org/#/
2. https://data.worldbank.org/indicator/EG.USE.ELEC.KH.PC
3. https://data.worldbank.org/indicator/SP.DYN.LE00.IN
4. https://data.worldbank.org/indicator/NE.TRD.GNFS.ZS
5. https://data.worldbank.org/indicator/NY.GDP.PCAP.KD
6. https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS

$$\Delta EFP_t = \omega_0 + \omega_1 EFP_{t-1} + \omega_2 EPC_{t-1} + \omega_3 LE_{t-1} + \omega_4 Trade_{t-1} + \omega_5 RGDP_{t-1} + \omega_6 Urban_{t-1}$$

$$+ \sum_{i=1}^{p} \beta_i \Delta EFP_{t-i} + \sum_{j=0}^{q} \beta_j \Delta EPC_{t-j} + \sum_{k=0}^{r} \beta_k \Delta LE_{t-k} + \sum_{l=0}^{s} \beta_l \Delta Trade_{t-l}$$

$$+ \sum_{m=0}^{t} \beta_m \Delta RGDP_{t-m} + \sum_{n=0}^{u} \beta_n \Delta Urban_{t-n} + \mu_t \qquad (1)$$

where ω_0 is the drift constant; p, q, r, s, t, and u denote the lag-length on each variable; ω_1, ...,ω_6 represent the long-run multipliers; Δ is the first difference operator; and μ_t the White Noise (WN) component.

The data cover the period 1960–2019. The time span is merely dictated by data availability. Data on EF (*EFP*, in global hectares per capita) were derived from the Global Footprint Network. The remaining series were obtained from the World Development Indicators (WDI) a freely consultable database by World Bank (WB).[1] Electric power consumption (*EPC*) is measured in kWh per capita; the total life expectancy at birth (*LE*) is measured in years; trade (*Trade*) is the sum of exports and imports of goods and services measured as a share of GDP; real GDP (*RGDP*) is the GDP per capita in constant 2010 US$; urban population (*Urban*) refers to people living in urban areas as defined by national statistical offices. For each variable the log-transformation is derived, to reduce the variability of data (Feng et al. 2014). Table 2 summarizes the main information on our dataset.
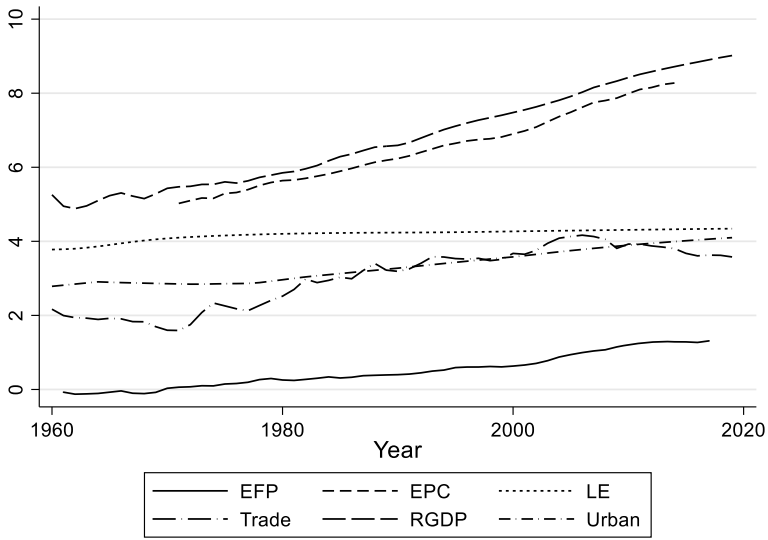
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[1] https://databank.worldbank.org/source/world-development-indicators.

Fig. 1 Evolution of the series (China, 1960–2019). *Sources* our elaborations in STATA

A visual inspection of the analyzed series is offered in Fig. 1.

4 Empirical results and discussion

In Table 3 the exploratory data analysis is given. As a preliminary check, we verify the absence of aberrant observations in the dataset.

