Economic Research-Ekonomska Istraživanja

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rero20

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To cite this article: Gengcan Zhu, Jiangquan Wang & Yuping Shang (2023) Revisiting economic growth and environment: evaluating the role of research and development for China, Economic Research-Ekonomska Istraživanja, 36:1, 2114922, DOI: 10.1080/1331677X.2022.2114922

To link to this article: https://doi.org/10.1080/1331677X.2022.2114922

Published online: 09 Sep 2022.

ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA
2023, VOL. 36, NO. 1, 2114922
https://doi.org/10.1080/1331677X.2022.2114922

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Taylor & Francis Group

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Revisiting economic growth and environment: evaluating the role of research and development for China

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ABSTRACT

One of the most alarming issues of the current times is the increasing level of carbon emissions and the depletion of Ozone layer, which is due to the increased fossil fuel usage. Scholars and governors are paying more attention towards identifying the factors and remedial measures of environmental degradation. The current study aims to analyse the influence of economic growth, research and development (R.D.D.), renewable electricity output (R.E.O.), and technological innovation (T.I.) on the carbon emissions in China throughout 1988–2021. This study uses the time series approach, that unveils the stationarity of variables, and the existence of cointegration between the variables. Due to the issue of data non-normality, this study uses the novel method of moment quantile regression (M.M.Q.R.). The estimated results asserted that economic growth and R.D.D. are the significant factors of increased carbon emission level in the country. On the other hand, renewable electricity is found adversely affecting the carbon emissions level. Also, the T.I. is found negative, but insignificantly affecting the carbon emission level of the country. These results are found robust by using the novel Bootstrap quantile regression (B.S.Q.R.). The empirical results suggest the constriction policies that could consider the increased investment in environmental-related R.D.D, T.I., and renewable energy sector to attain sustainable development.

ARTICLE HISTORY
Received 28 March 2022
Accepted 15 August 2022

KEYWORDS
environmental quality; economic growth; carbon emission; renewable electricity output (R.E.O.); research and development (R.D.D.); method of moment quantile regression (M.M.Q.R.)

JEL CODES
F64; P18; O3; O44

1. Introduction

Climate change is the biggest challenge that the contemporary world is confronting. The rise in global temperature has not only altered human lives but also profoundly affected the earth's sustainability. The industrial uprising has revolutionised the world nonetheless also caused increasing harmful greenhouse gases (G.H.G.) and CO_2 emissions. The emissions increased by more than 40% over the amount recorded in the 1970s (İnal

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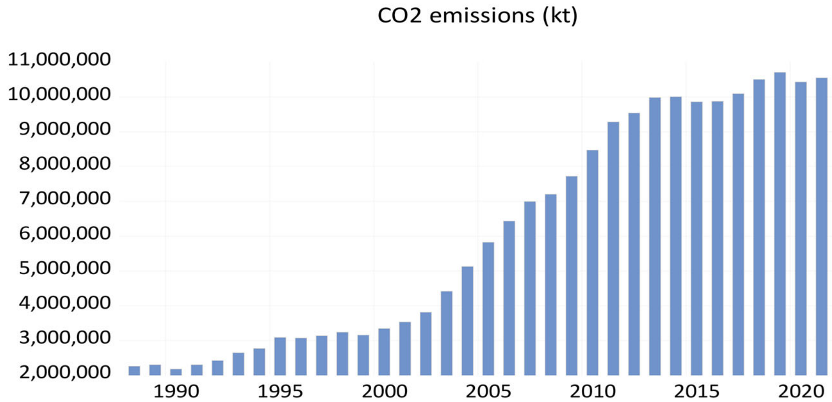

Figure 1. Carbon emissions (kt) in China. Source: World Bank.

et al., 2022). Besides, China lies among the top CO_2 emitting nations. China is an emerging developed nation with a fast-growing economy. The increased industrialisation has affected its citizens but also affected the world environmentally. The environmental concerns increased from 1.05 (million) in 2011 to approximately 1.77 (million) in 2015. However, the escalating air pollution and climatic concerns in China, the country has pledged in Paris Agreement to reduce emissions and achieve carbon neutrality by the year 2060. Further, collaborated with other developed nations and international organisations to abate emissions globally (Maizland, 2021). Now, economic and environmental sustainability has become the top priority of all nations worldwide (Zhao, Ma et al., 2022). Thus, the research inspects the potential of economic growth, renewable electricity, technological innovation (T.I.), and R.D.D. expenses in reducing carbon emissions.

In 2005, the U.S.A. was the top emitter under climate watch, while in the last few years, China has had the highest emission level after the U.S. In Figure 1, the CO_2 emissions in China are presented graphically. Over the past years, the emissions exaggerated and disturbed the sustainability of the country globally. According to the World Bank, China emitted 11,680.4 (mt) of CO_2 emissions in the year 2020 alone, as shown in the graph below. Like other economies, China will also suffer from climate change due to these carbon discharges caused by increasing economic development (Chen et al., 2022). The Chinese economy has risen by almost on average 10% annually over a decade which is the chief reason behind growing carbon emissions (Maizland, 2021). The annual G.D.P. in China shows a positive trend over the past decades as presented in Figure 2 below. In the year 2021, the annual G.D.P. of China increased by almost 20% from the previous year 2020. The G.D.P. recorded in 2021 and 2020 is $17734 billion and $14688 billion, respectively (Macrotrends, 2022).

