Economic Research-Ekonomska Istraživanja

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

The moderating role of technological innovation and renewable energy on CO_2 emission in O.E.C.D. countries: evidence from panel quantile regression approach

Najia Saqib, Muhammad Usman, Haider Mahmood, Shujaat Abbas, Fayyaz Ahmad, Daniela Mihai & Ray Saadaoui Mallek

To cite this article: Najia Saqib, Muhammad Usman, Haider Mahmood, Shujaat Abbas, Fayyaz Ahmad, Daniela Mihai & Ray Saadaoui Mallek (2023) The moderating role of technological innovation and renewable energy on CO_2 emission in O.E.C.D. countries: evidence from panel quantile regression approach, Economic Research-Ekonomska Istraživanja, 36:3, 2168720, DOI: 10.1080/1331677X.2023.2168720

To link to this article: https://doi.org/10.1080/1331677X.2023.2168720

Published online: 22 May 2023.

ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA
2023, VOL. 36, NO. 3, 2168720
https://doi.org/10.1080/1331677X.2023.2168720

Routledge
Taylor & Francis Group

OPEN ACCESS Check for updates

The moderating role of technological innovation and renewable energy on CO_2 emission in O.E.C.D. countries: evidence from panel quantile regression approach

Najia Saqib[a], Muhammad Usman[b], Haider Mahmood[c], Shujaat Abbas[d], Fayyaz Ahmad[e], Daniela Mihai[f] and Ray Saadaoui Mallek[g]

[a]Department of Finance, College of Business Administration, Prince Sultan University, Riyadh, Saudi Arabia; [b]Institute for Region and Urban-Rural Development, Center for Industrial Development and Regional Competitiveness, Wuhan University, Wuhan, China; [c]Department of Finance, College of Business Administration, Prince Sattam bin Abdulaziz University, Alkharj, Saudi Arabia; [d]Graduate school of Economics and Management, Ural Federal University, Yekaterinburg, Russian Federation; [e]School of Economics, Lanzhou University, Lanzhou, Gansu, PR China; [f]Department of Management and Business Administration, University of Pitesti, Pitești, Romania; [g]Department of Finance and Economics, College of Business Administration, University of Sharjah, Sharjah, UAE

ABSTRACT
This study analysed data from a panel consisting of 32 O.E.C.D. member countries for the years 1996–2020. This research explores the nexus between CO_2 emissions, G.D.P. per capita, renewable energy supply, the development of patents, and gross fixed capital formation in the context of 32 O.E.C.D. countries. Also, the panel quantile regression technique is being used to investigate potential variations in heterogeneity and asymmetry. The empirical evidence shows that technological innovation negatively impacts CO_2 emissions; however, the impact varies greatly between quantiles. This research also explores the potential for heterogeneity and asymmetry in the moderating effect of technological innovation with regards to economic growth and renewable energy. The investigation, which relied on the use of panel quantile regression, revealed that technological innovation exerts a wide variety of moderating effects. In conclusion, the study provided policy recommendations.

ARTICLE HISTORY
Received 29 September 2022
Accepted 10 January 2023

KEYWORDS
CO_2 emission; technological innovation; renewable energy; panel quantile regression; O.E.C.D. countries

JEL CLASSIFICATIONS
C31; O34; Q53; R11

1. Introduction

The 2015 United Nations Climate Change Conference (COP21) in Paris emphasised the importance of reviving public and private activities to boost the creation of greener energy sources. The O.E.C.D. countries that have signed on to this initiative have committed to further strengthening their collaboration on research and innovation initiatives with the goal of enhancing climate patterns. Since they have the largest economies and energy consumption, O.E.C.D. countries contribute disproportionately more to

CONTACT Najia Saqib nsaqib@psu.edu.sa

global warming than any other group of countries. The countries in the O.E.C.D. were responsible for about 32.50% of the world's total carbon emissions, which added up to about 10,292.73 Mt. Figure 1 shows that renewable energy accounts for 10.95% of the world's primary energy supply and also environmental technology patents are increasing at a rate of 10.43% annually (OECD, 2020).

A synergistic plan to manage excessive levels of CO_2 emissions is required in order to tackle challenges related to global warming and other vulnerabilities to the environment. It is possible that investments in innovation and technology will prove to be an efficient approach. This is due to the fact that the development of environmentally friendly innovations and technologies is necessary for the reduction of carbon emissions and the promotion of the growth of eco-friendly economic systems (Ganda, 2019; Ulucak et al., 2020). With the goal of keeping global warming well below 2 °C, the Paris Climate Change Conference (COP21) and the Paris Agreement (UNFCCC, 2015) emphasise the need to eliminate CO_2 emissions. It is evident that environmentally friendly innovations are needed to reach this goal, and activities encouraging clean energy technology through innovation processes are essential. Security of energy supply and climate change mitigation both depend on such measures, as both energy consumption and carbon emissions have been increasing rise in recent years (Erdoğan et al., 2021; Wang et al., 2012).