Moving to analyze the time-series nature of the data, the EJ test has a null hypothesis of nonstationarity (the results are reported in Table 4). Regarding the deterministic specification, we allow a constant in the representation of the dependent variable. We obtained a value of λ (4.41) greater than the tabulated value, thus we cannot reject the null hypothesis of stationarity at the 95% level of confidence.

Table 3 Descriptive statistics

Country	Mean	Median	Std. Dev	Skewness	Kurtosis	Range	IQR	CV
EFP	0.4939	0.3926	0.4528	0.4565	2.0593	1.4388	0.6297	0.9168
EPC	6.5216	6.4505	0.9792	0.2612	1.9097	3.2518	1.6209	0.1502
LE	4.1878	4.2355	0.1494	− 1.4714	4.2482	0.5647	0.1368	0.0357
Trade	3.0182	3.2396	0.8185	− 0.3507	1.6427	2.5729	1.4896	0.2712
RGDP	6.7631	6.5802	1.2936	0.2579	1.7201	4.1336	2.3053	0.1913
Urban	3.3309	3.2607	0.4383	0.3332	1.6432	1.3143	0.8520	0.1316

Std. Dev. Standard deviation, *IQR* Inter-quartile range, *CV* Coefficient of variation
Sources: our calculations on WDI data

Table 4 Elliott–Jansson unit roots test

λ	5% CV	Estimated R^2
4.4127	3.9357	0.9450

Table 5 Elliott–Müller unit roots test

Test Statistic	1% CV	5% CV	10% CV
− 44.281***	− 35.09	− 30.60	− 28.55

***$p < 0.01$, * $p < 0.05$, *$p < 0.10$

Afterward, we run the EM efficient test for general persistence in time variation in regression coefficients. Using two lags to calculate the long-run covariance matrix, the null hypothesis that the coefficients in the model of *EFP* are stable can be rejected at the 1% level of confidence. Therefore, the EM test indicates that the stability of this regression model, allowing for instability in the coefficient of the whole set of explanatory variables, can be rejected by the data (see Table 5).

Thus, we selected the QR approach to take into account this kind of instability. The R^2 values in each quantile regression are around 0.94, which demonstrates an optimal fit. As regards the diagnostics, the link test on each quantile regression does not detect any problem with the specification proposed.

These findings are broadly confirmed by those from several standard unit root and stationarity tests, which show that the analyzed series are non-stationary at levels, since—in general—we cannot reject the null hypothesis (H_0) of non-stationarity, for each series, regardless of the deterministic specification used (Table 6).

From the results in Table 7, the investigation revealed that an increase in EPC is responsible for a significant increase in EFP. More precisely, the QR estimates show that the electric consumption sensibly affects the EF, and the impact also increases toward the higher quantile (25th quantile = 0.67, and 75th quantile = 0.82). This finding confirms that electric consumption is a relevant driver of environmental quality. Importantly, this result is in line with Eregha et al. (2022), who clarified that energy consumption invigorates EFP in the Next-11 countries. Kutlar et al. (2021) highlighted that the increase in energy consumption increases the flexibility of the EF, studying the MINT (Mexico, Indonesia, Nigeria, and Turkey) countries. Majeed et al. (2021) highlighted that different sources of energy consumption have diverse asymmetric effects on EF in Pakistan. Shahzad et al. (2021) evidenced that energy utilization and economic complexity bring more EF in the long-run for the US. On the other hand, Sharma et al. (2021) established that the increased use of renewable energy has significantly reduced the EF in eight developing countries of South and Southeast Asia. In the same vein, Apergis et al. (2018) highlighted that the EF may be controlled by deepening the use of renewable energy over the long-run. However, Hastik et al. (2016) suggested that without the development of energy-saving production processes, renewable energy consumption alone would fail to respond effectively

