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Does renewable energy consumption reduce energy ecological footprint: evidence from China

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Abstract

The modern economic growth paradigm relies heavily on natural endowments. Renewable energy as a permanent energy source has the potential to reduce the ecological footprint (EF). We adopt the Vector Autoregressive model to examine the impact of renewable energy consumption on the energy EF and use the quantile regression method to test the heterogeneity and asymmetry between energy EF and photovoltaic, wind energy, and biomass energy. The results show that renewable energy has a long-term negative impact on the EF, and for every 1% increase in renewable energy consumption, the energy EF will decrease by 2.91%. The contribution of renewable energy consumption to reducing the EF is 1.34% on average. There is no two-way Granger causality between renewable energy consumption and energy EF. The reduction effect of wind energy consumption on the energy EF varies the most, followed by biomass energy and photovoltaic. In addition, under different energy EF distribution conditions, the impact of photovoltaic or wind energy or biomass energy consumption on the energy EF is different.

1. Introduction

Environmental degradation is one of the major problems facing the world, with adverse effects on people, air quality, ozone layer destruction, economy, biodiversity, and natural resources (Rahman 2020). On the other hand, Nathaniel (2021) argues that energy, food, water, and infrastructure pose hazards to ecosystems, thereby triggering ecological stress, and leading to adverse effects on the environment. To do this, countries need to reduce carbon emissions, energy consumption, and other activities to control air, water, and land pollution. However, numerous agreements in this area still fail to control environmental pollution on a global scale, as they have not shown any real and significant improvement in CO_2 emissions and other pollution (Gokmenoglu *et al* 2021). According to Solarin and Bello (2018), CO_2 is seen as a measure of environmental degradation. In contrast, some scholars believe that ecological footprint (EF) is an important indicator of environmental degradation (Al-Mulali *et al* 2015).

The EF is a concept and method proposed by William and Wackernagel in the 1990s to measure and evaluate sustainable development degrees based on biophysical quantities (Wackernagel and Rees 1996). EF is defined as the 'biologically productive and mutually exclusive areas necessary to continuously provide for people's resource supplies and the absorption of their wastes', which represents the influence scale of a specific population on the environment and the environment demand raised by persistent existence under the established technical conditions and consumption level (Wackernagel and Yount 1998). Hassan *et al* (2019a) explained that EF used the land and water to produce resources that were ultimately consumed by humans and to eliminate the waste produced. When calculating EF, various resources and energy consumption are converted into cropland, grazing land, forest land, fishing grounds, built-up land, and energy land. With the deepening of research, many scholars began to study EF of energy, transportation, aquaculture, industry, agriculture, tourism, and other specific industries and sectors. Energy ecological footprint (EEF) is the forest absorbing greenhouse gases emitted by fossil energy combustion (Liu *et al* 2019).

China has enjoyed rapid economic growth over the past 20 yr, with an annual GDP growth rate of 8.7% on average. With the massive burning of fossil energy to meet economic development and consumer demand, China's carbon emissions have surpassed the United States and become the world's largest carbon emitter since 2007, which makes China face increasing pressure from the international community to reduce carbon emissions. Economic growth-oriented human activities seem to pose a threat to existing ecosystems (Bekun *et al* 2019a). Despite the efforts of policymakers and environmental advocates, China's CO_2 emissions rose by more than 11.9 billion tonnes in 2021, accounting for 33% of the global total. Rising carbon emissions and proportions increase the EEF. At the same time, the International Energy Agency identified in its report that carbon-intensive energy resources and economic growth efforts contributed to increasing a country's EEF. According to Global Footprint Network, China's EEF is 3.91 billion hectares in 2018, accounting for 70.6% of China's total EF.

To reduce atmospheric pressure, the Chinese government has taken some direct and indirect measures, such as adjusting the industrial structure, optimizing energy structure, improving energy efficiency, promoting the construction of carbon market, and increasing forest carbon sink. Through these measures, China has achieved positive results in key areas such as control of greenhouse gas emissions, formulation of strategic plans, institutional and mechanism building, social awareness enhancement, and capacity building. In 2020, the Chinese government promises to peak CO_2 emissions by 2030 and strives to achieve carbon neutralization by 2060. The proposal of carbon peak and carbon neutrality goals has led China into the era of climate economy and opened a green and low-carbon society. A thorough green revolution means a comprehensive reformation in the fields of economy, energy consumption, and infrastructure. In 2020, China has started the preparation of the National Strategy for Adaptation to Climate Change 2035, researching and putting forward the task requirements of improving the ability of the natural, economic, and social fields to adapt to climate change. As can be seen from the discussion above, climate quality management has been given top priority, while land and water quality management has been neglected by the government. This can be seen in the rate at which water-induced diseases in specific areas are exacerbated (Biswas and Tortajada 2019). The continued increase in deforestation, flooding, and soil erosion shows that water and land management policies are inadequate to restore natural habitats and that the lack of synergies between economic and environmental policies increases environmental vulnerability (Tyler and Fajber 2009). Through the intertwining of water, energy, land, and economic policies, governments can kill two birds with one stone, one is to achieve economic growth, and the other is to restore the environment.

The given ecosystem scenario means that China needs cleaner energy and sustainable economic growth. However, China is one of the world's largest fossil energy consumers and relies heavily on non-renewable energy resources for economic activity. Thus, to deal with the negative impact of energy solutions, China must vigorously develop non-fossil energy, and the widespread use of renewable energy such as solar, wind, and biomass can play a vital role. The literature argues that renewable energy solutions are superior to fossil energy because they place less pressure on the environment (Sarkodie and Strezov 2019) without distorting the growth process (Destek and Sinha 2020). Another possible solution to improve the environment is to reduce the marginal consumption of energy at the production stage to minimize the harmful impact of energy on environmental quality (Bekun *et al* 2019b). In both cases, the government must strengthen research and development. Otherwise, the widespread and sustained use of fossil energy is likely to continue to pose long-term challenges such as import dependence, price volatility, low costs, and persistent ecological imbalances (Zafar *et al* 2019).

Therefore, renewable energy should be seen as a determinant of EEF to test its environmental viability in decision-making. In addition, by examining the impact of different types of renewable energy on EEF, we can get which renewable energy has the greatest impact on EEF at present. Except for per capita income and renewable energy, we have also introduced economic development, population size, scientific research funds, and energy structure as determinants of EEF. In terms of sustainable growth, these factors can play a key role in the long run (Kumar and Stauvermann 2019). The literature supports their role in curbing long-term CO_2 emissions or EEF growth (Chen *et al* 2019). In this study, we examine the impact of renewable energy, economic development, population size, per capita income, scientific research funds, and energy structure on China's EEF from 2000 to 2019 in a simplified way.

This paper raises the following questions: (a) does renewable energy consumption including photovoltaic, wind, and biomass reduce the EEF? (b) How much EEF will be reduced or increased by the increase of unit renewable energy consumption? (c) Does renewable energy consumption have a feedback effect on the EEF? (d) Do photovoltaic, wind, and biomass energy have an impact on the EEF and the magnitude of the impact under the horizontal distribution of different EEF.

To answer the above questions, we adopt vector autoregression (VAR) to study the impacts of renewable energy consumption, economic development, population size, per capita income, scientific research funds, and energy structure on the EEF. Then, we use the Granger causality to test the feedback effect of renewable energy consumption on the EEF. Finally, we use quantile regression to examine heterogeneous and asymmetric relationships among photovoltaic, wind energy, biomass energy, and EEF. By studying EEF and sustainable development, the importance of rational utilization of resources is revealed, which provides a theoretical basis for local governments to seek a win–win situation between environmental protection and sustainable economic development. The results will not only enrich the relevant literature on the fringe but also help provide recommendations for making sustainable and coordinated development policies.

The main contributions of this paper are the followings. Firstly, we find that there is a long-term cointegration relationship between renewable energy consumption and EEF, and for every 1% increase in renewable energy consumption, the EEF will decrease by 2.91%. The negative effect gradually weakens with time, but there is no two-way Granger causality between them. Secondly, we find that the contribution of renewable energy consumption to the reduction of the EEF first increases and then decreases with an average contribution of 1.34%. Finally, we find the heterogeneity and asymmetry in the EEF of different types of renewable energy. The reduction effect of photovoltaic, wind energy and biomass energy consumption on the EEF varies in descending order: wind energy, biomass energy, and photovoltaics. In addition, under different EEF distribution conditions, the impact of photovoltaic or wind energy or biomass energy consumption on the EEF is different.

This paper is organized as follows: section 2 presents the literature review. Section 3 introduces methods and data sources. Section 4 is results and discussions. Section 5 is conclusions and recommendations.

2. Literature review

In national and regional sustainable development studies, the relationship between EF and its influencing factors such as economic growth, urbanization level, per capita income, and population size is often analyzed. Most scholars have found that there is a significant linear positive correlation between economic growth and EF. For example, Çakmak and Acar (2022) found that economic growth of 1% will increase EF by 0.0283%. Zeraibi *et al* (2021) found economic growth would increase the EF. Hassan *et al* (2019b) revealed that economic growth increased the EF, leading to environmental degradation, but there was no causal relationship between them. In another study, a U-shaped relationship between economic growth and EF was found, suggesting that increasing income levels would promote EF growth (Ahmed *et al* 2022).

Wu and Bai (2022) estimated the ecological sustainability of China's resource-based cities at different scales in the process of urbanization and found that most of the resource-based cities in urbanization were in an ecological deficit state, but this result can only show that the ecological pressure on cities was even greater in the process of urbanization. While the results of Cui *et al* (2022) showed that the urbanization level increased the EF, further clarifying their relationship. The higher the urbanization level was, the higher the human capital required to improve environmental quality (Chen *et al* 2021), that is, the urbanization level affected EF and hindered sustainable development (Gupta *et al* 2022). However, whether urbanization level drives or hinders EF's growth also needs to consider the country's income level. Generally speaking, a high urbanization level in high-income countries will reduce EF's growth (Ali *et al* 2021). Feng and Wu (2011) observed that the relationship between EF and per capita income showed an inverted U-shaped relationship in the long run, which was confirmed by the research of Al-Mulali *et al* (2015).

In the long run, population size has a very significant impact on the EF. Air, water, and land quality may become more polluted as the population size increases (Sharma *et al* 2020). Technological innovation is also a factor that cannot be ignored. For example, Zeraibi *et al* (2021) confirmed that technological innovation will reduce the EF, and there was a two-way causal relationship between them (Kongbuamai *et al* 2020), while Ke *et al* (2020) found that industrial structure, energy structure, and energy efficiency played a mediating role among them. However, a recent study focusing on China found that only when the economy developed to a certain level, technological innovation would affect the EEF (Li *et al* 2022).

Of course, energy structure, renewable energy, and EEF are more closely related. Among them, the energy structure has the greatest impact on the EF (Zou 2010), that is, the energy consumption structure dominated by coal is not conducive to sustainable development, reducing crude oil consumption, increasing natural gas, and the proportion of renewable energy consumption, adjusting the energy structure is an effective measure for China to reduce the EF and the impact on the human environment. Shahzad *et al* (2021) found that fossil energy consumption significantly increased the EF of the United States when examining the links between economic complexity, fossil energy, and EF. In addition, Yousaf *et al* (2022) have confirmed the negative impact of fossil energy consumption on the EF when analyzing influencing factors of EF.