In Figure 3, the research and development (R.D.D.) expenditures of China are picturised. The country spends millions of dollars in the R.D.D. sector; the increasing trend can be seen in the graph. However, recently China has further increased R.D.D. spending and touched 2.79 trillion Yuan in 2021 (NBS, 2022). The R.D.D. has a noteworthy influence on environmental quality (Safi et al., 2021). Likewise, renewable energy also has a significant role in affecting the environment (Ehigiamusoe & Dogan, 2022; Zhao, Ramzan, et al., 2022). Besides, the renewable transition in China

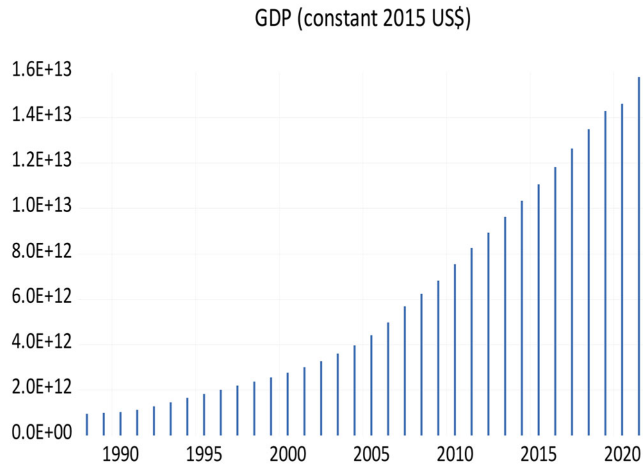

Figure 2. G.D.P. in China. Source: World Bank.

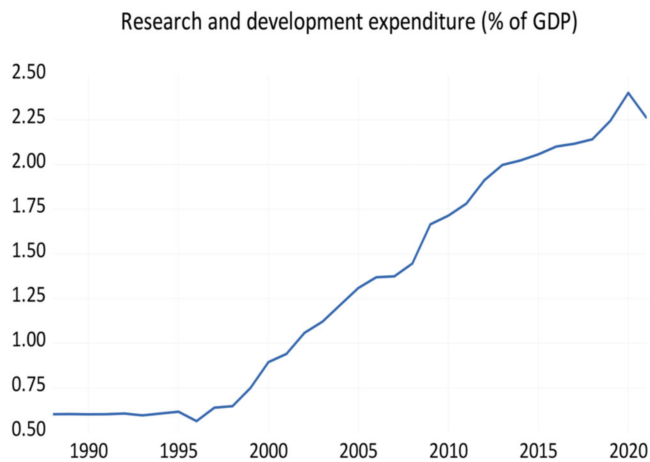

Figure 3. R.D.D. expenditures in China. Source: World Bank.

is critical in the country, which is depicted in Figure 4 above. Attributable to cumulative emissions, the transition towards renewable is tricky. In 2019, the country improved by almost utilising 15% of the energy mix as renewables (Maizland, 2021). The increasing pollutions cause millions of deaths across the world, including in China, becoming a threat to health, economy, and environment. Hence, based on the research requirements, the study appraises the determinants of CO_2 emissions in China with improved data set.

The current research attempts to examine the following set of objectives.

- First, the study re-visits the economic growth and environmental nexus in China. The authors used economic growth and carbon (CO_2) emissions to accomplish this objective.
- Second, the role of renewable energy is analysed on CO_2 emissions. For this, renewable electricity output (R.E.O.) is employed for the examination.

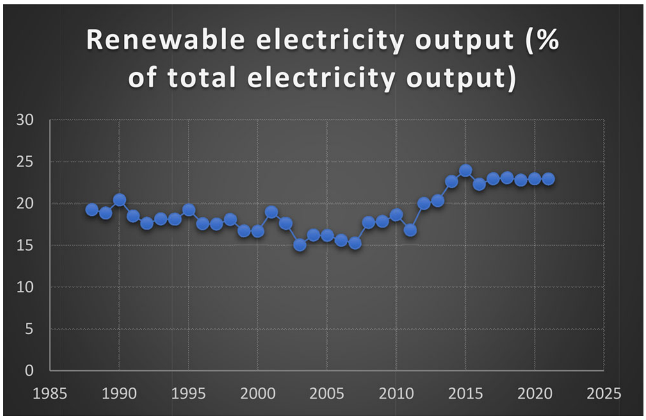

Figure 4. Renewable electricity in China.

- Third, the study assesses the nexus between T.I. and R.D.D. expenditures on carbon emissions. To fulfill these purposes, the study employs innovative modern econometric analysis.

The motivation behind the study is to evaluate the economic growth and environmental connection. The possible association between growth and the environment is still debatable in literature, inspiring scholars and researchers to scrutinise the relationship. Further, on the effect of growth on CO_2 emissions, positive and negative effects are reported in the literature (Chen et al., 2022; Jiang, Sakhare, et al., 2022) depending on various factors, which makes it interesting to re-examine the relationship. Second, the influence of R.D.D. expenditure and residential/non-residential needs more literature pragmatically. Over the years, R.D.D. expenses have escalated in the economy. Hence, the current study inspires us to assess the relationship between R.D.D. and environmental quality.