Table 6 Results for unit roots and stationarity tests

Variable	Leybourne	ERS	KSUR	KSSUR
1: Intercept				
EFP	0.475 (− 2.310)	1.655 (− 2.157)	0.533 (− 2.733)	0.805 (− 2.405)
EPC	0.352 (− 2.295)	0.145 (− 2.268)	− 0.822 (− 2.773)	− 0.666 (− 2.512)
LE	0.751 (− 2.316)	1.107 (− 2.149)	− 0.681 (− 2.742)	0.078 (− 2.400)
Trade	− 0.801 (− 2.316)	− 0.834 (− 2.149)	− 2.418 (− 2.742)	− 1.285 (− 2.400)
RGDP	1.347 (− 2.316)	1.538 (− 2.149)	− 0.225 (− 2.742)	− 0.223 (− 2.400)
Urban	− 1.299 (− 2.316)	− 1.273 (− 2.149)	− 1.486 (− 2.742)	− 0.656 (− 2.400)
2: Intercept and Trend				
EFP	− 1.786 (− 3.111)	− 1.205 (− 3.057)	− 1.520 (− 3.046)	− 1.631 (− 3.109)
EPC	− 2.437 (− 3.136)	− 1.729 (− 3.206)	− 2.501 (− 3.175)	− 2.389 (− 3.162)
LE	− 2.194 (− 3.109)	1.056 (− 3.046)	− 0.274 (− 3.119)	− 0.198 (− 3.044)
Trade	− 0.836 (− 3.109)	− 2.203 (− 3.046)	− 1.441 (− 3.119)	− 2.345 (− 3.044)
RGDP	0.058 (− 3.109)	− 0.511 (− 3.046)	− 1.758 (− 3.119)	− 1.400 (− 3.044)
Urban	− 2.233 (− 3.109)	− 2.486 (− 3.046)	− 5.191*** (− 3.119)	− 4.201*** (− 3.044)

KSUR Kapetanios and Shin (2008) test, *KSSUR* Kapetanios, Shin, and Snell test (2003), *ERS* Elliott et al. (1996) test

Lag length is chosen through SIC. 5% Critical Values in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table 7 Results of quantile regressions (with 100 bootstraps)

Variable	Quantile regressions		
	0.25	0.50	0.75
EPC	0.6675*** (0.0691)	0.7978*** (0.0724)	0.8194* (0.0795)
LE	0.8582 (0.5181)	0.9039* (0.4540)	0.5101 (0.6698)
Trade	− 0.0671** (0.0315)	− 0.0439 (0.0339)	− 0.0884* (0.0440)
RGDP	0.2566*** (0.1544)	0.0120 (0.1813)	0.3295 (0.2403)
Urban	− 0.9212*** (0.2424)	− 0.8320** (0.3803)	− 0.5137 (0.5508)
Pseudo R^2	0.9373	0.9412	0.9483

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

to environmental issues. Nathaniel (2021) indicated that energy consumption increases environmental degradation in Indonesia.

Furthermore, the impact of life expectancy on EF is positive but statistically weak. Indeed, only for the medium estimated quantile the β is statistically different from 0 (at a 10% level). In this case, we obtained an impact of 0.90. Analogously, Sharma et al. (2021) found that, in terms of EFP generation, the impact of life expectancy is not statistically significant. Boukhelkhal (2022) showed that life expectancy increases environmental degradation both in the short-run and long-run for Algeria. Dietz et al. (2007) found that life expectancy is not related to environmental impact. The empirical

findings in Charfeddine and Mrabet (2017) revealed that life expectancy improves the environment in the long-run for 15 Middle East and Northern Africa (MENA) countries. It is worth noticing how the life expectancy rate in urban areas might differ from that one in rural areas (Marquart-Pyatt 2015).