The literature is replete with studies of the overall impact of energy consumption on carbon emissions (Afridi *et al* 2019). Considering the need for sustainable economic growth, with the widespread use of non-renewable energy sources found to have higher carbon intensity, most countries have begun to focus on clean and renewable energy sources (Zaidi *et al* 2018). Here, it is undeniable that renewable energy consumption may also contribute to environmental pollution (Bulut 2017), for example, hydropower energy consumption Granger-causes CO_2 emissions (Bildirici *et al* 2016). However, renewable energy is less harmful to climate change and more cost-effective than non-renewable energy (Chen *et al* 2019). In this regard, using evidence from China, Long *et al* (2015) found that coal energy as a non-renewable energy source significantly increased the country's pollution levels. The study recommended increasing the use of hydro-based and nuclear-based electricity in the long run. Similarly, Inglesi-Lotz and Dogan (2018) showed in their research that the use of renewable energy was relatively more eco-friendly in the long run.

There are more and more studies on the impact of renewable energy consumption on the EF, but as the number of studies increases, the conclusions on the relationship between them become more diverse. Pata (2021) and Liu *et al* (2022) found that renewable energy consumption reduced EF. Ansari *et al* (2021) also found that renewable energy harms the EF. Abid *et al* (2022) confirmed that renewable energy can promote economic growth while improving the environment, and with the increase in urbanization rate, the negative effect of renewable energy consumption on the EF first weakened and then strengthened. Divided into different types of renewable energy, some scholars have empirically analyzed the reduction effect of solar and biomass energy on the EF (Hadj 2021, Sharif *et al* 2021). However, not all scholars' conclusions confirm renewable energy consumption will reduce EF. Kongbuamai *et al* (2021) found that renewable energy's growth also led to EF's growth, which contradicted the previous research results. The opposite result was most likely caused by the different periods and geographical scope of research. In addition, others argue that the relationship between them is minimal. When Pata and Samour (2022) explored the role of nuclear energy and renewable energy consumption on the EF, they found that nuclear energy improved environmental quality, but renewable energy had no long-term impact on environmental conditions, and the study of Çakmak and Acar (2022) also showed that renewable energy consumption has no significant impact on the EF.

3. Methods

3.1. Data

Energy land is an important component in EF accounting. Although there is no ecological productive land reserved for energy land in traditional EF accounting, with the urgency of CO_2 reduction and the increasing attention paid to the carbon sequestration effect of forests on CO_2, the approach of using the forest area required to absorb national or regional CO_2 emissions as a sustainable reference standard for energy land has been used in most studies. Moreover, according to the Living Planet Report 2020, the contribution rate of energy land to the national EF is 60%, which indirectly indicates that EEF is a feasible indicator to quantitatively characterize the change in national energy consumption.

3.1.1. Carbon absorption capacity of each ecologically productive land

The productive land with CO_2 absorption capacity is divided into cropland, grazing land, forest land, fishing grounds, and energy land. The essence of energy land is still forest land, but in most studies, no energy land is reserved to absorb CO_2. This paper also assumes that the area of energy land is 0. According to the calculation results of the global average net primary productivity (NPP) of each productive land by Venetoulis and Talberth (2010), as shown in table 1, there are significant differences in the NPP of different productive lands. All kinds of land area data come from the Food and Agriculture Organization of the United Nations, as shown in table 2. (www.fao.org/faostat/en/#data/RL/visualize)

Referring to the method of estimating the comprehensive carbon absorption capacity, the CO_2 absorption capacity of various productive lands is characterized by the carbon absorption rate, which is uniformly expressed as NPP:

$$\overline{\mathrm{NPP}} = \frac{\sum_{i=1}^{4} A_i \times \mathrm{NPP}_i}{\sum_{i=1}^{4} A_i} \qquad (1)$$

$\overline{\mathrm{NPP}}$ represents the carbon absorption capacity of comprehensive productive land, A_i represents the area of various types of productive land, NPP_i represents the global average NPP of various types of productive land. Table 3 shows the carbon absorption capacity of China's comprehensive productive land from 2000 to 2019.

3.1.2. Energy carbon emissions

The carbon emission coefficient refers to the amount of carbon corresponding to the heat released by fossil energy combustion. The net calorific value and carbon emission coefficient are shown in table 4. The calculation formula of carbon emission from various fossil energy combustion is as follows:

Table 1. Net primary productivity of lands.

	Cropland	Forest land	Grazing land	Fishing grounds	Energy land
NPP (tC $hm^{-2}\cdot a$)	4.243	6.583	4.835	5.344	6.583

Table 2. Ecological productive area in 2000–2019.

Type of land ($10^8 hm^2$)	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Cropland	1.3592	1.3571	1.3540	1.3603	1.3644	1.3663	1.3606	1.3589	1.3594	1.3606
Forest land	41.58	41.53	41.48	41.43	41.37	41.32	41.27	41.22	41.17	41.11
Grazing land	17.82	17.831	17.85	17.86	17.92	17.92	17.93	17.94	17.95	17.95
Fishing grounds	4.2993	4.3009	4.3035	4.2968	4.1844	4.1836	4.1861	4.1863	4.4017	4.4009
Energy land	0	0	0	0	0	0	0	0	0	0
Type of land ($10^8 hm^2$)	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Cropland	1.3611	1.3698	1.3788	1.3810	1.3819	1.3820	1.3828	1.3877	1.3854	1.3833
Forest land	41.06	41.02	40.97	40.93	40.88	40.84	40.80	40.74	40.69	40.63
Grazing land	17.96	17.99	18.00	18.01	18.02	18.02	18.01	18.01	18.10	18.13
Fishing grounds	4.3987	4.3943	4.2716	4.2736	4.2722	4.2752	4.2654	4.2693	4.2684	4.2686
Energy land	0	0	0	0	0	0	0	0	0	0

Table 3. Carbon absorption capacity of the integrated productive land from 2000 to 2019.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Carbon absorption capacity (C $hm^{-2}\cdot a$)	5.9734	5.9728	5.9721	5.9713	5.9707	5.9702	5.9697	5.9690	5.9663	5.9657
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Carbon absorption capacity (tC $hm^{-2}\cdot a$)	5.9651	5.9640	5.9643	5.9636	5.9630	5.9625	5.9624	5.9617	5.9597	5.9586

Table 4. Calorific value coefficients of various fossil energy.

Type of energy	Net calorific value ($TJ/10^3 t$)	Carbon emission coefficient (t/TJ)
Row coal	26.7	26.8
Coke	28.2	29.2
Crude oil	42.3	20.0
Gasoline	44.3	18.9
Kerosene	44.1	19.5
Diesel oil	43.0	20.2
Fuel oil	40.4	21.1
PLG	47.3	17.2
Natural gas	48.0	15.3

Note: Date comes from《IPCC Guidelines for National Greenhouse Gas Inventories 2006》.

$$G_{ec} = C_{ce} \times H_{ce} \times Cd_{ce} \tag{2}$$

G_{ec} represents carbon emission after certain fossil energy combustion, t; C_{ce} represents certain fossil energy consumption, t; H_{ce} represents the net calorific value of certain fossil energy, $TJ/10^3 t$; Cd_{ce} represents the carbon emission coefficient of certain fossil energy, t/TJ.

3.1.3. EEF

Given the carbon emissions of various energy and the carbon sink productivity of comprehensive productive land, this paper uses the formula (3) to calculate the EF of various energy:

$$\mathrm{EEF} = \frac{\mathrm{CO_2}}{\mathrm{NPP}}. \tag{3}$$

Besides, the data on per capita disposable income of residents, renewable energy consumption, economic development, population size, scientific research funds, and energy structure are all from the National Bureau of Statistics and IEA. To reduce the scale of variables to alleviate the impact of heteroscedasticity and make the characteristics of indicator variables easier to observe, all operations in this paper are performed after the

Table 5. Variable names and related descriptions.

Variable name	Symbol	Data source	Logarithmic symbol
Energy ecological footprint	EEF	Calculation	LNEEF、Zscore (EEF)
Renewable energy consumption	RE	IEA	LNRE
Economic development	GDP	National Bureau of Statistics	LNGDP、Zscore (GDP)
Population size	SIZE	National Bureau of Statistics	LNSIZE、Zscore (SIZE)
Per capita disposable income of residents	INC	National Bureau of Statistics	LNINC、Zscore (INC)
R&D expenditure as a percentage of GDP	RD	National Bureau of Statistics	LNRD、Zscore (RD)
Energy structure	STR	National Bureau of Statistics	LNSTR、Zscore (STR)
Photovoltaic	PV	IEA	LNPV、Zscore (PV)
Biomass energy	BIO	IEA	LNBIO、Zscore (BIO)
Wind energy	WIND	IEA	LNWIND、Zscore (WIND)

logarithmic transformation of the original data. Considering that there are 0 in the photovoltaic data, all the data are standardized by Z-score when doing quantile regression, specific variables are shown in table 5.

3.2. Model

3.2.1. VAR

VAR has gradually become a commonly used econometric model since it was proposed by Sims in 1980. The idea of the VAR model is to use endogenous variables lag for regression to obtain the dynamic relationship between endogenous variables. It is often used to deal with multiple interrelated and mutually restrictive time series data. A VAR model that obeys the order of P is expressed as follows:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + B x_t + \varepsilon_t, t = 1, 2 \ldots, n \tag{4}$$

y_t is a k-dimensional endogenous variable, x_t is a d-dimensional exogenous variable, p is the lag order, t is the samples number, B is the estimated coefficient, ε_t is the error term. The above formula can be expressed as the following formula (4) in matrix form, that is, VAR (p) model containing k time series consists of k equations:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{kt} \end{pmatrix} = A_1 \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \\ \vdots \\ y_{kt-1} \end{pmatrix} + A_2 \begin{pmatrix} y_{1t-2} \\ y_{2t-2} \\ \vdots \\ y_{kt-2} \end{pmatrix} + \cdots + B \begin{pmatrix} x_{1t} \\ x_{2t} \\ \vdots \\ x_{dt} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{kt} \end{pmatrix}. \tag{5}$$

3.2.2. Quantile regression

The quantile regression method was first proposed by Koenker and Bassett (1978), which was based on the median regression theory. The specific idea is to calculate any conditional quantile of the sample by making the objective function be solved to minimize the sum of the absolute values of errors. The quantile regression model expression is:

$$\begin{cases} y_i = f(x_i, \beta) + \varepsilon_i \\ \min \sum_{i=1}^{n} \rho_\tau \left(y_i - f(x_i, \beta) \right) \end{cases} \tag{6}$$

β is the regression coefficient, ε_i is the residual term, $\rho_\tau(u) = u(\tau - I(u))$, $I(u) = \begin{cases} 0, u \geqslant 0 \\ 1, u < 0 \end{cases}$, $f\left(x, \hat{\beta}\right)$ is the optimal solution, representing the quantile estimation function of y under the condition of x, $0 < \tau < 1$.

One of the prerequisites for the use of the least squares regression method is that the random errors obey a normal distribution, however, the data in this paper are derived from real life and are complex, and it is almost impossible to fully comply with the assumptions. In this case, the quantile regression estimation method is more advantageous, using the weighted least absolute deviation method for estimation, which is usually not affected by outliers and the results are more robust, but due to the difficulty of parameter estimation, it can only deal with cross-sectional data initially, and its application is narrow. It was not until Koenker and Park (1996) proposed an interior-point algorithm for computing nonlinear quantile regressions that greatly reduced the difficulty of estimation, allowing this regression method to capture the entire conditional distribution of the selected variables (Bildirici *et al* 2022). For this reason, quantile regression was chosen to investigate the relationship between the effects of the independent and dependent variables.