Firstly, the study contributes to the literature by providing additional empirical evidence on the growth environment nexus alongside other explanatory variables' role in improving environmental quality. Economic activities have a significant impact on environmental quality. Several authors have mentioned the negative impression. However, growth is a necessary prerequisite to obtaining sustainable growth. Therefore, the study is essential in contributing to the empirical literature. Renewable electricity is of vital importance currently and in the future in decreasing emissions. Therefore, the empirical evidence might be beneficial in strategising and policies in providing cheap renewable electricity in vulnerable regions of the country. Moreover, the role of R.D.D. expenditure is useful in curbing carbon emissions. In most economies around the world, R.D.D. does not have any noteworthy impact. However, a few show the momentous effect of R.D.D. expenses on carbon emissions (Petrović & Lobanov, 2020; Zhao, Shang, et al., 2022). Thus, the study signifies the scrutiny of R.D.D. on CO_2 emissions. Additionally, technological progress or patents help in improving environmental quality. Hence, assessing the relationship in the Chinese economy, and the top world emitter is pertinent. It is utterly substantial to re-visit the determinants of CO_2 emissions in China. Our research extends the literature on the importance of renewable energy consumption. As an important policy implication, it hopes to boost the production of renewable electricity for limiting carbon emissions in China as well as in other parts of the world. Lastly, the study contributes to analysing the above said linkages in the updated and long data period of three decades from 1988 to 2021 that has not been considered according to available knowledge in the literature.

After the introduction part, the next specific segment presents the review of the relevant literature concerning connections of the study variables. Later, Section 3 elaborates on the model and methodology of the study. The results and their discussion is presented in Section 4 of the manuscript. The conclusion and relevant policy implications are documented in Section 5.

2. Literature evaluation

2.1. Carbon emissions and economic growth

In the present body of knowledge, economic growth positively impacts carbon emissions. Increasing economic activities increases the emissions of harmful gases in an economy. For instance, in the case of China, Zou and Zhang (2020) examined the impact of economic growth on carbon dioxide emissions using the Spatial Durbin model from 2000 to 2017. The results depicted that economic growth is a positive driving force for the emissions of carbon. Likewise, using panel statistical analysis, Osadume (2021) observed the positive causal impact of economic growth on carbon emissions from 1980 to 2019 in six West African economies. The influence of economic growth on environmental quality has received much attention. Kais and Sami (2016) inspected the effect of economic growth on carbon emissions using panel econometric analysis from 1990 to 2012. The results demonstrated the positive influence of economic growth on emissions of carbon. Saidi and Omri (2020) presented a bidirectional causal association in the long- and short-run. Sun et al. (2022) validated the environmental Kuznets hypothesis and declared economic growth's positive impact on the M.E.N.A. region's carbon emissions. In the case of B.R.I.C.S. economies from 1990 to 2019, Chen et al. (2022) analysed the positive impact of economic growth on carbon emissions with a bi-directional causal relationship. Though in the case of Pakistan, Sufyanullah et al. (2022) observed a one-way directional causal relationship between economic growth and carbon emissions in the short run. Another study observed a positive and significant relationship between economic growth and carbon emissions (Raihan & Tuspekova, 2022). The results depicted that increasing economic growth deteriorates environmental quality by increasing emissions in the Malaysian economy. However, cumulative renewable energy consumption aids in limiting emissions. In divergence, Acheampong (2018) investigated the heterogeneous influence of economic growth on carbon emissions. At the global level and Caribbean-Latin America, economic growth negatively causes carbon emissions while other than these there is no causal relationship exists. Further, the carbon emissions positively affect the economic growth in the economies. Aye and Edoja (2017) examined developing economies by applying a dynamic panel threshold analysis besides discovering the negative impact of economic growth on carbon emissions in low regime economies while the positive impact in high regime economies.

2.2. Role of renewable energy in CO_2 emissions

Renewable energy has a substantial role in limiting harmful radiations of carbon. Saidi and Omri (2020) investigated 15 renewable energy consumption economies and the results depicted that the increasing consumption of renewable energy significantly decreases the carbon emissions in those economies. Vector error correlation method and fully modified least square method are applied for scrutiny of variable association and its efficiency. The causality analysis showed bidirectional causal association in the short run while no causal relationship exists in the long run of renewable consumption countries. In Chile, Kirikkaleli et al. (2022) showed a negative influence of renewable energy consumption on carbon emissions. Further, investment in low carbon technologies and R.D.D. can support reducing emissions. Moreover, Wang and Dong (2022) detected a significant negative influence of renewable energy consumption in reducing G.H.G. and carbon emissions. Likewise, Sun et al. (2022) inspected M.E.N.A. economies, the empirical findings demonstrated a negative relationship between renewable energy consumption on CO_2 emissions. For that reason, the improvement in renewable energy development leads to renewable consumption mitigating the impact on carbon dioxide emissions (Zheng et al., 2021). Also, Azam et al. (2021) inspected the inverse relationship between renewable energy consumption and carbon dioxide emissions. The encouraging consumption of renewable energy has a substantial negative impact on CO_2 emissions in the top ten emitter countries. In the case of Turkey, the negative influence of renewable energy consumption on carbon emissions is observed (Adebayo, Oladipupo, et al., 2022). However, Adebayo, Rjoub, et al. (2022) asymmetric influence of renewable energy consumption on carbon emissions was discovered. Among them, the majority quantile showed a negative correlation between renewable energy consumption and CO_2 emissions in the Swedish economy. Similarly, the mitigating impact of renewable energy consumption on carbon emissions is depicted in another recent novel study. The improvement in consumption of renewable positively affects the environmental quality in low-income economies (Ehigiamusoe & Dogan, 2022). Further, Acheampong et al. (2019) inspected similar results in sub-Saharan African nations.