The coefficient of trade is negative and statistically significant in two quantiles. In addition, it slightly increases passing to higher quantiles (25th quantile = − 0.07; 75th quantile = − 0.09). Interestingly, the magnitude of the effect is almost identical to the estimate reported by Lu (2020), who found that the long-run elasticity of trade openness is equal to − 0.07, using a different estimation method for a panel of 13 Asian countries. This implies that trade negatively impacts EF. Zahra et al. (2022) analyzed the asymmetric impact of trade openness on Pakistan's EF. The results indicate that a 1% increase in trade openness causes a 0.09% increase in the EF in the long-run, while a 1% reduction in trade openness causes a 0.61% reduction in the EF. Okelele et al. (2022), studying 23 Sub-Saharan African countries, showed that EF decreases with an increase in trade openness, while it increases with an increase in Foreign Direct Investments (FDIs) inflows. Rehman et al. (2021), using Pakistan as a case study, observed a statistically significant relationship between EF and trade both in the short-run and in the long-run. Alola et al. (2019), analyzing a panel of 16 EU countries, observed that trade openness in the long-run is responsible for decreasing environmental deterioration. Uzar (2020), examining a panel of 43 developed and developing countries, found that trade does not impact renewable energy consumption. Taking Macao City as a case study, Lei et al. (2009) indicated that EF trade among countries, regions, and cities can make up for shortages of domestic ecological resources and expand the population carrying capacity.

Furthermore, it is interesting to note that real aggregate income has a positive and significant effect, but only for the lowest quantile. The estimated coefficient is 0.26. Chen and Chang (2016) showed that the effect of GDP on the EF varies for different income levels. Ahmed et al. (2022), studying a panel of G7 nations, found that economic growth enhances EF. Ahmed et al. (2021) evidenced that economic growth positively affects Japan's EF. Ansari et al. (2020) explored the effect of economic growth on EF for the Gulf Cooperation Council (GCC) countries, showing that economic growth stimulates EF. Langnel and Amegavi (2020) highlighted that economic growth is positively affected by EF in Ghana. Sabir and Gorus (2019) found a positive association between EF and GDP in South Asian countries. Aşıcı and Acar (2016) detected an EKC-type relationship between per capita income and EF of domestic production in a panel of 166 countries. In a similar way, Wang et al. (2013), found that the consumption footprint is more sensitive to domestic income, at a global level. On the other hand, Kutlar et al. (2021) discovered no significant relationship between economic growth and environmental degradation. Uddin et al. (2016) revealed the existence of a cointegrating relationship between the variables in almost all 22 countries in their sample.

The urbanization rate plays a relevant role in determining the value of EF: in fact, its associated coefficient is negative and significant, being equal to − 0.92 and − 0.83 in the 25th quantile and 50th quantile, respectively. Zahra et al. (2022) concluded that urbanization is a major determinant of Pakistan's EF, since a 1% increase in urbanization causes a 1.31% increase in the EF in the long-run. Similarly, Charfeddine et al.

(2018) for Qatar economy and Ozturk et al. (2016) for 144 countries found a positive role of urbanization (with a negative sign of the coefficient) to reduce EF. Danish et al. (2020), studying the BRICS (Brazil, Russia, India, China, and South Africa) countries, found that urbanization decreases EF, which implies that this variable exerts a positive contribution to environmental quality. On the contrary, Charfeddine and Mrabet (2017) highlighted that urbanization improves the environment in the long-run. Also, Wang et al. (2016a, b) estimated a positive coefficient of urbanization for Chinese provinces. Chen and Chang (2016), analyzing data on 99 countries, revealed that the higher the urbanization rate in high- or low-income countries, the higher the EF. Salman et al. (2022) analyzed the non-linear effect of urbanization on ecological footprints in four countries of the Association of South East Asian Nations (ASEAN-4), revealing that urbanization and EF yield no inverted U-shape curve.

In order to examine the existence of a long-run relationship among the variables, the BH combined cointegration approach is performed. The lag selection is established following the Schwarz Bayesian Information Criterion (SBIC). Table 8 presents the combined cointegration tests including the EG-J and EG-J-Ba-Bo. The findings reveal that the Fisher statistics for EG-J and EG-J-Ba-Bo tests exceed the 1% Critical Values for our tested equation (when EF is used as the dependent variable). In particular, the null hypothesis of the absence of cointegration is soundly rejected, since all three specifications of the deterministic component show a P Value < 0.01. In this respect, we can affirm that a long-run relationship among EF, electric consumption, life expectancy, trade, real GDP, and urban population emerges for China.