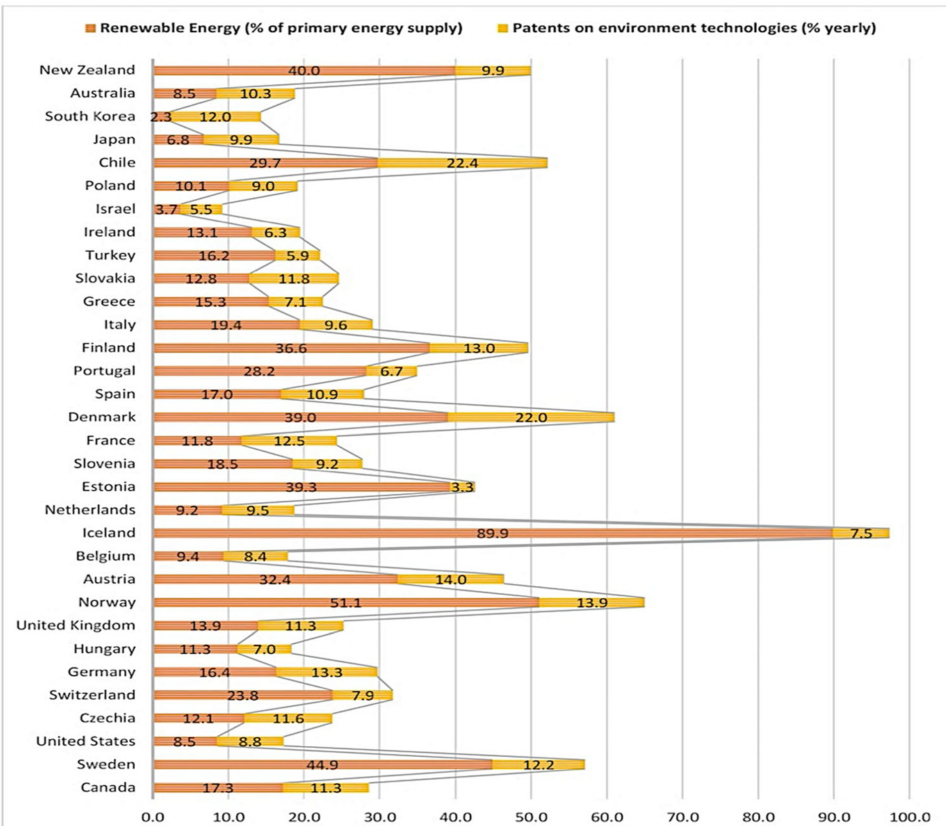

Figure 1. The O.E.C.D. countries' position on renewable energy and patents for environmental technology (Year: 2020).
Source: The authors.

Increases in environmental damage have been met with a variety of responses during the past few decades, including the creation of new technologies and the filing of patents linked to such technologies. Entrepreneurs may not be motivated by environmental technology innovations that are crucial for the mitigation of climate change (Zhang et al., 2016). Hence, strict and robust legislative measures are essential to regulate the large costs associated with creating renewable technologies (Su & Moaniba, 2017). Environmental technology innovation will be available primarily to countries with high per capita incomes (Du et al., 2019), though countries with the right policies in place may be able to bridge this gap regardless of wealth (Koçak et al., 2019).

Investments in renewable energy sources are of essential importance for achieving economic, social, and environmental sustainability (Ulucak et al., 2019) because of the central role that energy plays in sustainable development. As a result, green energy has been emphasised as having a crucial role in fostering economic growth, decreasing pollution and bettering society (Ulucak et al., 2019). Consumption of renewable energy, which incorporates sustainable technologies, is preferable to the use of fossil fuels, which are the primary source of greenhouse gas emissions (Ganda, 2019). All parts of the economy need cleaner technologies to increase the use of renewable energy and protect energy sources (Mensah et al., 2019).

More research and inventions, which play a significant role in reducing emissions, are needed in light of their dramatic ascent in recent years. Since patent counts are considered one of the most essential indicators of innovations and also a measurement for technical advancement (Lindman & Söderholm, 2016), studies in this context have focused on the patent's role as a representative for sustainable technological innovations (Du et al., 2019; Mensah et al., 2019). Different viewpoints have been presented in the literature on the topic of technological innovation and the CO_2 emission nexus, but the importance of technological innovation in reducing carbon emissions remains debatable. Some studies back up what was thought to be the expected effect of innovations (Su & Moaniba, 2017; Wang et al., 2012, 2019), while others find that innovations have a small effect on emissions or help raise them (Du et al., 2019; Hodson et al., 2018; Mensah et al., 2018).

It is crucial to learn more about the chain of events that begins with technological innovation and concludes with economic performance and carbon emissions by using cutting-edge research methods. This study analyses the effects of technological innovations on CO_2 emissions in O.E.C.D. countries, taking into account the role of renewable energy, G.D.P., and investment within a framework developed specifically for this purpose. This study investigated at how new technologies have changed CO_2 emissions in 32 O.E.C.D. countries between 1991 and 2020. This research uses the panel quantile regression method in order to further investigate the dilemma of whether or not the influence of technological innovation on CO_2 emissions in O.E.C.D. countries is heterogeneous and asymmetric. This is done in light of the fact that there are significant differences between the various countries that make up the O.E.C.D.. The following are the primary contributions that can be drawn from this research: (1) This research provides fresh evidence for designing efficient strategies to reduce emissions and encourage technological advancement in O.E.C.D. member countries, as well as a more in-depth analysis of the effect of technological innovation on CO_2 emissions in these countries; (2) In the majority of prior studies, researchers have neglected to take into account the likelihood of heterogeneity and asymmetry in the relationship between technological innovation and CO_2 emissions in O.E.C.D. member countries, leading to skewed and contradictory results (Gozgor et al., 2018). We use the panel quantile regression method to look into the possibility of heterogeneity and asymmetry to address this limitation.