Qin et al. (2021) examined the role of renewable electricity consumption in limiting CO_2 emissions. The study emphasised that achieving carbon neutrality targets the increasing usage of renewable electricity is crucial. Murshed et al. (2022) investigate that the combined effect of foreign direct investment on renewable electricity significantly reduces carbon emissions in the economy. Li et al. (2021) also discovered a significant relationship between renewable energy electricity and CO_2 emissions in the short and long run. The findings depicted an inverse linkage between the variables. For that reason, renewable electricity supports in reduction of carbon emissions by achieving neutrality targets (Zheng et al., 2021).

2.3. Nexus between T.I., R.D.D., and CO_2 emissions

T.I. has a substantial impact on mitigating carbon emissions. Huang et al. (2021) empirically examined the role of energy patents in limiting carbon dioxide emissions. T.I. substantially limits the emissions of carbon in B.R.I.C.S. nations (Khan et al., 2020). Salem et al. (2021) investigated that residential and non-residential patents (T.I.) negatively influence carbon emissions. Du et al. (2019) investigated 71 sets of economies in panel data analysis. The empirical results from patent data demonstrated that increasing T.I. significantly reduces emissions of carbon. Likewise, Erdoğan et al. (2020) revealed that increasing residential patents substantially reduces carbon emissions in the industrial sector. However, increasing patent innovation in the construction sector increases the emissions in the G20 economy. Raihan et al. (2022) also observed the mitigating impact of T.I. as residential and non-residential patents on carbon emissions. Similarly, in another recent study, Mo (2022) detected the negative impact of T.I. on CO_2 emissions in the case of Korean firms.

Jiang, Chishti, et al. (2022) inspected that increasing R.D.D. expenses substantially worsens the environmental quality by increasing carbon emissions. However, in Turkey from 1990 to 2020 the econometric analysis demonstrated that R.D.D. expenditures substantially limit carbon emissions (Kilinc-Ata, 2022). In the industrial sectors in China, Yang and Liu (2022) observed that increasing R.D.D. expenditures aids in mitigating emissions. Likewise, in G7 economies, Safi et al. (2021) significantly reduce carbon emissions. Similarly, Shahbaz et al. (2020) examined reducing the impact of R.D.D. expenses on carbon emissions.

3. Data and methodology

3.1. Data and model development

Following the study's objective and literature discussed in the previous section, this study considers carbon dioxide (CO_2) emission as a proxy for environmental degradation. However, in order to analyse the role of economic growth, this study uses the gross domestic product (G.D.P.), which indicates the health of an economy. Besides, this study also considers the role of R.D.D. in environmental quality. In addition, R.E.O., and T.I. are added as control variables. Data for the selected variables is extracted from a reliable source covering China's extended period from 1988 to 2021. The variables' unit and data source is presented in Table 1.

Following the study of Adebayo, Oladipupo, et al. (2022), this study developed the following model:

$$CO2_t = \beta_0 + \alpha_1 GDP_t + \alpha_2 RDD_t + \alpha_3 REO_t + \alpha_4 TI_t + \varepsilon_t \tag{1}$$

where the above equation reveals that β_0 is the intercept, $\alpha_1,\ \alpha_2,\ \alpha_3,$ and α_4 are the coefficients for GDP, RDD, REO, and IT, respectively. The t in the subscript indicates the time period (1988–2021), while the random error of the model is captured by vector ε.

Table 1. Variable's unit and data source.

Variable	Unit	Data source
CO_2	kilo ton (kt)	https://databank.world-bank.org/source/world-development-indicators
GDP	Constant US$ 2015 prices	
RDD	Percentage of GDP	
REO	Percent of total electricity output	
TI	Patents by residents and non-residents	

3.2. Estimation strategy

This study analysed descriptive statistics for the researched variables in order to present a far more thorough perspective of the time series data. The quantitative approach, for instance, includes the mean, median, and range (lowest and highest) of data values. This study also explores the standard deviation of the attribute, which indicates the fragility of the periodic variable by illustrating the scattering of data from the general mean. In addition, two normality indicators are used to evaluate the distributional features of the data. In particular, skewness and Kurtosis have been employed to determine if the distribution of a variable fits the normalcy criterion. Skewness and Kurtosis nonetheless give reliable information regarding the variables' dispersion. Nonetheless, this study addresses the topic of normalcy with greater clarity. The current study used the Jarque and Bera (1987) normality approximation, which evaluates both excess Kurtosis and skewness and maintains their critical values at zero, hence verifying the hypothesis that the variable is normally distributed. Below is the Jarque-Bera equation for normality:

$$JB = N.\frac{1}{6}\left(S^2 + \frac{(K-3)^{\ 2}}{4}\right), \tag{2}$$

After testing the normality of the variables, this study examines the presence of the unit root. In this context, the current study uses the Augmented Dickey-Fuller unit root test, which is a traditional unit root estimator and is considered as a powerful econometric tool in terms of identifying the unit root in the time series. It may be possible that not all the variables are stationary at level. Therefore, this test could also be used on the data at first difference.