BH test combines the cointegration approach providing efficient empirical results; notwithstanding, it fails to properly account for structural breaks inspecting cointegration. Thus, following Shahbaz et al. (2014), we run the ARDL bounds testing approach to cointegration in the presence of structural breaks. For the selection of the model, the Hannan–Quinn Information Criterion (HQIC) is applied, which suggests an ARDL (2,0,2,0,0,4) model; the coefficients' covariance matrix is calculated using the Newey-West Heteroskedasticity and Autocorrelation Consistent (HAC) procedure. The choice of the deterministic component allows for a restricted constant and no trend. Moreover, asymptotic critical values and approximate P Values provided by Pesaran et al. (2001) are chosen.

Table 9 shows the results of the ARDL bounds cointegration test. The results clearly indicate that the F-statistic value is above the upper bound critical values, at any

Table 8 Bayer–Hanck cointegration tests

Test	None	Constant	Trend
EG-J	57.5229*** (10.406)	56.5703*** (10.419)	59.4613*** (10.448)
EG-J-Ba-Bo	72.0297*** (19.747)	68.5794*** (19.888)	169.9854*** (20.1700)

EG-J Engle–Granger and Johansen, *EG-J-Ba-Bo* Engle–Granger, Johansen, Banerjee, and Boswijk. *None* do not include a trend or a constant

Constant: include an unrestricted constant in the model. Trend: include a linear trend in the cointegrating equations and a quadratic trend in the undifferenced data. Fisher-type test statistics are reported, with 5% Critical Value in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table 9 ARDL bounds test estimation results

Model for estimation	Lag length	Statistics		Significance level	Critical values	
					I(0)	I(1)
$F_{EFP}^{EPC,LE,Trade,RGDP,Urban}$	(2,0,2,0,0,4)	F	7.6460***	10	2.08	3.00
				5	2.39	3.38
				2.5	2.70	3.73
				1	3.06	4.15

Asymptotic critical values bounds are obtained from table F-statistic in Pesaran et al. (2001). ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

level of statistical significance; in addition, this conclusion is reinforced by t-statistic. Therefore, these results reinforce the previous one from BH test, confirming that a long-run relationship among the analyzed variables exists. Looking at the diagnostic tests, the correlogram of the residuals and of the squared residuals as well as the Q-statistics evidence the absence of autocorrelation at any lag. Moreover, the residuals are normally distributed, with a Skewness = 0.29 and a Kurtosis = 3.19 (the Jarque–Bera test statistic = 0.69, with a P Value = 0.71). The Breusch–Godfrey Serial Correlation Lagrange Multiplier (LM) test shows an F-statistic = 1.46 (P Value = 0.25), while the Durbin–Watson (DW) statistic is equal to 2.05 (definitely close to 2). The Auto-Regressive Conditional Heteroskedasticity (ARCH) test evidences the homoscedasticity condition (F-statistic = 1.04; P Value = 0.31). Finally, the results from Cumulative Sum (CUSUM) plots show that all the data series are within the 95% confidence band, hence, confirming the stability of the estimated model (see Fig. 3 in the Appendix). To summarize, the results clarify that the estimated model is appropriate.

As sensitivity tests, and to calculate the long-run relationship, we use three cointegrating estimators (FMOLS, DOLS, and CCR). The results in Table 10 are essentially in harmony, confirming the long-run effects of the independent variables on *EFP* as reported in Table 7. In the long-run, electrical consumption, life expectancy, and real GDP exert a negative impact on the environment, increasing EF. However, trade and urbanization show the opposite effect (with a negative sign for the estimated coefficient). It is interesting to note how these findings confirm the robustness of our results, since the signs of the coefficients for each variable are the same in the three regressions, but also in respect of QR estimates.