4. Results and discussions

The basic properties of the compiled data set are given in table 6. During the study period, as with renewable energy consumption, EEF series showed significant standard deviations. This indicates significant differences in the selected EEF and renewable energy consumption during the study period. In addition, because the Jerque–Bera test rejects the null hypothesis of normal distribution at the 10% significance level, all the sequences are distributed abnormally.

Owing to the long study period, it is required to confirm whether series are stationary at the level or first difference. In this connection, group unit root tests are carried out. The augmented Dickey–Fuller (ADF) tests given in table 7 reveal that all the series are stable at second differences at the 1% significance level, which is a prerequisite for examining the long-run relationship. ADF tests of the original sequence at the level and the first differences are shown in table A1.

Table 7 shows that all variables pass the stationarity test, so the VAR model can be established and the optimal lag order of variables can be determined. In this paper, according to Akaike's Information Criterion (AIC) and Schwarz Criterion (SC) criteria, the optimal lag order of variables is determined to be 2 (table 8). After the optimal lag order is determined, to avoid the phenomenon of false regression, the Johansen cointegration test is conducted on all variables, and the results are shown in table 9.

Generally speaking, the first cointegration equation contains the most variables and can explain more problems. According to the results of the Johansen cointegration test, there are seven cointegration equations at the significance level of 5%, indicating that there is a long-term stable relationship between variables, to construct the following cointegration equation:

$$\begin{aligned} \mathrm{LNEEF} = &- 6.9878\mathrm{LNGDP} + 10.7000\mathrm{LNINC} - 1.3376\mathrm{LNRD} - 2.9095\mathrm{LNRE} \quad (7) \\ &+ 31.1236\mathrm{LNSIZE} + 7.3453\mathrm{LNST}. \quad (7) \end{aligned}$$

The coefficient of LNRE is −2.9095, indicating that renewable energy consumption and EEF have a negative cointegration relationship. For every 1% increase in renewable energy consumption, EEF will decrease by 2.9095%. There is a certain substitution between renewable energy and fossil energy. Increasing renewable energy consumption will inevitably reduce the demand and consumption of fossil energy, which will have a certain negative impact on the EEF. The coefficient of LNGDP is −6.9878, indicating that there is a negative cointegration relationship between economic development and EEF, and economic development increases by 1%, EEF will decrease by 6.9878%. China's industrial structure is mainly composed of three major industries. The secondary industry mainly includes mining, manufacturing, electricity, gas and water production, and supply and construction, which are most dependent on fossil energy. Since 2000, although China's GDP is on the rise, the overall contribution rate of the secondary industry shows a downward trend, and the driving effect of the secondary industry on GDP is only 1% by 2020. Thus, GDP growth not only reduces fossil energy consumption but also reduces EEF.

There is a positive cointegration relationship between per capita disposable income of residents and EEF For every 1% increase in per capita disposable income of residents, EEF will increase by 10.7000%. The increase in per capita disposable income of residents will stimulate people's daily consumption and increase the consumption expenditure on services such as food, clothing, housing, and transportation that are closely related to oil and other energy sources, thereby promoting energy consumption, and increasing the EEF. EEF and scientific research funds have a negative cointegration relationship. For every 1% increase in scientific research funds, EEF will decrease by 1.3376%. The investment of scientific research funds is conducive to strengthening scientific and technological progress and innovation, reducing the output consumption of unit fossil energy, promoting the large-scale utilization of clean energy and its replacement of fossil energy, thereby reducing EEF.

According to the coefficient of LNSIZE, the population size and EEF have a negative cointegration relationship. For every 1% increase in the population size, EEF will increase by 31.1236%. The increase in population size has promoted the rise in China's total energy demand, and China's energy structure is dominated by fossil energy consumption such as coal and oil. Therefore, the increase in population size will stimulate fossil energy consumption and increase EEF. The energy structure and EEF have a positive cointegration relationship. For every 1% reduction in the energy structure, EEF will decrease by 7.3453%. Energy structure refers to the proportion of coal in total energy consumption. From 2000 to 2020, China's energy structure has dropped from 68.5% to 56.8%, while coal still accounts for more than 50% of primary energy, so the decline in energy structure will decrease EEF.

Table 10 shows the ADF test of the residual item. It can be seen that the residual item is stable at the 1% significance level, so it can explain EEF, renewable energy consumption, economic development, per capita disposable income of residents, scientific research funds, energy structure, and population size have a

Table 6. Data description.

	LNEEF	LNGDP	LNINC	LNRD	LNRE	LNSIZE	LNSTR
Mean	10.8066	3.5387	9.3304	−4.1097	6.5508	11.8051	−0.3952
Median	10.8989	3.6254	9.3652	−4.0530	6.5848	11.8038	−0.3765
Maximum	11.2226	4.6105	10.3654	−3.7985	7.6429	11.8577	−0.3181
Minimum	10.0381	2.2563	8.1920	−4.6373	5.2969	11.7472	−0.5573
Std. Dev.	0.3923	0.7461	0.6827	0.2490	0.6894	0.0332	0.0686
Skewness	−0.6503	−0.2558	−0.1407	−0.4236	−0.0517	0.0053	−0.9648
Kurtosis	2.0230	1.6979	1.6614	1.8817	1.6925	1.7636	2.7642
Jarque–Bera	8.8197	6.5241	6.2368	6.5610	5.7343	5.0957	12.5966
Probability	0.0122	0.0383	0.0442	0.0376	0.0569	0.0782	0.0018
Sum	864.5247	283.095	746.4307	−328.7795	524.0634	944.4082	−31.6124
Sum Sq. Dev.	12.1577	43.9766	36.8229	4.8989	37.5422	0.0868	0.3717

Table 7. ADF unit root test results.

Variable	Test form (C,T,K)	*P*-value	Conclusion
D(LNEEF,2)	(0,0,11)	0.0000	Stable***
D(LNGDP,2)	(0,0,11)	0.0000	Stable***
D(LNINC,2)	(0,0,11)	0.0000	Stable***
D(LNRD,2)	(0,0,11)	0.0000	Stable***
D(LNRE,2)	(0,0,11)	0.0000	Stable***
D(LNSIZE,2)	(0,0,11)	0.0000	Stable***
D(LNSTR,2)	(0,0,11)	0.0000	Stable***

Table 8. Lag order selection criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1054.9790	NA	0.0000	−27.5784	−27.3637	−27.4926
1	2108.6570	1885.5280	0.0000	−54.0173	−52.2999	−53.3309
2	2250.2060	227.2235*	7.44e-34*	−56.45278*	−53.23269*	−55.16588*
3	2275.9990	36.6542	0.0000	−55.8421	−51.1193	−53.9546
4	2295.9290	24.6497	0.0000	−55.0771	−48.8516	−52.5891

Table 9. Unrestricted cointegration rank test (trace).

Hypothesized No. of CE (s)	Eigenvalue	Trace statistic	0.05 critical value	Prob.**
None*	0.4310	184.3686	125.6154	0.0000
At most 1*	0.3872	140.9490	95.7537	0.0000
At most 2*	0.3758	103.2354	69.8189	0.0000
At most 3*	0.3212	66.9500	47.8561	0.0003
At most 4*	0.2331	37.1159	29.7971	0.0060
At most 5*	0.1245	16.6840	15.4947	0.0330
At most 6*	0.0803	6.4480	3.8415	0.0111

Table 10. Augmented Dickey–Fuller unit root test on resid.

		t-Statistic	Prob
ADF		−8.5171	0.0000
Test critical values:	1%level	−2.5989	
	5%level	−1.9456	
	10%level	−1.6137	

long-term equilibrium relationship. In addition, according to the unit root distribution diagram (figure 1), the values of the test results are all less than 1, and the moduli of all units and reciprocals fall within the unit circle, so the established model is stable.

Table 11 shows the results of the Granger causality test. There is no two-way Granger causality between economic development, renewable energy consumption, population size, scientific research funds, and EEF, but there is a one-way Granger causality between per capita disposable income of residents, energy structure, and EEF, that is, EEF is a Granger cause of per capita disposable income of residents and energy structure.

The impulse response function of one variable to another variable can intuitively reflect the trajectory of the time and degree of impact of the variables in the model after the shock. After a stable time series model is

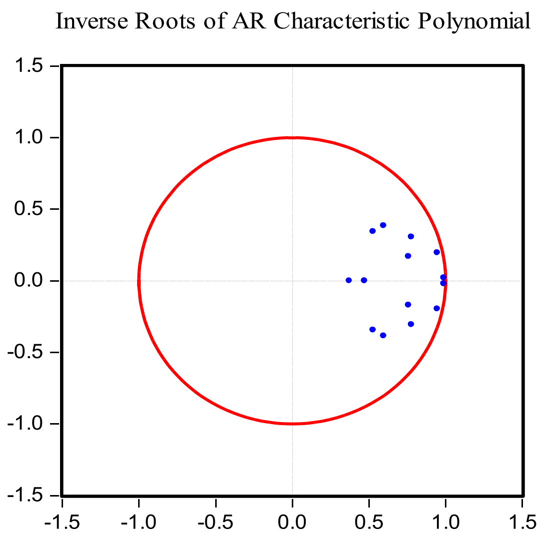

Figure 1. Test results of unit circle.

Table 11. Granger causality test.

Null hypothesis	Prob	Accept
LNGDP does not Granger Cause LNEEF	0.5957	Yes
LNEEF does not Granger Cause LNGDP	0.1148	Yes
LNINC does not Granger Cause LNEEF	0.9536	Yes
LNEEF does not Granger Cause LNINC	0.0173	No
LNRE does not Granger Cause LNEEF	0.3122	Yes
LNEEF does not Granger Cause LNRE	0.1646	Yes
LNSIZE does not Granger Cause LNEEF	0.9177	Yes
LNEEF does not Granger Cause LNSIZE	0.3991	Yes
LNSTR does not Granger Cause LNEEF	0.3312	Yes
LNEEF does not Granger Cause LNSTR	0.0114	No
LNRD does not Granger Cause LNEEF	0.1214	Yes
LNEEF does not Granger Cause LNRD	0.0536	Yes

impacted, the first few periods will be in a state of change, but in the long run, it will be in a relatively stable state. To determine the changes of each variable to EEF, an impulse response analysis is performed.

Figure 2 is the impulse response function of each variable to EEF. When the population size, energy structure, and scientific research funds are respectively impacted by one-unit standard deviation, the current response value of EEF is 0, and then gradually increases, but the response degree gradually weakens. When a positive standard deviation shock is given to the per capita disposable income of residents, the current response value of EEF is 0, then gradually increases, and gradually weakens after reaching the peak in the fifth period, but it is still a positive response. When a positive standard deviation shock is given to GDP, the current response value of EEF is 0, then increases negatively, gradually decreases after reaching the peak in the sixth period, and becomes a positive response in the tenth period. When a unit positive standard deviation shock is given to renewable energy consumption, the current response value of EEF is 0, then increases negatively, and gradually decreases after reaching the peak in the seventh period, but it is still negative, which indicates that renewable energy consumption harms the EEF regardless of both short and long term.