After establishing the stationarity of the time series, the long-term relationship between variables is studied. The Bayer-Hanck combined cointegration test, which combines the cointegration testing methodologies of Engle and Granger (1987), Johansen (1991), Banerjee et al. (1998), and Boswijk (1994), was applied to evaluate the cointegration relationship between the research variables. Nevertheless, if the preceding approaches are executed independently, the reliability coefficient of the cointegration test may provide wrong predictions (Shahbaz et al., 2018). We used the combined cointegration testing methods outlined by Bayer and Hanck (2009) for enhanced cointegration analysis and to prevent unclear or misleading computations. This test combines all previously published cointegration tests using Fisher's F-statistics and provides reasonable results (Shahbaz et al., 2018). Moreover, this evaluation requires a distinct sequence of integration, i.e., I(1). This test implies the variables under investigation are not cointegrated. The statement may be refused, however, if the predicted values exceed the specified threshold. This section describes Fisher's formula for Bayer-Hanck cointegration, given as:

$$EG - J = -2\left[\ln(P_{EG}) + \ \ln(P_J)\right], \tag{3}$$

$$EG - J - Ba - Bo = -2\left[\ln(P_{EG}) + \ \ln(P_J) + \ln(P_{Ba}) + \ln(P_{Bo})\right], \tag{4}$$

where P EG, P j, P Ba, and P Bo are the probabilities for the cointegration tests conducted by Engle and Granger (1987), Johansen (1991), Banerjee et al. (1998), and Boswijk (1994), respectively.

Since the examined variables exhibited stationarity, one of the prerequisites for calculating long-run elasticities. In addition, the variables exhibit hallmarks of long-term associations. Consequently, long-run elasticity may be computed using a suitable estimating technique. Hence, this study takes into account the non-normal data distribution, necessitating the employment of a Method of Moment Quantile Regression (M.M.Q.R.) estimation technique. Koenker and Bassett, (1978) pioneered the quantile regression modelling technique for assessing the conditional variance and mean reliance for the reduction of nonlinearity difficulties. Machado and Silva (2019) have just created the innovative M.M.Q.R. method for examining the dispersion of quantile predictions based on quantile approaches, using the described approach (Sarkodie & Strezov, 2018). The formula for the conditional location-scale variance $Q_y(\tau|R)$ is as follows:

$$Y_{it} = \alpha_i + \beta R_{it} + \left(\gamma_i + \rho \acute{Z}_{it}\right)\mu_{it}, \tag{5}$$

In the above equation, the probabilistic formula $p\left(\gamma_i + \rho \acute{Z}_{it} > 0\right)$ is identical to just one, whereas, and reflects the forecasted model parameters in the current research. The subscript i signifies the fixed effect defined by the parameters α_i and γ_i which are restricted to the values $= 1, 2, \ldots, n$. However, the characteristic element of R, described by Z, is the k-vector, while the variability is marked by the vector '$\imath$'.

$$Z_{\mathbb{1}} = Z_\imath(R), \quad \imath = 1, 2, \ldots, k, \tag{6}$$

where R_{it} is autonomous and symmetrically distributed for the total fixed i and time (t), which would be orthogonal to both i and t. (Machado & Silva, 2019). Therefore, both the exterior components and reserve are steady. Based on the above reasoning, the research framework (Equation [1]) might be restated as follows:

$$Q_y(\tau R_{it}) = (\alpha_i + \gamma_i q(\tau)) + \beta R_{it} + \rho \acute{Z}_{it} q(\tau), \tag{7}$$

In the most recent study model, R_{it} represents the collection of explanatory variables, which includes GDP, RDD, REO, and TI. To describe the estimated result as a percent, all of these variables are transformed into natural logarithms, leaving them unitless and allowing for the use of percentages. In addition, R_{it} highlights the quantile distribution of the regressors, as demonstrated by Y_{it}, which in this example represents the CO_2 and is likewise dependent on the quantile position (location). In addition, the equation $-\alpha_i(\tau) \equiv \alpha_i + \gamma_i q(\tau)$ represents the vector constituent that produces the fixed influence of τ quantiles on i. However, such quantiles still had no effect on the intercept. Because of the structural independence of the variables, several outcomes are sensitive to change. Lastly, $q(\tau)$ indicates the $\tau - th$ quantile sample, which has the values $Q_{0.25}$, $Q_{0.50}$, $Q_{0.75}$, $Q_{0.80}$, and $Q_{0.85}$. Accordingly, below is the quantile equation used in this study:

$$min_q \sum_i \sum_t \theta_\tau \left(R_{it} - \left(\gamma_i + \rho \acute{Z}_{it} \right) q \right) \tag{8}$$

where $\theta_\tau(A) = (\tau - 1) \ AI\{A \leq 0\} + TAI\{A > 0\}$ reflects the expression to be evaluated.

Nonetheless, the M.M.Q.R. method gives precise projections at a certain location and scale by displaying quantile values. However, this research concentrates on evaluating the robustness of the model. Consequently, the present research used the Bootstrap Quantile Regression (B.S.Q.R.) technique. The B.S.Q.R. approach is an intermediate technique for analysing confidence intervals and significance levels. The benefit of these limitations is that they resample the data set to obtain statistical inferences while avoiding the asymptotically uniform sampling distribution limitation (Efron & Tibshirani, 1994). To be more precise, the B.S.Q.R. employs algorithmic capabilities for estimating the sampling distribution of the assessed model. In addition, this methodology enables more reliable estimating methods and empirical results (Efron & Tibshirani, 1994).