The remaining sections of the study are as follows: In the Section 2, we analyse the literature that has come before. Methodology, including model design, estimating strategy and data, are presented in Section 3. The Section 4 contains the discussion and reporting of the empirical findings. Several policy implications are discussed in the final section of this article.

2. Literature review

As the intensity of technological innovation persists, more and more government officials and academics recognise the significance of technological innovation for reducing CO_2 emissions (Chen et al., 2018; Saqib, 2022c; Sharif et al., 2022; Song et al., 2019). For this reason, many academics have begun studying how technological innovation affects carbon dioxide (CO_2) emission. The growth of patents is one widely-used indicator of technical innovation that has sprung from this research. To begin, some academics have attempted to quantify the level of technological innovation by looking at energy savings and R&D spending, and they have also investigated how these factors affect carbon dioxide emissions. Firstly, the impact of patents on carbon dioxide emissions has been extensively studied since patent growth is typically used as a proxy for technological innovation, such as the works of Álvarez-Herránz et al. (2017), Dong et al. (2020), Hashmi and Alam (2019), Wang et al. (2019) and Wurlod and Noailly (2018) also came to identical conclusions on the relationship between energy efficiency and CO_2 emissions. Some researchers explore the dynamic links connecting research & development and CO_2 emissions, as the research & development scale is also considered an important indicator for gauging technological innovation trends (Churchill et al., 2018; Fernández Fernández et al., 2018; Petrović & Lobanov, 2020). The findings of these research are extremely important since they reveal the effects of technological progress on CO_2 emissions. Despite this, study did not present a comprehensive analysis of the mechanism of influence that technological innovation has on carbon emissions.

An expert contends that further pollution can be reduced without a corresponding reduction in productivity if the amount of energy used in industrial processes is controlled (Requate & Unold, 2003; Zhang et al., 2022). The development of technologies that are less harmful to the environment can also contribute to increasing the efficiency with which energy is generated (Ahmad et al., 2022; Goulder & Mathai, 2000; Lantz & Feng, 2006; Pao & Tsai, 2011; Peng et al., 2022; Saqib, Duran, et al., 2022; Socolow et al., 2004; Tang et al., 2022). Climate policy can promote the economy in two distinct ways: first, by making use of or investing in already existing 'eco-friendly' technologies; and second, by funding R&D efforts so, environmental laws that tax businesses that pollute and give subsidies to businesses that use technology that is good for the environment can encourage and help the development of these technologies (Irfan et al., 2022; Jin et al., 2022; Markewitz et al., 2012; Li et al., 2022; Saqib, Sharif, et al., 2022). The CO_2 emission can be reduced with environmentally sustainable technologies, according to numerous studies, which in turn promotes sustainable economic growth (Kaygusuz et al., 2007; Saqib, 2022a; Yin et al., 2015) and reach the UN's SDG-7 and SDG-13 targets.

Since Grossman and Krueger (1991) established the environmental Kuznets curve (E.K.C.) hypothesis to evaluate the connection between economic growth and environmental pollution levels, many researchers have started to estimate the effect of economic growth on CO_2 emissions using the E.K.C. hypothesis (Alam et al., 2019; Munir et al., 2020). Numerous more previous research accept the inverted U-shaped E.K.C. concept, including Atici (2009) for Central and Eastern Europe, Al-Mulali et al. (2015) and Al-Mulali and Ozturk (2016) for advanced countries and Rauf et al. (2018) for Belt and Road Initiative countries. Contrary to this, some past studies contradict the E.K.C. concept, including Ozcan (2013) for Middle East countries.

Second, the renewable energy supply sources are often cited as a key component that can decrease CO_2 emissions; this viewpoint has been confirmed by Li et al. (2020) and Wang, Dong, et al. (2020). Most researchers agree that renewable energy sources are among the most sustainable when it comes to the health of the environment and the economy (Saqib, 2018; Yang et al., 2022). Evidenced by Sarkodie and Strezov (2019) as well as studies like Ali et al. (2019) and Özokcu and Özdemir (2017) which discovered that overall pollution level in O.E.C.D. countries increased dramatically between 1980 and 2010 due to higher energy usage; in Nigeria. According to the research conducted by Ali et al. (2019) the use of energy has a good effect on the environment, whereas replenishing energy sources has the adverse impact. Based on concrete fact, it is clear that using renewable energy sources can significantly boost environmental quality over time. Renewable energy, according to previous research by Saqib (2022c) results in a considerable decrease in pollution levels and carbon emissions, both of which have a positive effect on the environment. Integrating renewable energy technology into the country's power supply is a great way to lessen reliance on fossil fuels and broaden the economy's base of support (Saqib, Sharif, et al., 2022; Usman & Balsalobre-Lorente, 2022).