A linear trend is selected for the trend specification, while the long-run covariance is calculated using the Automatic SBIC for the whitening options, the Bartlett's kernel, and the Automatic Newey–West estimator for the bandwidth method. The high values for R^2 and Adjusted R^2 demonstrate an optimal goodness of fit, confirmed by the low values of the Standard Error of the Regression (SER).

In Fig. 2, 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

Table 10 Results of cointegrating regressions

Variable	Cointegrating regressions		
	FMOLS	DOLS	CCR
EPC	0.6730*** (0.0212)	0.5513*** (0.0220)	0.6896*** (0.0167)
LE	0.9877*** (0.1287)	0.9193*** (0.0479)	0.9243*** (0.1012)
Trade	− 0.0697*** (0.0086)	− 0.0035 (0.0109)	− 0.0596*** (0.0082)
RGDP	0.2442*** (0.0440)	0.3204*** (0.0.0450)	0.2429*** (0.0390)
Urban	− 0.2438** (0.1189)	− 0.9018*** (0.1352)	− 0.1015 (0.0995)
R^2	0.9969	0.9989	0.9971
Adjusted R^2	0.9964	0.9978	0.9966
SER	0.0221	0.0166	0.0217

SER Standard error of the regression

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Wald statistics over all frequencies $\omega \in (0; \pi)$. The test statistics for the Granger non-causality from electrical power consumption to EF (Fig. 2a) are significant at the 10% level for frequencies with $\omega < 1.22$, while the null hypothesis of no GC is rejected at the 5% significance level for frequency in the range $\omega \in (0; 1.03)$. Life expectancy is found to cause EF both at a 5% and a 10% level for all frequencies, and at a 1% level for $\omega > 0.09$ (Fig. 2b). On the other hand, trade does not cause EF since the calculated test statistic is lower than the Critical Values over the whole spectrum of frequency (Fig. 2c). Real GDP is found to significantly affect EF for frequencies $\leq$ 0.44 at a 5% level; for frequencies in the range $\omega \in (0.45; 0.66)$ at a 10% level in the range; while, for $\omega \geq 0.67$ the calculated test statistic is lower than the Critical Values (Fig. 2d). Finally, for the last couple of variables, the urban population causes EF at a 1% level for $\omega > 0.74$, and at a 5% level everywhere, given the fact that the calculated test statistic is always higher than the Critical Values (Fig. 2e).

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

5 Conclusion and policy implications

The complexities of climate change and its serious effects require novel empirical strategies to analyze the dynamics and interactions with the environment. The aim of this paper is to explore the determinants of environmental quality in China, using annual data over the period 1960–2019.