Overall, population size, energy structure, and scientific research funds have had a positive impact on the EEF for a long time. The positive impact of the per capita disposable income of residents on the EEF is gradually weakening. Economic development harms the EEF in the short term but has a positive impact in the long run. Renewable energy consumption has always harmed the EEF, but the long-term impact is gradually weakening.

Variance decomposition is to further evaluate the importance of different structural shocks by analyzing the contribution of each structural shock to the change of endogenous variables. By comparing the size of different variables' contribution percentages, the size of each variable effect can be estimated. At the same time, according to the contribution percentage changing over time, determine the time lags effect of one variable on another variable. Figure 3 shows that EEF has the largest contribution to itself, but it shows a downward trend. Among the contributions of all independent variables to EEF, the population size has a

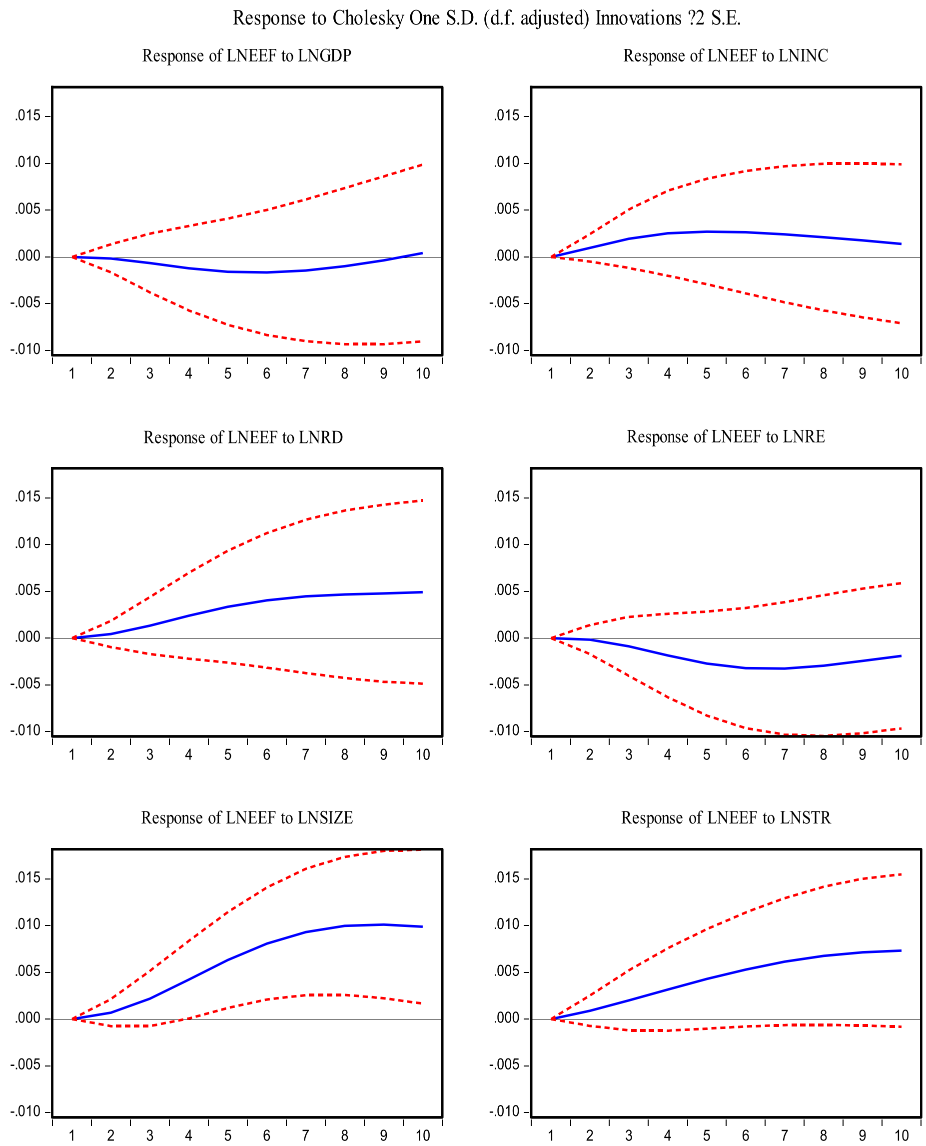

Figure 2. Impulse response of different variables to EEF.

larger contribution, followed by energy structure, scientific research funds, renewable energy consumption, per capita disposable income of residents, and GDP. The contribution of population size, energy structure, and scientific research funds to EEF continues to increase, but the degree of contribution decreases in turn. The contribution of renewable energy consumption to EEF first increases and then decreases, and the average contribution rate of the first ten periods is 1.34%. The variance decomposition results are shown in table A2 for details.

The different regression coefficients of different quantiles indicate that the explanatory variables have different effects on the response variables at different levels, and we can obtain the influence of the explanatory variables on the quantiles of the response variables. To clearly show the degree of influence of each variable on different quantiles, the dependent variable is assumed to be a linear function of a conditional distribution, and the influence of the corresponding quantiles is obtained through quantile regression.

Table 12 shows the model quality under the five quantiles of 0.1, 0.25, 0.5, 0.75, and 0.9. Under the same control variables, the three types of renewable energy consumption are used to fitting the regression of the EEF. Under different quantiles, the Pseudo R Squared of the fitted model is greater than 0.85, and the MAE is about 0.1, which indicates that the fitting effect of the model is good. Parameter estimates at different quantiles of photovoltaics, wind energy, and biomass energy are shown in tables A3–A5.

Table 13 shows the changes in the regression coefficients and their significant results on the variables affecting the EEF under each quantile of the three renewable energy sources. The model estimation results show that photovoltaic, wind energy, and biomass energy consumption coefficients are significantly negative and gradually increase. Under the condition of controlling other conditions unchanged, when $q = 0.1$, EEF

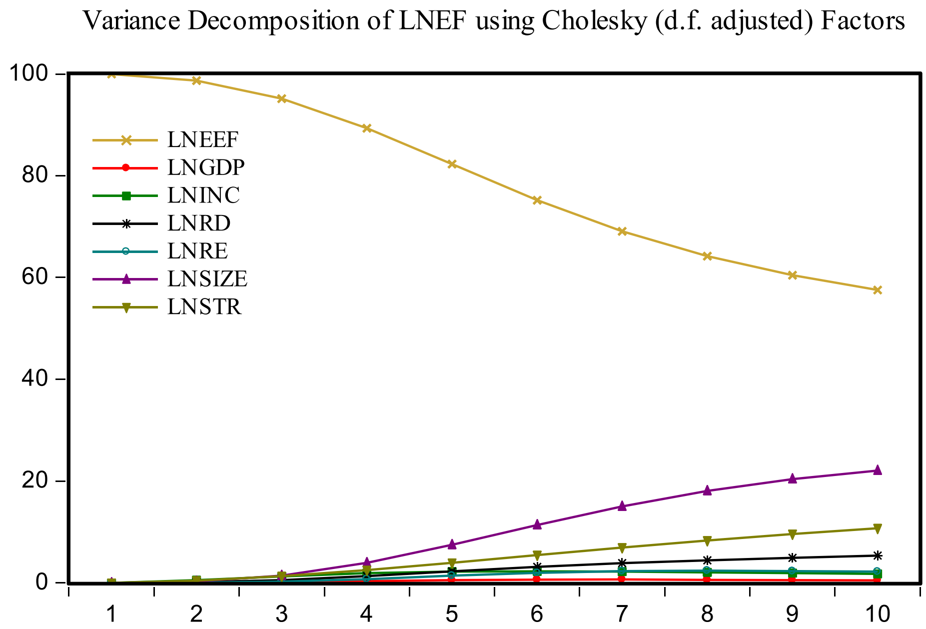

Figure 3. Variance decomposition of LNEF.

Table 12. Model quality[a, b, c].

Type	Criteria	$q = 0.1$	$q = 0.25$	$q = 0.5$	$q = 0.75$	$q = 0.9$
PV	Pseudo R squared	0.9276	0.9305	0.9257	0.9143	0.9003
	MAE	0.0985	0.0778	0.0671	0.0751	0.1062
WIND	Pseudo R squared	0.9102	0.9096	0.9201	0.9065	0.8921
	MAE	0.1310	0.1037	0.0722	0.0841	0.1093
BIO	Pseudo R squared	0.9304	0.9299	0.9298	0.9095	0.8979
	MAE	0.1045	0.0844	0.0635	0.0792	0.1096

Note: MAE is mean absolute error.

[a] Dependent Variables: Zscore(EEF).

[b] Model: [%1, (Intercept)].

[c] Method: simplex algorithm.

decreases by 0.4206, 1.3015, and 1.0072 units respectively for each unit increase in photovoltaic, wind energy, and biomass energy consumption; when $Q = 0.25$, EEF decreases by 0.3596, 1.0199, and 1.0359 units for each unit increase in photovoltaic, wind energy and biomass energy consumption; when $Q = 0.5$, EEF decreases by 0.2362, 0.7749, and 0.9643 units for each unit increase in photovoltaic, wind energy and biomass energy consumption; when $Q = 0.75$, EEF decreases by 0.2017, 0.5223 and, 0.5113 units for each unit increase in photovoltaic, wind and biomass energy consumption; when $Q = 0.9$, EEF decreases by 0.1521, 0.4340, and 0.4904 units for each additional unit of photovoltaic, wind energy and biomass energy consumption. With the increase of the EEF, the reduction effect of photovoltaic, wind energy, and biomass energy consumption on the EEF is significantly reduced, but the impact degree is different. When EEF is small, wind energy plays a greater role in reducing EEF, followed by biomass energy, and photovoltaics is the smallest. With the increase of EEF, the reduction effect of wind energy on the EEF decreases rapidly, followed by biomass energy. When EEF is large, the reduction effects of three renewable energy sources tend to be the same, but biomass energy is the largest, followed by wind energy and photovoltaics.

To further explore the characteristics of each explanatory variable on the distribution of the EEF under different renewable energy consumption, we draw the regression model estimation results under all quantiles. Figures 4–6 show the estimated coefficients and confidence intervals of the six explanatory variables and the intercepts at all quantiles for different renewable energy consumption. The black line shows the parameter estimates for different regression quantiles, and the blue area represents the 95% confidence interval for the parameter estimate. For comparison, the solid red line represents the parameter estimates of the ordinary linear regression with the same predictors, and the dashed red line is the 95% confidence interval of the ordinary linear regression.

Table 13. Parameter estimates by different quantiles [a, b].