Thirdly, several studies have examined at the dynamic links between investment levels and CO_2 emissions (Shahbaz et al., 2020; Zhao et al., 2016), demonstrating that rising investment is also a major source of CO_2 emissions. So, as the economy grows, investment in clean industries and service sectors will strengthen environmental laws and, as a result, reduce CO_2. A recent study by Liu et al. (2017) and Ozcan (2013) reveals that investment has the potential to cut CO_2 emissions, and they propose the use of advanced clean technology acquired through F.D.I.

3. Data and methodology

3.1. Data

The sample consists of panel data for 32 O.E.C.D. countries for the timeframe 1991–2020, retrieved from the International Energy Agency and O.E.C.D. databases of environmental data and indicators. In addition, we employ G.D.P. per capita, the supply of renewable energy, the development of patent technologies and gross fixed capital formation as exogenous variables, while CO_2 emissions per capita serve as the endogenous variables in our analysis.

Variable definitions are provided in Table 1. To be more precise, 'CO_2' denotes the annual average global CO_2 emissions per person. To determine this, we divide the total CO_2 emissions attributable to fossil fuel use by the total population. Per capita G.D.P. measures a country's economic well-being at current value and purchasing power parity (P.P.P.). R.E.N. is the renewable energy source's primary energy output in kilowatt-hours. In many earlier studies, researchers have used the I.N.O.V. definition of a country's inventive capacity as a collection of patents on environmental technologies. Investment in fixed assets (G.F.C.F.) is the difference between the value of new purchases and sales of existing assets over the course of a year. In this analysis, we adopted a logarithmic scale for all variables.

3.2. Descriptive statistics

The descriptive statistics of the six variables are shown in Table 2. As both skewed and kurtosis have high values, it is clear that the variables are not normally distributed, except for CO_2 and G.F.C.F. This means that the ordinary least squares (O.L.S.) method cannot be used.

3.3. Model specification

Model-1:

Carbon-dioxide emission = f (Economic growth, Renewable energy supply, Technological innovations, Investment)

$$CO2_{i,t} = \beta_i + \alpha_1 GDP_{i,t} + \alpha_2 GDP^2_{i,t} + \alpha_3 REN_{i,t} + \alpha_4 INOV_{i,t} + \alpha_5 GFCF_{i,t} + \mu_t \quad (1)$$

Model-2:

Carbon-dioxide emission = f (Economic growth, Renewable energy supply, Technological innovations, Investment, Technological innovations * Economic growth, Technological innovations * Renewable energy supply)

Table 1. Data variables and sources.

Parameters	Symbol	Metrics	Resources
CO_2 emissions per capita	COE	Tonnes per person	IEA
GDP per capita	GDP	Million US dollars	OECD
Renewable energy Supply	REN	Thousand tonnes of oil equivalent	OECD
Development of patent	INOV	Number	OECD
Investment	GFCF	Million US dollars	OECD

Source: Authors' based on data from International Energy Agency (IEA) and Organisation for Economic Co-operation and Development (OECD) databases.

Table 2. Descriptive statistics.

Variables	COE	GDP	REN	INOV	GFCF
Minimum	1.1457	7.9574	3.3328	0.0012	7.1657
Maximum	2.7852	10.8217	10.8759	8.7854	14.9223
Mean	2.2152	10.2598	7.9996	5.0147	10.8996
SD	0.3657	0.4214	1.5647	2.2241	1.6598
Skewness	0.1868	−0.5485	−0.4215	0.1282	−0.1310
Kurtosis	−0.2133	0.4011	0.4827	−0.9587	−0.0814

Source: Authors' Estimation.

$$CO2_{i,t} = \beta_i + \alpha_1 GDP_{i,t} + \alpha_2 GDP^2_{i,t} + \alpha_3 REN_{i,t} + \alpha_4 INOV_{i,t} + \alpha_5 GFCF_{i,t} + \alpha_6 (INOV*GDP)_{i,t} + \alpha_7 (INOV*REN)_{i,t} + \mu_t \tag{2}$$

4. Methodological strategy

4.1. Normal distribution test

This study makes use of a normality test procedure that was created recently by Galvao et al. (2013) in order to carry out the normality test. In order to determine whether or not the data is normal, this test uses both the individual and joint skewness and kurtosis measures, as utilisation of this normality test for panel data is very common. For a standard panel-data model presented as in Equation (3):

$$y_{it} = x_{it} b + u_i + e_{it}, i = 1, \ldots N, t = 1, \ldots, T \tag{3}$$

The parameters are contained in the p-vector b, which does not have any constants. As is traditional, the subscript i denotes the individual, while the subscript t refers to the time, where t represents a time indicator. Error components with zero-mean in this context are the individual-specific error u_i and the residual error e_{it}. The following formula as presented in Equations (4)–(7) are used to determine the skewness and kurtosis of the u_i and e_{it} separately:

$$s_u = \frac{E[u^3]}{(E[u^2])^{3/2}} \tag{4}$$

$$k_u = \frac{E[u^4]}{(E[u^2])^2} \tag{5}$$

$$s_e = \frac{E[e^3]}{(E[e^2])^{3/2}} \tag{6}$$

$$k_e = \frac{E[e^4]}{(E[e^2])^2} \tag{7}$$

In order to check for skewness and kurtosis, Galvao et al. (2013) create statistics for both the individual-specific component and the residual component. Both of these tests can be performed separately or jointly. It is possible to formulate null hypotheses for skewness and kurtosis at the individual level when the underlying distribution is normal and can be written as:

$$H_0^{s_u} : s_u = 0 \text{ and } H_0^{s_e} : s_e = 0$$

$$H_0^{k_u} : k_u = 3 \text{ and } H_0^{k_e} : k_e = 3$$

Even the symmetry statistics can be reported in a standard format, as Equations (8) and (9):

$$\widehat{SK}_e^{(2)} = \frac{\widehat{E[e^3]}}{\left(\widehat{E[e^2]}\right)^{3/2}} \tag{8}$$

$$\widehat{SK}_u^{(2)} = \frac{\widehat{E[u^3]}}{\left(E[u^2]\right)^{3/2}} \tag{9}$$