QR estimates revealed that an increase in electric power consumption generates a significant increase in EF (for all the estimated quantiles). This result implies that electricity consumption deteriorates the quality of the environment. Also, for real GDP we found a positive association, even though it is statistically significant only for the lower quantile (0.25). Thus, environmental quality, economic growth, and electricity
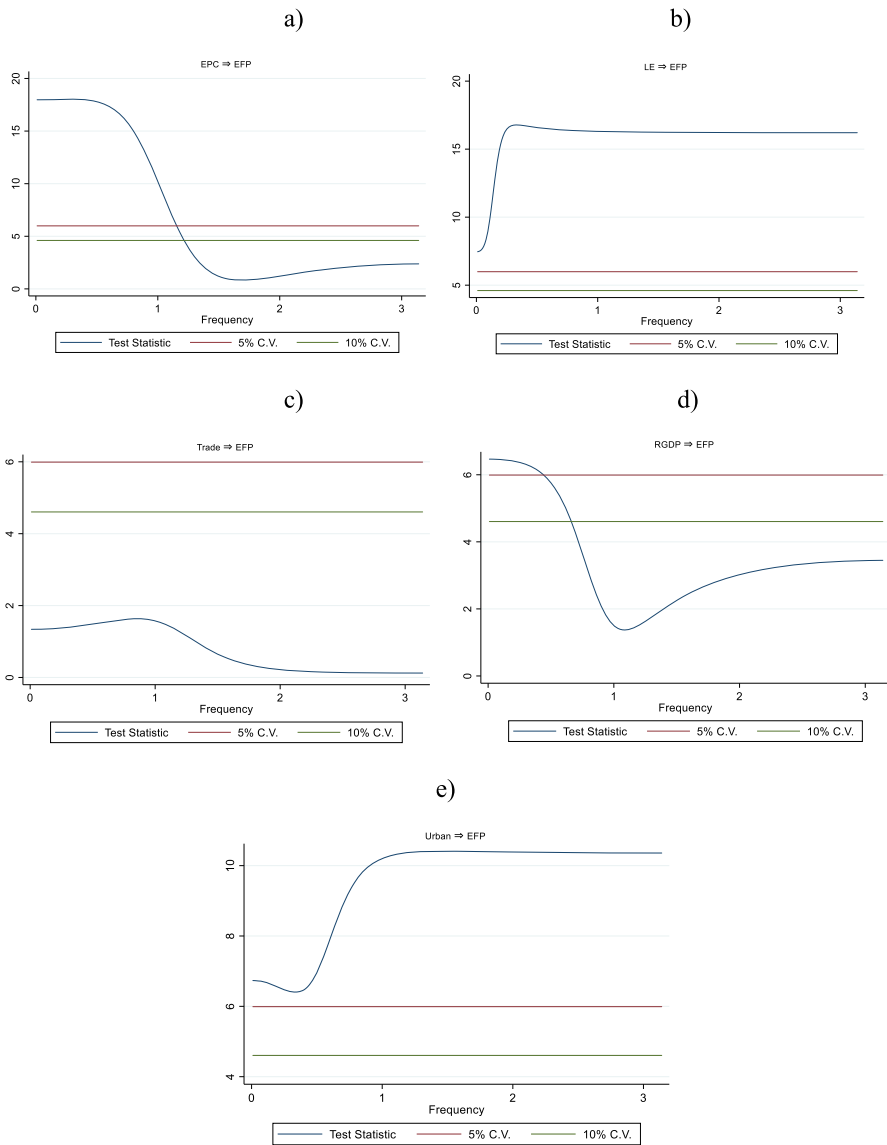
Fig. 2 Breitung–Candelon Spectral Granger causality test results. *Notes* Confidence level on *y-axis*. Geweke-type conditioning was used. The following relationships are empirically tested: EPC → EFP: innovation in electrical power consumption causes ecological footprint. LE → EFP: innovation in life expectancy causes ecological footprint. Trade → EFP: innovation in trade causes ecological footprint. RGDP → EFP: innovation in real GDP causes ecological footprint. Urban → EFP: innovation in urban population causes ecological footprint. *Source* author's elaboration in STATA through the command "bcgcausality"

consumption are integral parts of the development process. Therefore, regional policy measures that do not account for this aspect may not lead to effective energy strategies.

On the other hand, trade openness and urbanization rate show a negative and significant coefficient, indicating that they contribute to an improvement in the environment (especially for the lower quantile). The results show that EF decreases with an increase in both of these variables. Therefore, a cautious effort is needed, since we observe that an increase in free trade and urbanization are responsible for decreasing environmental deterioration.

Given these empirical results, sustainable and conservation management practices for natural resources' extraction are required to enhance China's bio-capacity for economic development. Decoupling economic development from natural resource extraction and consumption patterns improve environmental sustainability and sustainable development. Increasing the penetration of renewable energy technologies in the energy mix would reduce energy-related GHG emissions.

China should also significantly encourage Public–Private Partnership (PPP) investments given their long-term benefits. These desirable actions might significantly control and reduce the EF and promote environmental sustainability. Finally, the country needs to increase investments and development in Information and Communications Technology (ICT), which should raise energy efficiency.