Type	Parameter	$q = 0.1$	$q = 0.25$	$q = 0.5$	$q = 0.75$	$q = 0.9$
PV	Intercept	−0.0941***	−0.0591***	0.0183*	0.0597***	0.1045***
	Zscore (GDP)	2.7797***	2.2285***	1.5577***	2.0157***	1.9498***
	Zscore (SIZE)	−0.6339***	−0.57***	−0.2542**	0.0384	0.2227***
	Zscore (INC)	−1.1629**	−0.6335**	−0.2079	−1.1399***	−1.3436***
	Zscore (RD)	0.5098***	0.4788***	0.3729***	0.4078***	0.4127***
	Zscore (STR)	0.2014***	0.2885***	0.4023***	0.2707***	0.2023***
	Zscore (PV)	−0.4206***	−0.3596***	−0.2362***	−0.2017***	−0.1521***
WIND	Intercept	−0.1277***	−0.0821***	0.0232***	0.0693***	0.1061***
	Zscore (GDP)	3.3784***	2.6279***	1.9837***	1.3531***	0.7550***
	Zscore (SIZE)	−0.7686***	−0.4558***	0.1808*	0.0056	−0.0423***
	Zscore (INC)	−1.0619***	−0.8044	−0.3777	−0.2856	0.1746***
	Zscore (RD)	0.5669***	0.5558***	0.0489	0.4918***	0.6024***
	Zscore (STR)	−0.1553***	−0.0480	0.2159***	0.1780***	0.1910***
	Zscore (WIND)	−1.3015***	−1.0199***	−0.7749***	−0.5223***	−0.4340***
BIO	Intercept	−0.1027***	−0.0717***	0.0049	0.0627***	0.1080
	Zscore (GDP)	0.7100***	1.4652***	1.9700***	2.1460***	3.2740***
	Zscore (SIZE)	−0.2170**	−0.3514***	0.0322	0.0953	0.2526***
	Zscore (INC)	1.5636***	0.8249**	0.0215	−0.9605***	−2.1202***
	Zscore (RD)	0.1073*	0.2421***	0.0673	0.3460***	0.2113***
	Zscore (STR)	0.3180***	0.2780***	0.2984***	0.2188***	0.1832***
	Zscore (BIO)	−1.0072***	−1.0359***	−0.9643***	−0.5113***	−0.4904***

Note: [a]Dependent Variables: Zscore (EEF).
[b] Model: [%1, (Intercept)].

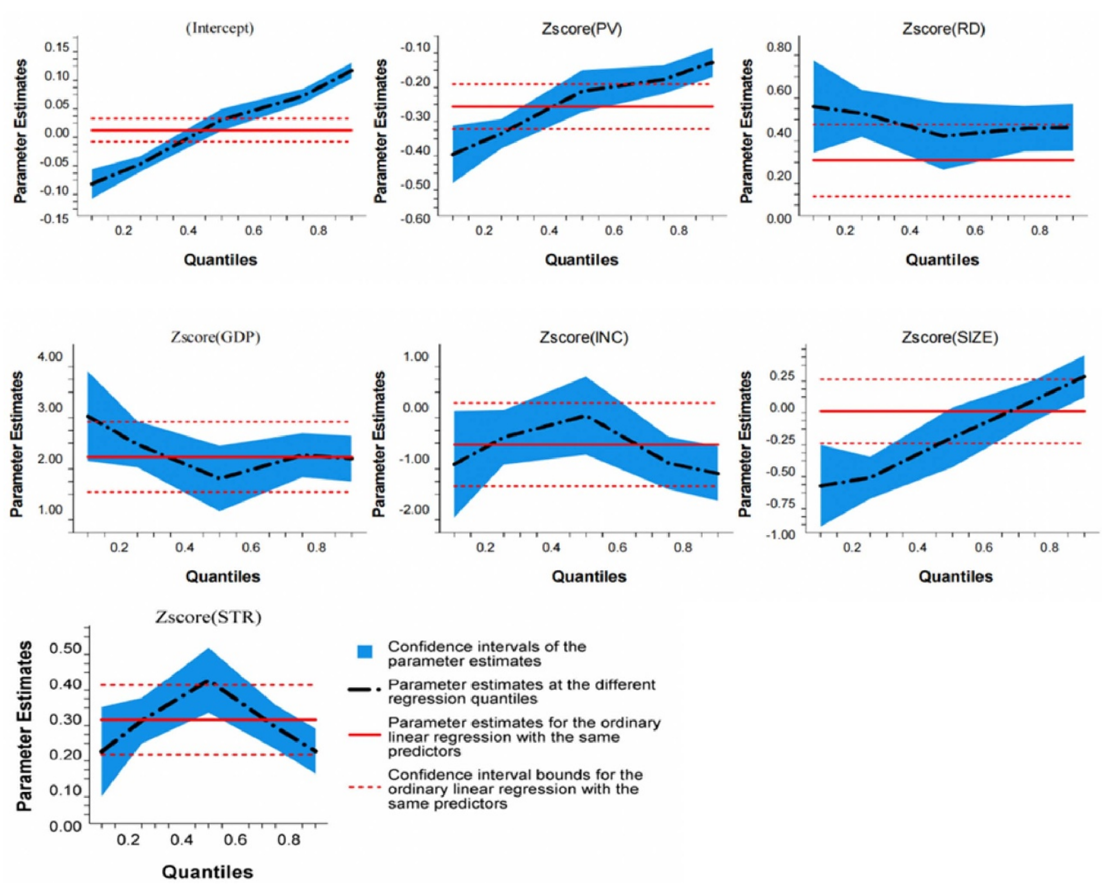

Figure 4. Plot of the estimated parameters of photovoltaic.

As shown in figure 4, the coefficient and confidence interval of photovoltaics are significantly negative, indicating that the impact of photovoltaic consumption on each quantile of the EEF is negative and significant, and with the increase of EEF, the negative influence gradually weakens. The coefficients and

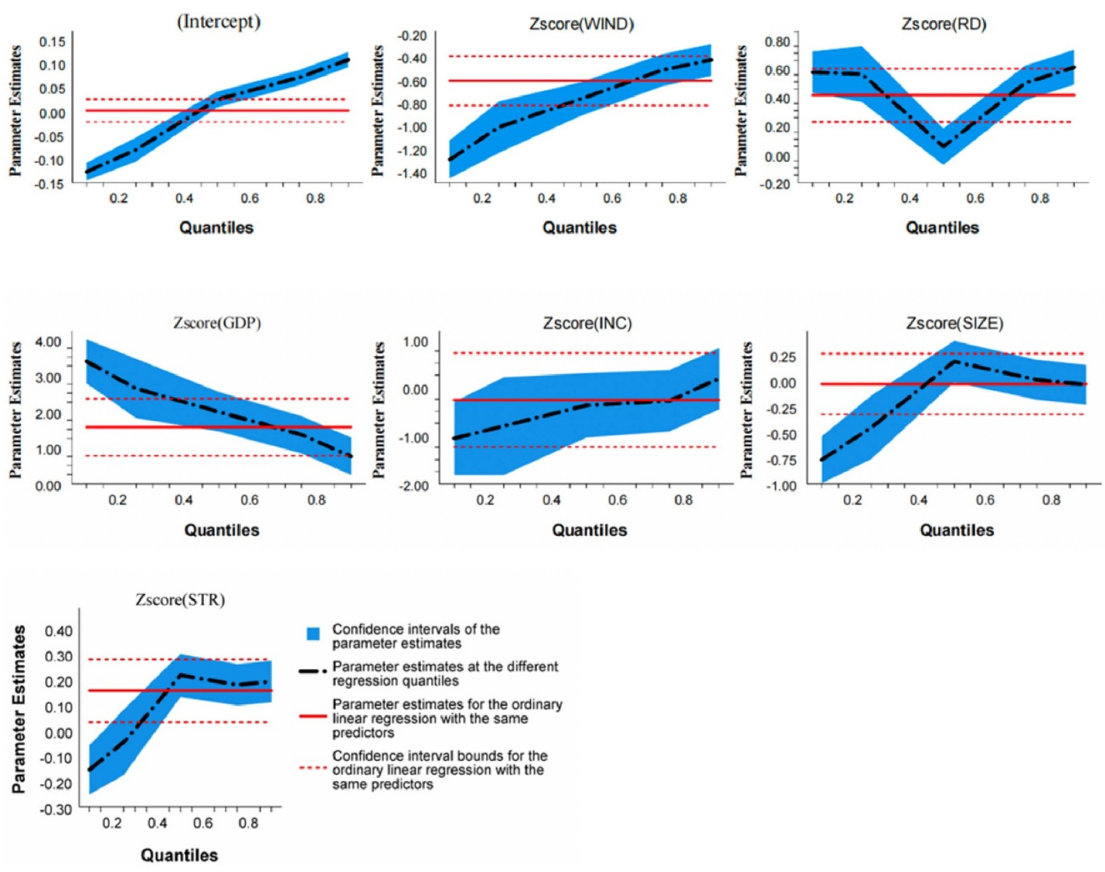

Figure 5. Plot of the estimated parameters of wind energy.

confidence intervals of scientific research funds, economic development, and energy structure are significantly positive, indicating that the impact of scientific research funds, economic development, and energy structure on each quantile of the EEF is positive and significant. When EEF is low, the positive impact of scientific research funds and economic development on it is larger and gradually decreases; when EEF is large, the positive impact of scientific research funds and economic development is similar under different quantiles, while the positive impact of energy structure on the EEF first increases and then decreases with the increase of it.

As shown in figure 5, the coefficient and confidence interval of wind energy are significantly negative, indicating that the impact of wind energy consumption on each quantile of the EEF is negative and significant, and has a decreasing trend with the increase of the EEF. The coefficient and confidence interval of economic development are significantly positive, indicating that the impact of economic development on each quantile of the EEF is positive and significant. With the increase of the EEF, the positive impact of economic development on it is gradually decreasing.

As shown in figure 6, the coefficient and confidence interval of biomass energy are significantly negative, indicating that the impact of biomass energy consumption on each quantile of the EEF is negative and significant. When EEF is small, the negative influence is large, and then gradually weakens. The coefficients and confidence intervals of economic development and energy structure are significantly positive, indicating that the impact of economic development and energy structure on each quantile of the EEF is positive and significant. With the increase of the EEF, the positive impact of economic development on it is gradually increasing, while the overall impact of energy structure on the EEF shows a downward trend.

Figure 7 and table A6 respectively show the prediction results of the impact of photovoltaic, wind energy, and biomass energy on the EEF when the control variables such as economic development, population size, per capita disposable income of residents, scientific research funds, and energy structure are 0. The results show that with the growth of photovoltaic, wind energy, and biomass energy consumption, EEF shows a downward trend in different quantiles, but the declining gap is large. The growth of photovoltaic, wind energy, and biomass energy consumption has a more obvious negative impact on the low EEF and a weaker negative impact on the high EEF.