4. Results and discussion

This section covers the empirical results and their discussion in details. Initially, the current study computes the descriptive as well as the normality statistics of the given data – containing the mean, median, and range values, given in Table 2. This study observed from the empirical estimate of the stated table that the mean, median, and range values are positive. Besides, the mean value for each variable is found to be greater than the median value, which indicates the progressiveness of each variable. Specifically, the results demonstrate that along with the increase in carbon emissions, the economic growth, R.D.D. expenditure, R.E.O., and T.I. also boost in China. Since there is a significant difference between the minimum observation value and the maximum observation of the variables. Therefore, this study also estimates the standard deviation for each variable. Nonetheless, the standard deviation also reports volatility of the variable. Therefore, the results asserted that G.D.P. is the most volatile variable, followed by T.I., carbon emissions, R.E.O., and R.D.D. expenditure. Additionally, this study also provides the normality statistics in the stated table. Specifically, the skewness and Kurtosis are estimated, which provides a different value than their critical values of 1 and 3, respectively. Therefore, it could be concluded that the variables are following non-linear path of distribution. Further, this study also uses the Jarque and

Table 2. Normality and descriptive statistics.

	CO_2	GDP	RDD	REO	TI
Mean	6066543.	5.96E + 12	1.310777	18.99649	440816.0
Median	5474725.	4.19E + 12	1.261450	18.29820	151855.5
Maximum	10707220	1.58E + 13	2.400930	23.92682	1542002.
Minimum	2173360.	9.49E + 11	0.563240	15.03704	9652.000
Std. Dev.	3252541.	4.68E + 12	0.640545	2.559837	546168.3
Skewness	0.204230	0.687394	0.225626	0.471670	1.017397
Kurtosis	1.352505	2.120498	1.511000	2.085154	2.420887
Jarque-Bera	4.081529	3.773384	3.429398	2.446345	6.340658
Probability	0.129929	0.151572	0.180018	0.294295	0.041990
Observations	34	34	34	34	34

Source: Authors own estimation from the data obtained from the given source(s).

Table 3. Unit root test.

Augmented Dickey-Fuller		
Variable	I(0)	I(1)
CO_2	−1.406386	−3.028725**
GDP	−1.964145	−3.286951*
RDD	−1.529185	−4.307881***
REO	−2.060723	−7.175823***
TI	−1.186163	−5.120622***

Note: Asterisks *, **, *** denote significance of 10%, 5% and 1% levels.
Source: Authors own estimation from the data obtained from the given source(s).

Table 4. Cointegration tests.

Bayer-Hanck combined cointegration (2009)			
Engle-Granger (EG)	Johansen (J)	Banerjee (Ba)	Boswijk (Bo)
−2.9958	71.8086***	−6.9241***	145.1719***
EG-J		EG-J-Ba-Bo	
56.360482**		166.88457**	

Note: Asterisks *, **, *** denote significance of 10%, 5% and 1% levels.
Source: Authors own estimation from the data obtained from the given source(s).

Bera (1987) test of normality for a comprehensive analysis of the normality issue. The estimated results indicate that only the statistical values of T.I. exceed the critical values at $p < 0.05$. Therefore, the null hypothesis of the said test may be rejected by validating the non-normal distribution of the variable.

After the normality test, this study tends to investigate the stationarity/non-stationarity of the variables by employing the A.D.F. unit root testing approach. The empirical results of the said test is provided in Table 3. From the estimated results, this study noted that all the variables possessed a unit root when analysed the data at level [I(0)]. This reveals that the data is suffering from a severe shock(s) during the specified period of time. However, the stationarity of the data is crucial for the long-run estimation. In this context, the current study examines the unit root in CO_2, G.D.P., R.D.D., R.E.O., and T.I. at the first difference [I(1)]. At the I(1), all the non-stationary variables become stationary at $p < 0.10$, 0.05, and 0.01, which allows this research to investigate the long-run association between the variables empirically.

After validating the stationarity of the variables at I(1), this study investigate for the long-run equilibrium relationship between CO_2, G.D.P., R.D.D., R.E.O., and T.I. Particularly, the cointegration is estimated via employing the Bayer-Hanck combined cointegration test, which is more powerful by simultaneously considering the EG, J, Ba, and Bo cointegration tests. The results after estimation are portrayed in Table 4. From the estimation outcomes, this research observed that the statistical values of J, Ba, and Bo exceeds their critical values at $p < 0.01$. Also, the combined tests of EG-J and EG-J-Ba-Bo are significant at $p < 0.05$. These significant estimates lead toward rejecting the null assumption concerning no cointegration between the variables. Instead, the results demonstrate that the cointegration association exists between the said variables.

After verifying the cointegration between the variables, this study moves toward estimating the long-run coefficients via utilising the novel estimation technique. Since this study observed irregular data distribution (as mentioned in Table 2), it is essential to

Table 5. Estimates of quantile regression – MMQR.