Consequently, the null hypotheses for these situations are as follows, based on the normality test:

$$H_0^{s_u\&k_u} : s_u = 0 \text{ and } k_u = 3,$$

$$H_0^{s_e\&k_e} : s_e = 0 \text{ and } k_e = 3$$

4.2. Panel unit root test

The panel unit root tests based on a heterogeneous model consist of examining the significance of the findings from N independent individual tests. This testing is done in order to determine whether or not the results are statistically significant. In this particular setting, I.P.S. makes use of an average statistic, but there is another testing approach that is based on aggregating the significant values that were found in the various tests. In meta-analysis, this strategy that is based on p-values has a long and illustrious pedigree (Choi, 2001; Maddala & Wu, 1999) are two notable researchers who employed an approach that was based on Fisher (1932) type tests when conducting panel unit root testing. The statistic that was proposed by (Maddala & Wu, 1999) was defined as in Equation (10) as follows, with the very essential constraint of cross-sectional independence.

$$P_{MW} = -2\sum_{i=1}^{N}\log(p_i) \tag{10}$$

When T approaches infinity and N remains constant, the chi-square statistic has a distribution with $2N$ degrees of freedom. According to Banerjee (1999), the evident simplicity of this test, in addition to its robustness to statistic choice, lag time, and sample size, make it an exceptionally viable proposition. Choi (2001) suggests a comparable standardised statistic for large N samples, such as $E[-2\log(p_i)] = 2$ and $\mathrm{Var}[-2\log(p_i)] = 4$. This statistic represents as in Equation (11), the cross-sectional average of the individual p-values that have been normalised.

$$Z_{MW} = \frac{\sqrt{N}\{N^{-1}P_{MW} - E[-2\log(p_i)]\}}{\sqrt{\mathrm{Var}[-2\log(p_i)]}} = -\frac{\sum_{i=1}^{N}\log(p_i) + N}{\sqrt{N}} \tag{11}$$

Levin et al. (2002) suggest using the following adjusted t-statistic as presented in Equation (12):

$$t_{\rho}^{*} = \frac{t_{\rho}}{\sigma_T^{*}} - NT\hat{S}_N\left(\frac{\hat{\sigma}_{\hat{\rho}}}{\hat{\sigma}_{\tilde{\varepsilon}}^{2}}\right)\left(\frac{\mu_T^{*}}{\sigma_T^{*}}\right) \tag{12}$$

where the mean adjustment denoted by μ_T^{*} and the standard deviation adjustment denoted by σ_T^{*} are simulated for different sample sizes T.

4.3. Panel quantile regression test

In this research, a panel quantile regression model with non-additive fixed effects, which was proposed by Powell (2022) is utilised in order to study the heterogeneity effects of technological innovation under various CO_2 emission distributions. If the variables have distinct impacts at the various quantiles of the independent variable, then it is reasonable to apply quantile regression for empirical research. This is because quantile regression takes into account the distribution of the dependent variable. As a direct consequence of this, an ever-expanding corpus of research has begun to combine quantile estimates with panel data. The inclusion of the fixed effects in the mean panel regression is required in order to accurately capture the within-group variation. To estimate the quantile panel data, a number of researchers utilised a similar methodology, which takes into consideration additive fixed effects. However, the additive fixed effects are different every time a different model is applied. Powell (2022) suggests that when working with panel data, the non-additive fixed effects quantile regression be used.

Compared with the traditional fixed effects quantile model that provides $\ln(CO_2)_{it} - \alpha_i$ given D_{it} the non-additive fixed effects quantile model provides an estimation of the distribution of $\ln(CO_2)_{it}$ given D_{it}. D_{it} represents the explanation variables. Powell (2022) noted that the observations at the top of the $\left(\ln(CO_2)_{it} - \alpha_i\right)$ distribution might be at the bottom of the $\ln(CO_2)_{it}$ distribution mentioned that the estimation might be expressed in a manner that was comparable to the cross-sectional regression. The model can be expressed in the form of the following Equation (13):

$$\ln(CO_2)_{i,t} = \sum_{j=1}^{5} D_{it}^{'}\beta_j(U_{it}^{*}) \tag{13}$$

where $\ln(CO_2)_{i,t}$ is the amount of CO_2 that at is produced per person in country i at year t, and β_j is the parameter of interest. Except for technological innovation, we set the following control variables: G.D.P. per capita, renewable energy and investment. U_{it}^{*} is the error term. The model is linear in parameters and $D_{it}^{'}\beta(\tau)$ is strictly increasing in (τ). For the τ^{th} quantile of $\ln(CO_2)_{i,t}$ the quantile regression relies on the following condional restiriction presented in Equation (14).