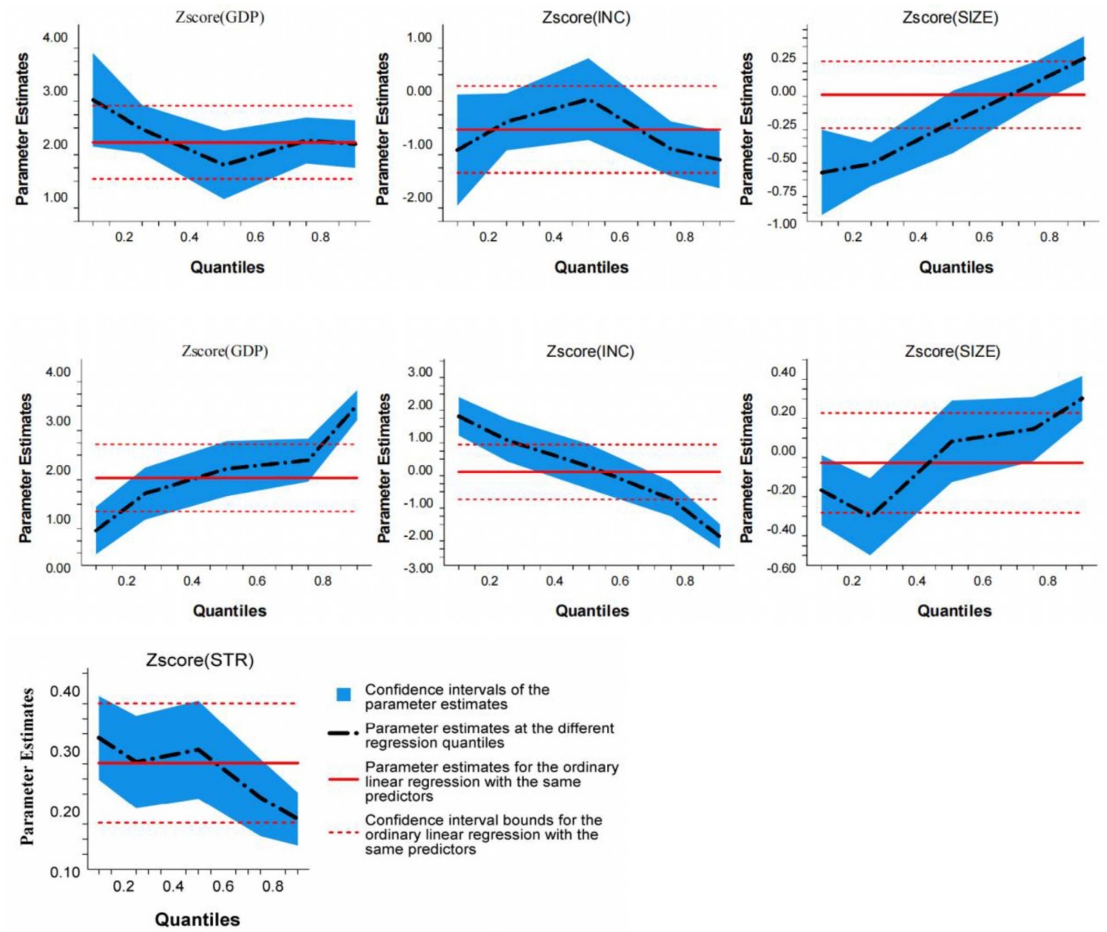

Figure 6. Plot of the estimated parameters of biomass energy.

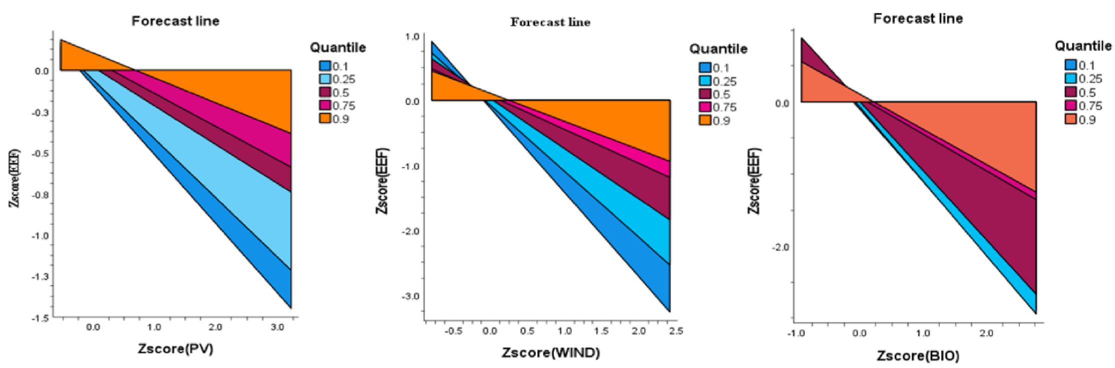

Figure 7. Prediction lines.

To sum up, photovoltaic, wind energy and biomass energy can reduce EEF by replacing fossil energy consumption, but the share of primary power and other energy in China's total primary energy production is less than 20% in 2020, so the reduction effect is limited. Simultaneously, restricted by factors such as technology, the increase in the consumption of photovoltaic, wind energy and biomass energy are lower than the increase in the EEF. Therefore, with the increase in the EEF, the reduction effect of three renewable energy consumption is gradually reducing, and the changing trend is in line with the expected results.

5. Conclusions and recommendations

The paper offers two methodologies for assessing the impact of renewable energy consumption on the EEF. The study uses the VAR model to explore the impact of economic development, population size, per capita disposable income of residents, scientific research funds, energy structure, and renewable energy consumption on the EEF. The Granger causality test shows that all variables are not the Granger causes of the EEF. The cointegration test shows that there is a long-term cointegration relationship between them. Increasing economic development, scientific research funds, energy structure, and renewable energy consumption will decrease EEF while increasing population size, and per capita disposable income of residents will increase EEF. The impulse response analysis finds that population size, energy structure, and scientific research funds have a large positive impact on the EEF, but the degree of impact decreases in turn, the positive impact of per capita disposable income of residents on the EEF first increases and then decreases, while the negative impact of economic development on the EEF becomes positive as time increases, and the negative impact of renewable energy consumption on the EEF gradually increases with time. The variance decomposition results show that the average contribution rate of the EEF to its changes is 79.19%, the average contribution rate of renewable energy consumption to EEF changes is 1.34%, economic development, population size, scientific research funds, per capita disposable income of residents, and energy structure contribute to EEF changes are 0.38%, 9.99%, 2.58%, 1.60%, and 4.91%, respectively.

In addition, the paper uses the quantile regression method to explore the impact of photovoltaic, wind energy, and biomass energy on the EEF. The results show that the impact of photovoltaic, wind energy, and biomass energy consumption on each quantile of the EEF is negative and significant, and the negative effect gradually weakens with the increase of the EEF. When economic development, population size, per capita disposable income of residents, scientific research funds, and energy structure are 0, EEF shows a downward trend in different quantiles with the growth of photovoltaic, wind energy, and biomass energy consumption. When EEF is low, the reduction effect of photovoltaic, wind energy, and biomass energy consumption on the EEF decreases the most, that is, the increase of photovoltaic, wind energy, and biomass energy consumption has a more obvious negative impact on low EEF, the negative effect of EEF is weak on high EEF, and with the increase of the EEF, the decreasing effect of three kinds of renewable energy on the EEF is wind energy, biomass energy, and photovoltaic in descending order.

To reduce EEF and promote the development of renewable energy, we consider the following suggestions: (a) Vigorously promote international cooperation in renewable energy technology, make full use of China's advantages in the market, capital, critical minerals, and some technologies, actively promote the construction of transnational power grids with neighboring countries, and support Chinese enterprises with technological advantages to go global, to improve China's market participation and recognition in the development of renewable energy in the Belt and Road region. (b) Optimizing the use of land and sea resources related to renewable energy. Do a good job in the land occupation plan for the development of clean energy such as solar energy and wind energy, and ensure the land demand for clean energy development while ensuring the safety of food arable land and the ecological environment. In addition, vigorously develop distributed photovoltaics, offshore wind energy, and other clean energy with less land and reduced land occupation. (c) Further improve the supporting policies related to the development of renewable energy, accelerate the improvement of the renewable energy power market trading mechanism, improve the consumption capacity of renewable energy through market-oriented methods, strengthen support policies for the research and development and application of energy storage technology, and improve the coordinated development guarantee mechanism and policy of renewable energy and social and natural ecological environment protection.

Data availability statement

The datasets generated during and analyzed during the current study are available in the following repositories:

- Food and Agriculture Organization of the United Nations: www.fao.org/faostat/en/#data/RL/visualize
- IEA: www.iea.org/articles/renewables-2021-data-explorer?mode=market&region=World&publication=2021&product=Total
- National Bureau of Statistics: www.stats.gov.cn/

The data that support the findings of this study are openly available at the following URL/DOI: www.fao.org/faostat/en/#data/RL/visualize. Data will be available from 28 July 2022.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author contributions

Results and discussions, Yu Nan; introduction and methodology, He Mei; literature review, Sun Yue; conclusions and recommendations, Li Yuliang; review and editing, Renjin Sun; All authors have read and agreed to the published version of the manuscript.

Appendix

Table A1. ADF unit root test results.

Variable	Test form (C,T,K)	*P*-value	Conclusion
LNEEF	(C,0,11)	0.0212	Stable**
LNGDP	(C,0,11)	0.0669	Stable*
LNINC	(C,0,11)	0.1340	Unstable
LNRD	(C,0,11)	0.5070	Unstable
LNRE	(C,0,11)	0.9483	Unstable
LNSIZE	(C,0,11)	0.8427	Unstable
LNSTR	(C,0,11)	0.8113	Unstable
D (LNEEF)	(0,0,11)	0.1359	Unstable
D (LNGDP)	(0,0,11)	0.4881	Unstable
D (LNINC)	(0,0,11)	0.5568	Unstable
D (LNRD)	(0,0,11)	0.0397	Stable**
D (LNRE)	(0,0,11)	0.4069	Unstable
D (LNSIZE)	(0,0,11)	0.3011	Unstable
D (LNSTR)	(0,0,11)	0.5276	Unstable

Table A2. Variance decomposition results.

Period	S.E.	LNEF	LNGDP	LNINC	LNRD	LNRE	LNSIZE	LNSTR
1	0.0073	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.0136	98.6823	0.0130	0.5150	0.1044	0.0155	0.2512	0.4186
3	0.0192	95.1381	0.1219	1.2804	0.5294	0.2185	1.4191	1.2926
4	0.0243	89.3527	0.3263	1.8852	1.3007	0.7277	3.9036	2.5038
5	0.0290	82.2630	0.5262	2.1950	2.2398	1.3917	7.4560	3.9284
6	0.0335	75.2052	0.6384	2.2611	3.1282	1.9553	11.3782	5.4337
7	0.0378	69.0884	0.6489	2.1885	3.8548	2.2780	15.0248	6.9167
8	0.0417	64.1995	0.5902	2.0566	4.4227	2.3691	18.0507	8.3112
9	0.0452	60.4347	0.5092	1.9064	4.8907	2.3095	20.3714	9.5781
10	0.0482	57.5482	0.4536	1.7545	5.3257	2.1800	22.0417	10.6964

Table A3. Parameter estimates at different quantiles of photovoltaics [a, b].