Variable	Location	Scale	Quantiles $Q_{(25th)}$	$Q_{(50th)}$	$Q_{(75th)}$	$Q_{(80th)}$	$Q_{(85th)}$
GDP	0.260	0.256***	0.046	0.307	0.506***	0.555***	0.575***
	[0.188]	[0.098]	[0.249]	[0.204]	[0.177]	[0.178]	[0.177]
REO	−0.137	−0.085	−0.065	−0.152	−0.219*	−0.235**	−0.242**
	[0.126]	[0.066]	[0.168]	[0.1056]	[0.120]	[0.122]	[0.123]
RDD	0.407***	0.112	0.313*	0.428***	0.515***	0.537***	0.546***
	[0.132]	[0.069]	[0.167]	[0.134]	[0.124]	[0.126]	[0.127]
TI	0.080	−0.157***	0.212	0.052	−0.069	−0.100	−0.112
	[0.112]	[0.058]	[0.149]	[0.122]	[0.105]	[0.106]	[0.105]
Constant	3.154*	−2.295**	5.072**	2.738	0.959	0.517	0.340
	[1.899]	[0.991]	[2.479]	[2.022]	[1.792]	[1.807]	[1.803]

Note: The dependent variable is CO_2. Asterisks *, **, *** denote significance of 10%, 5% and 1% levels.
Source: Authors own estimation from the data obtained from the given source(s).

use an appropriate estimator that allows for the data non-normality issue. Using the novel M.M.Q.R. estimating approach, the empirical estimates are portrayed in Table 5. From the estimation output, this study noted that G.D.P. and R.D.D. expenditure enhance the CO_2 emissions level. In contrast, R.E.O. and T.I. reduce it. More specifically, the enhancement of 1% in the G.D.P. causes an increase of 0.046–0.575%, which is significant only in 75th, 80th, and 85th quantile at 1% level. It is typical for the economic expansion of emerging nations to result in a rise in CO_2 emissions due to the increased number of industries that emit CO_2 as a consequence of economic activity. Thus, negative externalities are expected to grow with rising productivity and consumption. Increased levels of economic activity are often accompanied by increased energy usage and the use of natural resources. As fossil fuels continue to make up 80% of the overall energy mix, the relationship between energy use, carbon emissions, and climate change remain strong. The environmental effect of the economic expansion comprises the increasing use of non-renewables, global warming, rising pollution levels, and the prospective loss of natural ecosystems. The empirical findings of current study are consistent with the earlier studies of Zou and Zhang (2020), Chen et al. (2022) and Raihan and Tuspekova (2022) that validates the positive influence of economic growth on environmental degradation. The empirical results suggest that an increase of 1% in R.D.D. significantly increases environmental degradation by 0.313–0.546% from lower to higher quantile. R.D.D. is an important element of a company that seeks information to create, design, and improve its goods, services, processes, or technologies. In addition to generating new goods and improving existing ones, R.D.D. investments or expenditure integrates different aspects of a company's business plan and strategies, such as cost-cutting and advertisement. R.D.D. is a key economic growth engine since it stimulates innovation, invention, and development. R.D.D. expenditures might be capital-intensive but may also result in innovations that boost earnings and customer well-being. As a matter of fact, China is an emerging economy, where most of the attention has been paid to industrial growth and economic expansion. Therefore, the R.D.D. expenditure is highly directed towards industrial growth, which further increase the energy demand and utilisation. As a result, the environmental quality is damaged via increased CO_2 emissions. Similar results can also be evident in the existing literature (see Jiang, Chishti, et al., 2022).

Table 6. Robustness – BSQR.

Variable	Quantiles				
	$Q_{(25th)}$	$Q_{(50th)}$	$Q_{(75th)}$	$Q_{(80th)}$	$Q_{(85th)}$
GDP	0.060	0.313	0.600***	0.591***	0.603***
REO	0.087	−0.227	−0.174	−0.105	−0.181
RDD	0.226	0.535**	0.544***	0.587***	0.622***
TI	0.221	0.013	−0.130	−0.135	−0.148
Constant	4.654	2.955	0.021	0.068	0.087

Note: The dependent variable is CO_2. Asterisks *, **, *** denote significance of 10%, 5% and 1% levels.
Source: Authors own estimation from the data obtained from the given source(s).

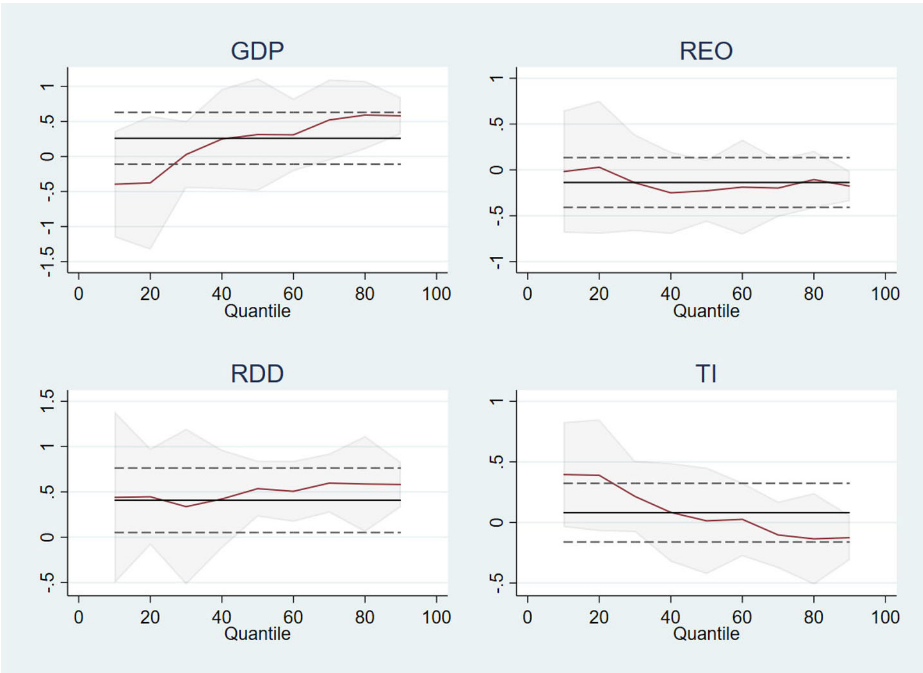

Figure 5. Graphical depiction of coefficients – BSQR.
Source: Authors own estimation from the data obtained from the given source(s).