Future research could analyze the relationship between renewable and non-renewable energy consumption with EF, also using innovative applied methodologies (Artificial Intelligence tools, threshold regressions, Panel VAR) (Magazzino and Mele 2021; Magazzino 2014).

Appendix

Seec Figs. 3 and 4.

a) CUSUM test
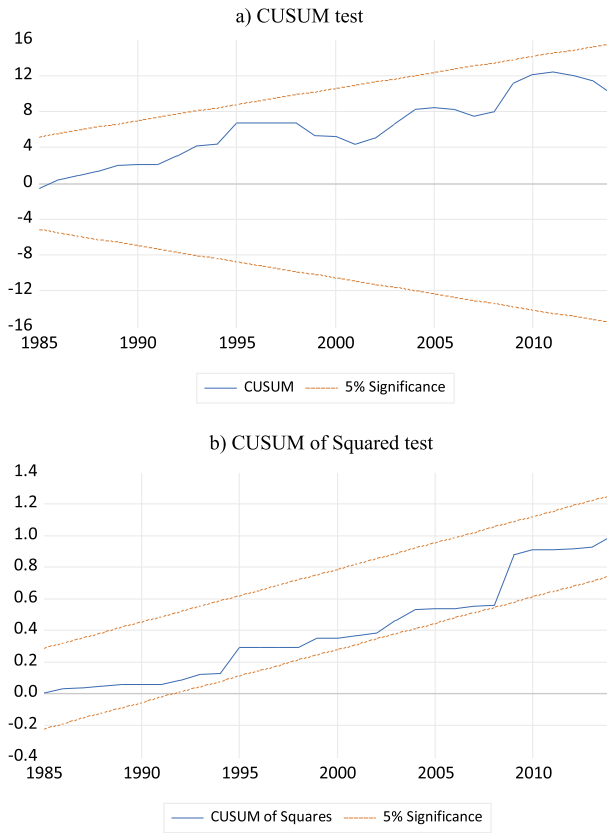

b) CUSUM of Squared test

Fig. 3 Stability diagnostics (recursive estimates). *Sources* our elaborations in EVIEWS
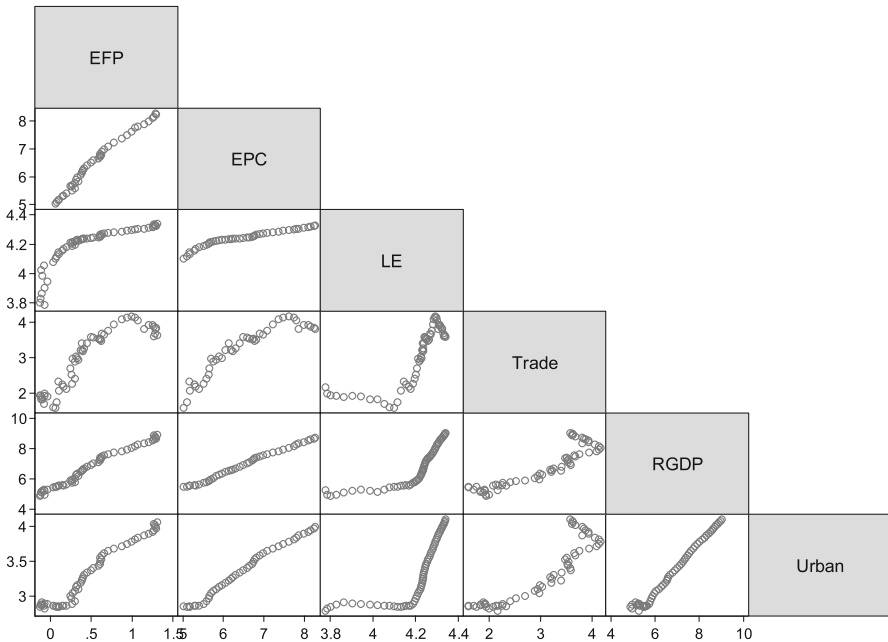
Fig. 4 Scatterplot matrices. *Sources* our elaborations in STATA

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