							95% confidence interval	
Quantile	Parameter	Coefficient	Std. Error	t	df	Sig.	Lower bound	Upper bound
0.10	Intercept	−0.0941	0.0131	−7.1833	73	<0.001	−0.1203	−0.0680
	Zscore (PV)	−0.4206	0.0422	−9.9599	73	<0.001	−0.5048	−0.3365
	Zscore (GDP)	2.7797	0.4422	6.2857	73	<0.001	1.8984	3.6610
	Zscore (SIZE)	−0.6339	0.1612	−3.9326	73	<0.001	−0.9551	−0.3126
	Zscore (INC)	−1.1629	0.5245	−2.2174	73	0.0297	−2.2082	−0.1177
	Zscore (RD)	0.5098	0.1080	4.7222	73	<0.001	0.2946	0.7250
	Zscore (STR)	0.2014	0.0629	3.2008	73	0.0020	0.076	0.3269
0.25	Intercept	−0.0591	0.0067	−8.821	73	<0.001	−0.0725	−0.0458
	Zscore (PV)	−0.3596	0.0216	−16.6432	73	0.0000	−0.4026	−0.3165
	Zscore (GDP)	2.2285	0.2262	9.8508	73	<0.001	1.7777	2.6794
	Zscore (SIZE)	−0.5700	0.0825	−6.9118	73	<0.001	−0.7343	−0.4056
	Zscore (INC)	−0.6335	0.2683	−2.3612	73	0.0209	−1.1682	−0.0988
	Zscore (RD)	0.4788	0.0552	8.6698	73	<0.001	0.3687	0.5889
	Zscore (STR)	0.2885	0.0322	8.9593	73	<0.001	0.2243	0.3526
0.50	Intercept	0.0183	0.0096	1.916	73	0.0593	−0.0007	0.0374
	Zscore (PV)	−0.2362	0.0308	−7.6602	73	<0.001	−0.2976	−0.1747
	Zscore (GDP)	1.5577	0.3229	4.8247	73	<0.001	0.9142	2.2012
	Zscore (SIZE)	−0.2542	0.1177	−2.1597	73	0.0341	−0.4887	−0.0196
	Zscore (INC)	−0.2079	0.3829	−0.5429	73	0.5888	−0.971	0.5552
	Zscore (RD)	0.3729	0.0788	4.7309	73	<0.001	0.2158	0.5300
	Zscore (STR)	0.4023	0.0459	8.7551	73	<0.001	0.3107	0.4939
0.75	Intercept	0.0597	0.0065	9.2126	73	<0.001	0.0468	0.0726
	Zscore (PV)	−0.2017	0.0209	−9.6628	73	<0.001	−0.2434	−0.1601
	Zscore (GDP)	2.0157	0.2186	9.2204	73	<0.001	1.5800	2.4514
	Zscore (SIZE)	0.0384	0.0797	0.4822	73	0.6311	−0.1204	0.1972
	Zscore (INC)	−1.1399	0.2593	−4.3966	73	<0.001	−1.6566	−0.6232
	Zscore (RD)	0.4078	0.0534	7.6405	73	<0.001	0.3014	0.5141
	Zscore (STR)	0.2707	0.0311	8.7000	73	<0.001	0.2087	0.3327
0.90	Intercept	0.1045	0.0067	15.6632	73	0.0000	0.0912	0.1178
	Zscore (PV)	−0.1521	0.0215	−7.0735	73	<0.001	−0.195	−0.1092
	Zscore (GDP)	1.9498	0.2251	8.6599	73	<0.001	1.5011	2.3985
	Zscore (SIZE)	0.2227	0.0821	2.7137	73	0.0083	0.0591	0.3863
	Zscore (INC)	−1.3436	0.2670	−5.0319	73	<0.001	−1.8757	−0.8114
	Zscore (RD)	0.4127	0.0550	7.5085	73	<0.001	0.3032	0.5223
	Zscore (STR)	0.2023	0.0320	6.3125	73	<0.001	0.1384	0.2661

Note: [a] Dependent Variable: Zscore (EEF).
[b] Model: [%1, (Intercept)].

Table A4. Parameter estimates at different quantiles of wind energy [a, b].

							95% confidence interval	
Quantile	Parameter	Coefficient	Std. Error	t	df	Sig.	Lower bound	Upper bound
0.10	Intercept	−0.1277	0.0093	−13.7514	73	0.0000	−0.1462	−0.1092
	Zscore (WIND)	−1.3015	0.0832	−15.6462	73	0.0000	−1.4673	−1.1358
	Zscore (GDP)	3.3784	0.3066	11.0174	73	0.0000	2.7673	3.9896
	Zscore (SIZE)	−0.7686	0.1142	−6.7290	73	<0.001	−0.9963	−0.5410
	Zscore (INC)	−1.0619	0.3783	−2.8072	73	0.0064	−1.8158	−0.3080
	Zscore (RD)	0.5669	0.0722	7.8539	73	<0.001	0.423	0.7107
	Zscore (STR)	−0.1553	0.048	−3.2338	73	0.0018	−0.251	−0.0596
0.25	Intercept	−0.0821	0.0125	−6.5621	73	<0.001	−0.107	−0.0571
	Zscore (WIND)	−1.0199	0.1120	−9.1041	73	<0.001	−1.2431	−0.7966
	Zscore (GDP)	2.6279	0.4129	6.3638	73	<0.001	1.8049	3.4509
	Zscore (SIZE)	−0.4558	0.1538	−2.9631	73	0.0041	−0.7624	−0.1492
	Zscore (INC)	−0.8044	0.5094	−1.5791	73	0.1186	−1.8196	0.2108
	Zscore (RD)	0.5558	0.0972	5.7182	73	<0.001	0.3621	0.7495
	Zscore (STR)	−0.0480	0.0647	−0.7429	73	0.4600	−0.1769	0.0809
0.50	Intercept	0.0232	0.0083	2.8105	73	0.0063	0.0067	0.0397
	Zscore (WIND)	−0.7749	0.0739	−10.4785	73	<0.001	−0.9222	−0.6275
	Zscore (GDP)	1.9837	0.2726	7.2770	73	<0.001	1.4404	2.5269
	Zscore (SIZE)	0.1808	0.1015	1.7808	73	0.0791	−0.0216	0.3832
	Zscore (INC)	−0.3777	0.3363	−1.1233	73	0.2650	−1.0479	0.2924
	Zscore (RD)	0.0489	0.0642	0.7617	73	0.4487	−0.079	0.1767
	Zscore (STR)	0.2159	0.0427	5.057	73	<0.001	0.1308	0.3010
0.75	Intercept	0.0693	0.0078	8.833	73	<0.001	0.0537	0.085
	Zscore (WIND)	−0.5223	0.0703	−7.4305	73	<0.001	−0.6624	−0.3822
	Zscore (GDP)	1.3531	0.2591	5.2221	73	<0.001	0.8367	1.8695
	Zscore (SIZE)	0.0056	0.0965	0.0582	73	0.9538	−0.1867	0.1980
	Zscore (INC)	−0.2856	0.3196	−0.8936	73	0.3745	−0.9226	0.3514
	Zscore (RD)	0.4918	0.061	8.0635	73	<0.001	0.3702	0.6133
	Zscore (STR)	0.1780	0.0406	4.3862	73	<0.001	0.0971	0.2589
0.90	Intercept	0.1061	0.0079	13.4700	73	0.0000	0.0904	0.1218
	Zscore (WIND)	−0.4340	0.0706	−6.1502	73	<0.001	−0.5747	−0.2934
	Zscore (GDP)	0.7550	0.2601	2.9021	73	0.0049	0.2365	1.2734
	Zscore (SIZE)	−0.0423	0.0969	−0.4366	73	0.6637	−0.2354	0.1508
	Zscore (INC)	0.1746	0.3209	0.5442	73	0.5879	−0.4649	0.8142
	Zscore (RD)	0.6024	0.0612	9.8377	73	<0.001	0.4804	0.7244
	Zscore (STR)	0.1910	0.0407	4.6889	73	<0.001	0.1098	0.2722

Note: [a]Dependent Variable: Zscore (EEF).
[b] Model: [%1, (Intercept)].

Table A5. Parameter estimates at different quantiles of biomass energy [a, b].

							95% confidence interval	
Quantile	Parameter	Coefficient	Std. Error	t	df	Sig.	Lower bound	Upper bound
0.10	Intercept	−0.1027	0.0073	−14.1382	73	0.0000	−0.1172	−0.0883
	Zscore (BIO)	−1.0072	0.0597	−16.8722	73	0.0000	−1.1262	−0.8883
	Zscore (GDP)	0.7100	0.2419	2.9353	73	0.0045	0.2279	1.1920
	Zscore (SIZE)	−0.2170	0.0896	−2.4231	73	0.0179	−0.3955	−0.0385
	Zscore (INC)	1.5636	0.2958	5.2853	73	<0.001	0.974	2.1533
	Zscore (RD)	0.1073	0.0584	1.8379	73	0.0701	−0.0091	0.2237
	Zscore (STR)	0.3180	0.0349	9.1114	73	<0.001	0.2485	0.3876
0.25	Intercept	−0.0717	0.0080	−8.9300	73	<0.001	−0.0877	−0.0557
	Zscore (BIO)	−1.0359	0.0660	−15.6986	73	0.0000	−1.1674	−0.9043
	Zscore (GDP)	1.4652	0.2673	5.4806	73	<0.001	0.9324	1.9980
	Zscore (SIZE)	−0.3514	0.0990	−3.5496	73	<0.001	−0.5487	−0.1541
	Zscore (INC)	0.8249	0.3270	2.5226	73	0.0138	0.1732	1.4766
	Zscore (RD)	0.2421	0.0645	3.7510	73	<0.001	0.1135	0.3707
	Zscore (STR)	0.2780	0.0386	7.2049	73	<0.001	0.2011	0.3549
0.50	Intercept	0.0049	0.0085	0.5741	73	0.5677	−0.0121	0.0218
	Zscore (BIO)	−0.9643	0.0699	−13.8020	73	0.0000	−1.1035	−0.8251
	Zscore (GDP)	1.9700	0.2831	6.9592	73	<0.001	1.4058	2.5342
	Zscore (SIZE)	0.0322	0.1048	0.3076	73	0.7593	−0.1767	0.2411
	Zscore (INC)	0.0215	0.3462	0.0620	73	0.9508	−0.6686	0.7115
	Zscore (RD)	0.0673	0.0683	0.9844	73	0.3282	−0.0689	0.2035
	Zscore (STR)	0.2984	0.0409	7.3053	73	<0.001	0.2170	0.3799
0.75	Intercept	0.0627	0.0067	9.3761	73	<0.001	0.0493	0.0760
	Zscore (BIO)	−0.5113	0.0549	−9.3129	73	<0.001	−0.6208	−0.4019
	Zscore (GDP)	2.1460	0.2225	9.6465	73	<0.001	1.7026	2.5893
	Zscore (SIZE)	0.0953	0.0824	1.1563	73	0.2513	−0.0689	0.2594
	Zscore (INC)	−0.9605	0.2721	−3.5299	73	<0.001	−1.5028	−0.4182
	Zscore (RD)	0.346	0.0537	6.4419	73	<0.001	0.2389	0.4530
	Zscore (STR)	0.2188	0.0321	6.8164	73	<0.001	0.1549	0.2828
0.90	Intercept	0.1080	0.0046	23.5424	73	0.0000	0.0989	0.1172
	Zscore (BIO)	−0.4904	0.0377	−13.0071	73	0.0000	−0.5656	−0.4153
	Zscore (GDP)	3.2740	0.1528	21.4307	73	0.0000	2.9695	3.5784
	Zscore (SIZE)	0.2526	0.0566	4.4656	73	<0.001	0.1399	0.3653
	Zscore (INC)	−2.1202	0.1869	−11.3464	73	0.0000	−2.4926	−1.7478
	Zscore (RD)	0.2113	0.0369	5.7303	73	<0.001	0.1378	0.2849
	Zscore (STR)	0.1832	0.0220	8.3096	73	<0.001	0.1393	0.2271

Note: [a] Dependent Variable: Zscore (EEF).
[b] Model: [%1, (Intercept)].

Table A6. Prediction table [a, b, c].