On the other hand, the empirical results suggest that enhancing the R.E.O. increases environmental sustainability by reducing the CO_2 emissions level by 0.065–0.242%, which is significant only in the upper three quantiles. In other words, geothermal energy, solar energy, ocean wave, wind generators, tidal energy, wastes and biomass energy, and hydroelectric power are examples of renewable energy sources. As they create power, these sources of renewable energy would not discharge carbon gases into the environment since they do not consume fossil fuels. Since all these systems generate no toxic byproducts as their energy source is carbon-free, they do not produce any harmful emissions. Thus, only avoiding or replacing fossil-fuel production with renewable or non-emitting electricity generating systems will decrease atmospheric emissions. The present empirical results are found in consistency to many existing studies, such as Acheampon et al. (2019), Saidi and Omri (2020), Azam et al. (2021), Kirikkaleli et al. (2022) and Wang and Dong (2022). On the other hand, the empirical results T.I.

illustrates negative but insignificant impact on the CO_2 emissions in China. Although the impact is insignificant across the quantiles, the magnitude towards carbon emissions is still negative, demonstrating that increasing T.I. could lead to reducing the emissions level in China. Therefore, appropriate policy level attention to efficiently utilise technology in terms of environmental sustainability.

Nonetheless, the M.M.Q.R. approach provides substantial results by unveiling the specific influence of each regressor on CO_2 emissions at a specific location, scale, and quantile. Still, this study employed B.S.Q.R. to test the robustness of the model under consideration. The empirical estimates of B.S.Q.R. are portrayed in Table 6. The estimated results asserted that economic growth and R.D.D. positively affects CO_2 emissions. This validates the earlier statement that both variables are significant factors of environmental quality degradation as these sectors significantly enhance industrial activities by enhancing demand for non-renewable energy. As a result, increased emissions lead to serious environmental issues such as climate change and global warming. The findings of the B.S.Q.R. concerning these variables are statistically significant. On the other hand, the empirical results asserted that R.E.O. and T.I. are adversely affecting the CO_2 emissions in China (Khan et al., 2019). Albeit the fact that both of these variables are insignificant across the selected quantiles. Still, the impact is negative, which indicates that policy-makers could use these variables as remedial measures for environmental recovery and attaining environmental sustainability. The coefficient values for each of the study variable can also be depicted in Figure 5.

5. Conclusion and policy implications

In the current times, the issue of increased global warming and climate change has attracted scholars to identify the possible solution for emissions reduction. Nonetheless, traditional non-renewable energy consumption is a major source of increased environmental degradation. Besides, China is the leading fossil fuel energy importer globally and is also among the top pollution-emitting economies. In this sense, the current study aims to analyse the factors affecting the CO_2 emissions in China. Specifically, the study investigates the role of economic growth, R.D.D. expenditure, R.E.O., and T.I. in the CO_2 emissions from 1988 to 2021. The study uses various time series econometric approaches for empirical estimations. Among others, this study considers the issue of data non-normality more comprehensively, where it is observed that the variables adopted for empirical examination are non-normally distributed. Based on such fact, this study uses the novel M.M.Q.R. technique, which is more powerful in dealing the non-linear data. From the empirical results, this study noted that economic growth, research, and development expenditure are positively associated with China's increased environmental degradation. As a matter of fact, China is an emerging economy which is still aiming for higher economic growth via expansion of the industrial sector. However, the industrial setup is still relying on the consumption of traditional fossil fuels, which encourages the CO_2 emissions in the country. Besides, the R.D.D. are also aiming the increased output to get more revenue while ignoring the environmental quality. Therefore, these two variables are the significant factors of increased CO_2 emissions in the region. On the other hand, R.E.O. and T.I. adversely affect the CO_2 emission level. Since renewable energy is obtained from renewable natural resources, T.I. plays a major part: therefore, the energy demand of fossil fuels can be replaced by renewable energy resources. Consequently, the decreased demand and consumption of fossil fuels could reduce emissions and promote environmental sustainability.

Based on the estimated results, this study proposed policies that could benefit China in terms f environmental sustainability without sacrificing its economic growth. Specifically, economic growth is a factor in environmental degradation. Therefore, policies are suggested that could consider the higher economic as a source of increased investment in the structural transformation of the industrial sector towards environmentally-friendly energy resources. The structural transformation of the said sector could reduce the traditional fossil fuel demand and consumption, ultimately reducing the emissions level. In addition, China needs to invest more in the R.D.D. sector by aiming for environmental related R.D.D. This will promote the culture of knowledge transformation and technical development of the country, which further boosts energy efficient equipment and techniques and reduces the emissions level. Further, this study suggests China increase investment in renewable energy and T.I. sectors. As the economy is rapidly expanding in terms of economic growth. Therefore, considering these two measures could reduce dependence on fossil fuel while providing alternative energy sources to fulfill energy demand for both the industrial as well as the household. Hence, the Chinese economy could attain sustainable development and the environment by appropriately implementing such policies.

Disclosure statement

No potential conflict of interest was reported by the authors.

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