$$P\left(\ln(CO_2)_{i,t} \le D_{it}^{'}\beta(\tau) \mid D_{it}\right) = \tau \tag{14}$$

The likelihood of the dependent variable is shown by Equation (14). With Q.R.P.D. estimation, the probability might differ between and even among individuals if the difference is orthogonal to the variables. This means that Q.R.P.D. uses a configuration where restrictions are both conditional and unconditional, as shown in Equation (15).

$$D_i = (D_{it}, \ldots, D_{iT}): \; P\left(\ln(CO_2)_{i,t} \leq D_{it}^{'}\beta(\tau) \mid D_{i,t}\right) = P\left(\ln(CO_2)_{i,t} \leq D_{i,s}^{'}\beta(\tau) \mid D_{i,t}\right) \; P\left(\ln(CO_2)_{i,t} \leq D_{i,t}^{'}\beta(\tau)\right) = \tau \tag{15}$$

The estimation with instruments $Z_{it} = (Z_{i1}, \ldots, Z_{iT})$ was also proposed by Powell (2022). However, if the variables were exogenous, as $D_i = Z_i$, then the identification conditions were easily satisfied. Consequently, we make our estimations using an extended version of the method of moments. The seconds of the samples can be written as in Equation (16):

$$\hat{g}(b) = \frac{1}{N}\sum_{i=1}^{N} g_i(b) \text{ with } g_i(b) = \frac{1}{T}\left\{\sum_{i=1}^{T}(Z_{it} - \bar{Z}_i)\left[1\left(\ln(C_2)_{i,t} \leq D_{i,t}^{'}b\right)\right]\right\} \tag{16}$$

where $\overline{Z}_i = \frac{1}{T}\sum_{i=1}^{T} Z_{it}$ using Equation (16) the parameter set can be expressed as $B \equiv \{b \mid \tau - \frac{1}{N} \leq \frac{1}{N}\sum_{t=1}^{N}\left(\ln(C_2)_{i,t} \leq D_{i,t}^{'}b\right) \leq \tau\}$ for all t. The parameter can then be estimated as $\hat{\beta}(\tau) = \text{argmin}_{b\in\beta}\, \hat{\hat{g}}(b)\hat{A}\hat{\hat{g}}(b)$ with weighting matrix $\hat{A}$. The model is estimated using the Markov Chain Monte Carlo (M.C.M.C.) optimisation method.

5. Empirical results and discussion

5.1. Normal distribution test results

The normality of the variables must be confirmed to determine if the conditional mean regression model is appropriate for the data. If sample data follows a normal distribution, conventional mean regression models can be used to analyse the effects of technological innovation and other variables on CO_2 emissions in O.E.C.D. countries. If not, conditional mean estimates would be skewed and not very reliable, which would make traditional mean regression models impossible to use. Because of this, panel quantile regression, which accounts for distribution heterogeneity, is a preferable choice in this case. Because of this, we use two normal distribution tests to make sure that our data follows a normal distribution before deciding that the panel quantile regression model is right for our needs.

Table 3 shows the findings of the normality test proposed by Galvao et al. (2013). Using this table, we may conclude that, with the exception of S_e, it is appropriate to reject the null hypothesis for the other four variables. Results shows that our sample's distribution of CO_2 emissions deviates significantly from the normal distribution in both directions. The normality test for CO_2 emissions indicates that the data in sample do not follow a normal distribution. Therefore, O.L.S. techniques do not work well with our data. For this reason, the panel quantile regression technique is preferable.

Table 3. Normality test results.

Test	Coeff.	St. Error	z-test	*p*-value
S_e	0.1923	0.1625	1.0130	0.284
K_e	3.0251	0.5921	5.1288	0.000
S_u	41.1222	0.4836	65.3614	0.000
K_u	300.5241	1.1213	268.2257	0.000
SK_e	19.2550	–	–	0.000
SK_u	80120.1442	–	–	0.000

Note: individual-specific error component (u) and to the residual error component (e).
Source: Authors' Estimation.

5.2. Panel unit root test results

Non-stationary data may cause differences in regression results; hence the panel unit root test must be performed before empirical analysis. We utilise three panel unit root tests to ensure the stationarity of five variables, i.e., CO_2, G.D.P., R.E.N., I.N.O.V. and G.F.C.F. These tests for the unit root were provided by Levin et al. (2002), Choi (2001) and Maddala and Wu (1999).

Table 4 displays the results of the panel unit root tests. At a significance threshold of 10%, we may conclude that practically all of the variables with the exception of I.N.O.V. are non-stationary. The first-difference sequence is stationary because the null hypothesis for all five variables at the first difference could be entirely rejected at the 1% significance level.

5.3. Panel quantile regression test results

For this reason, we will perform our empirical study using the panel quantile regression technique, which accounts for the fact that our sample variables do not have a normal distribution. Unlike traditional regression methods, which only calculate the mean. As a result, it is appropriate to provide greater details about how technological innovations effect CO_2 emissions in O.E.C.D. countries.