Zscore (PV)	$q = 0.1$	$q = 0.25$	$q = 0.5$	$q = 0.75$	$q = 0.9$
−0.5286801	0.1282	0.131	0.1432	0.1663	0.1849
3.2227373	−1.4498	−1.218	−0.7429	−0.5905	−0.3857
Zscore (WIND)	$q = 0.1$	$q = 0.25$	$q = 0.5$	$q = 0.75$	$q = 0.9$
−0.7953	0.9074	0.7290	0.6395	0.4847	0.4513
2.4143	−3.2700	−2.5443	−1.8475	−1.1916	−0.9417
Zscore (BIO)	$q = 0.1$	$q = 0.25$	$q = 0.5$	$q = 0.75$	$q = 0.9$
−0.9187	0.8226	0.8799	0.8908	0.5324	0.5586
2.7728	−2.8956	−2.944	−2.669	−1.3552	−1.2519

[a] Dependent Variable: Zscore (EEF).
[b] Model: [%1, (Intercept)].
[c] Predictions in the model are evaluated at Zscore (GDP) = 0.0000000, Zscore (SIZE) = 0.0000000.
Zscore (INC) = 0.0000000, Zscore (RD) = 0.0000000, Zscore (STR) = 0.0000000.

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References

Abid M, Gheraia Z and Abdelli H 2022 Does renewable energy consumption affect ecological footprints in Saudi Arabia? A bootstrap causality test *Renew. Energy* **189** 813–21
Afridi M A, Kehelwalatenna S, Naseem I and Tahir M 2019 Per capita income, trade openness, urbanization, energy consumption, and CO_2 emissions: an empirical study on the SAARC region *Environ. Sci. Pollut. Res.* **26** 29978–90
Ahmed Z, Caglar A E and Murshed M 2022 A path towards environmental sustainability: the role of clean energy and democracy on ecological footprint of Pakistan *J. Clean. Prod.* 132007
Al-Mulali U, Weng-Wai C, Sheau-Ting L and Mohammed A H 2015 Investigating the environmental Kuznets curve (EKC) hypothesis by utilizing the ecological footprint as an indicator of environmental degradation *Ecol. Indic.* **48** 315–23
Ali Q, Yaseen M R, Anwar S, Makhdum M S A and Khan M T I 2021 The impact of tourism, renewable energy, and economic growth on ecological footprint and natural resources: a panel data analysis *Resour. Policy* **74** 102365
Ansari M A, Haider S and Masood T 2021 Do renewable energy and globalization enhance ecological footprint: an analysis of top renewable energy countries? *Environ. Sci. Pollut. Res.* **28** 6719–32
Bekun F V, Alola A A and Sarkodie S A 2019b Toward a sustainable environment: nexus between CO_2 emissions, resource rent, renewable and nonrenewable energy in 16-EU countries *Sci. Total Environ.* **657** 1023–9
Bekun F V, Emir F and Sarkodie S A 2019a Another look at the relationship between energy consumption, carbon dioxide emissions, and economic growth in South Africa *Sci. Total Environ.* **655** 759–65
Bildirici M E *et al* 2016 Environmental pollution, hydropower energy consumption and economic growth: evidence from G7 countries *Renew. Sustain. Energy Rev.* **75** 68–85
Bildirici M E, Castanho R A, Kayıkçı F and Genç S Y 2022 ICT, energy intensity, and CO_2 emission nexus *Energies* **15** 4567
Biswas A K and Tortajada C 2019 Water quality management: a globally neglected issue *Int. J. Water Res. Dev.* **35** 913–6
Bulut U 2017 The impacts of non-renewable and renewable energy on CO_2 emissions in Turkey *Environ. Sci. Pollut. Res.* **24** 15416–26
Çakmak E E and Acar S 2022 The nexus between economic growth, renewable energy and ecological footprint: an empirical evidence from most oil-producing countries *J. Clean. Prod.* **352** 131548
Chen Y, Lee C C and Chen M 2021 Ecological footprint, human capital, and urbanization *Energy Environ.* **33** 487–510
Chen Y, Wang Z and Zhong Z 2019 CO_2 emissions, economic growth, renewable and non-renewable energy production and foreign trade in China *Renew. Energy* **131** 208–16
Cui L, Weng S, Nadeem A M, Rafique M Z and Shahzad U 2022 Exploring the role of renewable energy, urbanization and structural change for environmental sustainability: comparative analysis for practical implications *Renew. Energy* **184** 215–24
Destek M A and Sinha A 2020 Renewable, non-renewable energy consumption, economic growth, trade openness and ecological footprint: evidence from organisation for economic co-operation and development countries *J. Clean. Prod.* **242** 118537
Feng Z and Wu J 2011 Relationship between the ecological footprint and the economic growth in China *2011 Int. Conf. on Remote Sensing, Environment and Transportation Engineering* (IEEE) pp 6205–11
Gokmenoglu K K, Taspinar N and Rahman M M 2021 Military expenditure, financial development and environmental degradation in Turkey: a comparison of CO_2 emissions and ecological footprint *Int. J. Finance Econ.* **26** 986–97
Gupta M, Saini S and Sahoo M 2022 Determinants of ecological footprint and PM2.5: role of urbanization, natural resources and technological innovation *Environ. Challenges* **7** 100467
Hadj T B 2021 Nonlinear impact of biomass energy consumption on ecological footprint in a fossil fuel–dependent economy *Environ. Sci. Pollut. Res.* **28** 69329–42
Hassan S T, Baloch M A, Mahmood N and Zhang J 2019b Linking economic growth and ecological footprint through human capital and biocapacity *Sustain. Cities Soc.* **47** 101516
Hassan S T, Xia E, Khan N H and Shah S M A 2019a Economic growth, natural resources, and ecological footprints: evidence from Pakistan *Environ. Sci. Pollut. Res.* **26** 2929–38
Inglesi-Lotz R and Dogan E 2018 The role of renewable versus non-renewable energy to the level of CO_2 emissions a panel analysis of sub-Saharan Africa's 10 electricity generators *Renew. Energy* **123** 36–43
Ke H, Yang W, Liu X and Fan F 2020 Does innovation efficiency suppress the ecological footprint? Empirical evidence from 280 Chinese cities *Int. J. Environ. Res. Public Health* **17** 6826
Koenker R and Bassett J G 1978 Regression quantiles *Econometrica* **46** 33–50
Koenker R and Park B J 1996 An interior point algorithm for nonlinear quantile regression *J. Econ.* **71** 265–83
Kongbuamai N, Bui Q and Nimsai S 2021 The effects of renewable and nonrenewable energy consumption on the ecological footprint: the role of environmental policy in BRICS countries *Environ. Sci. Pollut. Res.* **28** 27885–99
Kongbuamai N, Zafar M W, Zaidi S A H and Liu Y 2020 Determinants of the ecological footprint in Thailand: the influences of tourism, trade openness, and population density *Environ. Sci. Pollut. Res.* **27** 40171–86
Kumar R R and Stauvermann P J 2019 The effects of a revenue-neutral child subsidy tax mechanism on growth and GHG emissions *Sustainability* **11** 2585
Li X, Xiao L, Tian C, Zhu B and Chevallier J 2022 Impacts of the ecological footprint on sustainable development: evidence from China *J. Clean. Prod.* **352** 131472
Liu L Y, Zheng J, Li G and Wang Y 2019 Regional scale dynamic prediction of energy ecological footprint and its influencing factors *Int. J. Environ. Prot. Policy* **7** 17
Liu X *et al* 2022 Analysis of asymmetries in the nexus between bioenergy and ecological footprint: evidence from European economies *Biomass Bioenergy* **167** 106605
Long X, Naminse E Y, Du J and Zhuang J 2015 Nonrenewable energy, renewable energy, carbon dioxide emissions and economic growth in China from 1952 to 2012 *Renew. Sustain. Energy Rev.* **52** 680–8
Nathaniel S P 2021 Ecological footprint, energy use, trade, and urbanization linkage in Indonesia *GeoJournal* **86** 2057–70
Pata U K 2021 Renewable and non-renewable energy consumption, economic complexity, CO_2 emissions, and ecological footprint in the USA: testing the EKC hypothesis with a structural break *Environ. Sci. Pollut. Res.* **28** 846–61

Pata U K and Samour A 2022 Do renewable and nuclear energy enhance environmental quality in France? A new EKC approach with the load capacity factor *Prog. Nucl. Energy* **149** 104249

Rahman M M 2020 Environmental degradation: the role of electricity consumption, economic growth and globalization *J. Environ. Manage.* **253** 109742

Sarkodie S A and Strezov V 2019 Effect of foreign direct investments, economic development and energy consumption on greenhouse gas emissions in developing countries *Sci. Total Environ.* **646** 862–71

Shahzad U, Fareed Z, Shahzad F and Shahzad K 2021 Investigating the nexus between economic complexity, energy consumption and ecological footprint for the United States: new insights from quantile methods *J. Clean. Prod.* **279** 123806

Sharif A, Meo M S, Chowdhury M A F and Sohag K 2021 Role of solar energy in reducing ecological footprints: an empirical analysis *J. Clean. Prod.* **292** 126028

Sharma R, Sinha A and Kautish P 2020 Examining the impacts of economic and demographic aspects on the ecological footprint in South and Southeast Asian countries *Environ. Sci. Pollut. Res.* **27** 36970–82

Solarin S A and Bello M O 2018 Persistence of policy shocks to an environmental degradation index: the case of ecological footprint in 128 developed and developing countries *Ecol. Indic.* **89** 35–44

Tyler S and Fajber L 2009 Land and water resource management in Asia: challenges for climate adaptation *International Institute for Sustainable Development* **13** 20093177721 (available at: www.iisd.org/pdf/2009/asia_bac)

Venetoulis J and Talberth J 2010 Refining the ecological footprint *Sustainable Development* (Boca Raton, FL: CRC Press) pp 83–120

Wackernagel M and Rees W 1996 *Our Ecological Footprint: Reducing Human Impact on the Earth* vol 9 (Canada: New society publishers)

Wackernagel M and Yount J D 1998 The ecological footprint: an indicator of progress toward regional sustainability *Environ. Monit. Assess.* **51** 511–29

Wu J and Bai Z 2022 Spatial and temporal changes of the ecological footprint of China's resource-based cities in the process of urbanization *Resour. Policy* **75** 102491

Yousaf U S, Ali F, Aziz B and Sarwar S 2022 What causes environmental degradation in Pakistan? Embossing the role of fossil fuel energy consumption in the view of ecological footprint *Environ. Sci. Pollut. Res.* **29** 1–11

Zafar M W, Mirza F M, Zaidi S A H and Hou F 2019 The nexus of renewable and nonrenewable energy consumption, trade openness, and CO_2 emissions in the framework of EKC: evidence from emerging economies *Environ. Sci. Pollut. Res.* **26** 15162–73

Zaidi S A H, Hou F and Mirza F M 2018 The role of renewable and non-renewable energy consumption in CO_2 emissions: a disaggregate analysis of Pakistan *Environ. Sci. Pollut. Res.* **25** 31616–29

Zeraibi A, Balsalobre-Lorente D and Murshed M 2021 The influences of renewable electricity generation, technological innovation, financial development, and economic growth on ecological footprints in ASEAN-5 countries *Environ. Sci. Pollut. Res.* **28** 51003–21

Zou Y F 2010 Empirical analysis of the impact of technological progress on the efficiency of China's energy ecological footprint *Sci. Sci. Manage. Sci. Technol.* **31** 53–59