During the process of running the regression, we select nine different quantiles so that we can present a comprehensive view of the various quantiles. In addition, in order to facilitate a comparison between the outcomes of the conventional mean regression approach and the panel quantile regression method, we present the outcomes of the O.L.S. regression as well as the panel quantile regression in Table 5 and Figure 2.

As can be seen, the influence that each of the four independent variables has on the amount of CO_2 emitted is quite varied. As seen in Table 5, technological innovation reduces CO_2 emissions, which is beneficial for O.E.C.D. countries. Nevertheless, the

Table 4. Panel unit-root tests results.

	MW test (Maddala & Wu, 1999)		CMP test (Choi, 2001)		LLC test (Levin et al., 2002)	
Variables	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
COE	37.2679	866.6963*	−2.6333	70.1001*	4.5220	−25.0127*
GDP	10.5972	398.1255*	−5.1611	30.3285*	2.1589	−15.5524*
REN	33.2680	981.6697*	2.9852*	79.6421*	10.2223	−27.8566*
INOV	139.0298*	964.6110*	5.0065*	76.5548*	−4.0021*	−29.8857*
GFCF	31.0215	355.3651*	−3.1290	27.5279*	0.2988	−13.8725*

Note: * indicates the significance level at 1%.
Source: Authors' Estimation.

Table 5. Panel quantile regression and O.L.S. results.

Model-1: $COE_{i,t} = \beta_i + \alpha_1 GDP_{i,t} + \alpha_2 GDP^2_{i,t} + \alpha_3 REN_{i,t} + \alpha_4 INOV_{i,t} + \alpha_5 GFCF_{i,t} + \mu_t$

		Quantiles								
Variables	OLS	10	20	30	40	50	60	70	80	90
GDP	0.3521*	0.6724*	0.3014*	0.4125*	0.4152*	0.3675*	0.2701*	0.2230*	0.1311*	0.3210*
	−0.0501	−0.0051	−0.0350	−0.0121	−0.0201	−0.0041	−0.0320	−0.0312	−0.0033	−0.0100
GDP^2	−0.0061	−0.0222*	−0.0009	−0.00751*	−0.0052**	−0.00597*	−0.00457*	−0.0034**	−0.00421*	−0.0008
	−0.0024	−0.0002	−0.0021	−0.0006	−0.0018	−0.0001	−0.0010	−0.0012	−0.0001	−0.0004
REN	−0.0712*	−0.9865*	−0.0698*	− 0.0699*	−0.0764*	−0.0914*	−0.0669*	−0.0750*	−0.1310*	−0.1251*
	−0.0180	−0.0008	−0.0078	−0.0036	−0.0013	−0.0011	−0.0062	−0.0055	−0.0012	−0.0044
INOV	−0.00521	−0.0021**	−0.0070*	−0.0092*	−0.0036***	0.0008	−0.0072*	−0.0075*	−0.00644*	−0.0101*
	−0.0059	−0.0005	−0.0012	−0.0014	−0.0009	−0.0002	−0.0015	−0.0009	−0.0004	−0.0019
GFCF	0.00033	−0.0530*	−0.0321*	−0.0351**	0.0205	−0.0021	−0.0032	−0.0095***	0.0126*	−0.0341*
	−0.0210	−0.0012	−0.0073	−0.0110	−0.0130	−0.0012	−0.0091	−0.0040	−0.0009	−0.0042

*Significant at 1% level, **significant at 5% level and ***significant at 10% level.
Source: Authors' Estimation.

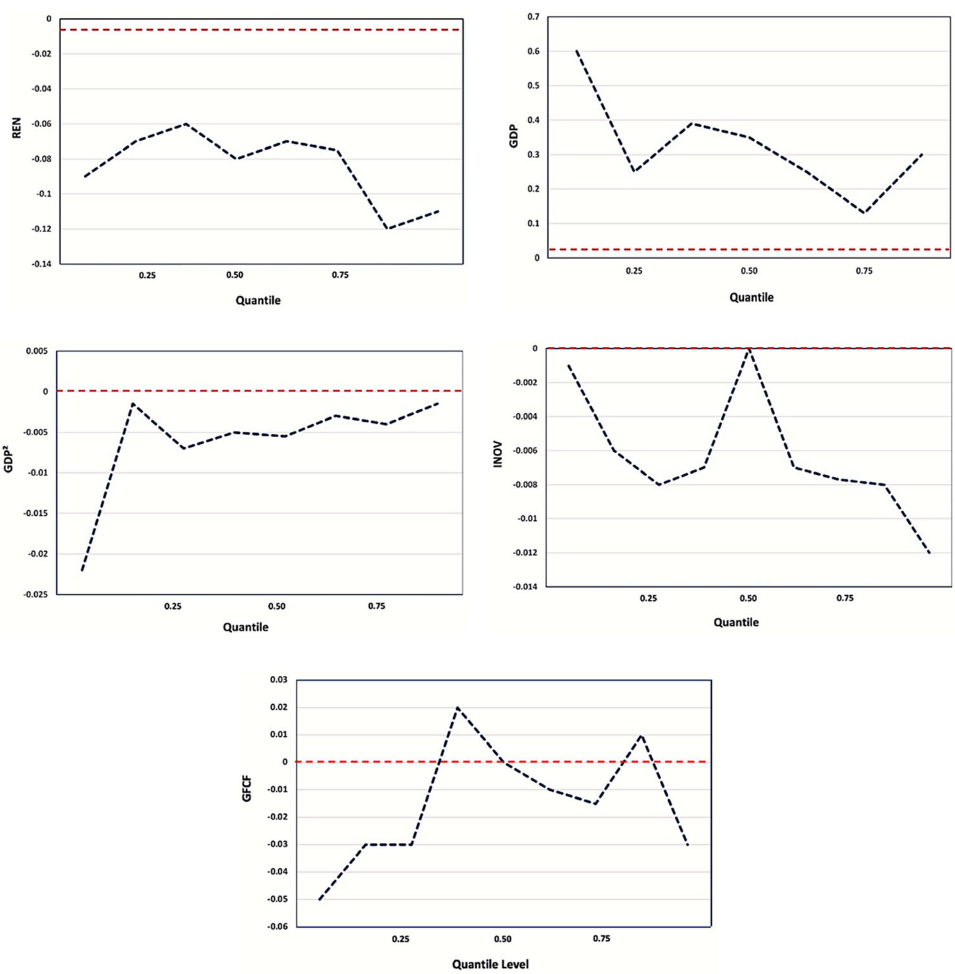

Figure 2. Technology-induced change in panel quantile regression coefficients.
Source: The authors.

effects are not uniform throughout the various quantiles and instead take the form of a W-shaped curve, as shown in Figure 2. To be more specific, the negative impact is −0.0021 at the 30th quantile, and it subsequently falls slightly at the 40th and 50th quantiles after reaching its peak at the 30th quantile. After that, the adverse effects, when measured at high quantiles, practically continued to worse.

Positive effects of the G.D.P. and negative effects of G.D.P.^{2} are observed in Table 5. The results confirmed the E.K.C. hypothesis by these findings, which was also proved by (Churchill et al., 2018). The majority of member countries in the Organization for Economic Cooperation and Development are themselves developed nations. They were less dependent on manufacturing and more on the service sector. The growth of industry necessitates more energy and, consequently, produces more carbon dioxide emissions than the growth of service sector (Wang & Lin, 2016). At different quantiles, the effects of G.D.P. and G.D.P.^{2} are distinct from one another. In general, when contrasted with their counterparts in the high quantiles, the beneficial effects of G.D.P. were greater for the quantiles that were lower. It is possible that this is due to the high standard of living in high-income countries. Consumption contributes significantly, on average, to the rate of economic expansion in the developed countries. In the meantime, there is a favorable correlation between consumption and quality of life. The ongoing expansion of the economy will result in significant improvements to the quality of life, including the simplification of traffic patterns and the expansion of simple access to utilities like electricity and the internet. To live a life of high quality, however, would need a greater expenditure of energy.

High-quantile countries are more vulnerable to the negative effects of renewable energy than middle-quantile and low-quantile countries. This may be due to the potential of renewable energy and its diminishing marginal effects, as noted in Saqib (2022b), which study the relationship between renewable energy and CO_2 in Asian countries. Table 5 shows I.N.O.V.'s direct impact on reducing CO_2 emissions, which varies by quantile. We investigate why technological innovation can reduce CO_2 emissions and why the direct consequences vary across O.E.C.D. members. Patents development can demonstrate the negative impacts of technological innovation on the environment. Based on the findings in Table 5, it appears that technological innovation has a W-shaped detrimental influence as shown in Figure 2. In particular, impacts kept growing from the tenth quantile through the 30th quantile, before leveling out at the 50th quantile. Once again, the impacts begin to rise at this point, only to level out again after the 80th quantile. Table 5 also shows that there are adverse effects that fixed investment has on CO_2 emissions. O.E.C.D. countries' greater investment in environmental infrastructure causes fixed investment's negative effects. Song et al. (2019) shown that investments in environmental infrastructure can dramatically reduce CO_2 emissions in China. These findings are quite similar to those presented above. The data from the database maintained by the O.E.C.D. show that over the past few years, there has been a consistent rise in the amount of money spent by the government on programs designed to safeguard the environment.

There is the possibility that technical innovation will have a mitigating effect on the interaction between economic growth and renewable energy . To further support this conclusion, the relationship between technological innovation and economic growth as well as technological innovation and renewable energy demonstrates direct impacts of both variables on CO_2 emissions when the two interact with one another. The interaction effect measures the stability of the relationship between model parameters and the dependent variable. In order to evaluate the moderating effects, we conduct a second panel quantile regression, this time using the modified regression model-2 that is followed. Table 6 contains an estimation of the results obtained from model-2. Based on the results of the quantile regression shown in Table 6, we can say two things about the moderating effects of I.N.O.V.: Firstly while the effect coefficients of the I.N.O.V. * G.D.P. is on the negative side, CO_2 emissions and patents in particular have the potential to offset this at higher quantiles. This moderating effect might be explained by the fact that technological innovation makes a contribution to the lowering of energy intensity and, as a result, counteracts some of the beneficial effects that are caused by economic expansion (Hille & Lambernd, 2020). More and more patents, products, and processes are being developed to save energy; when put into practice, these innovations can significantly lessen energy use. If energy use per unit of G.D.P. dropped, the economy would produce less carbon dioxide. According to O.E.C.D. statistics, O.E.C.D. countries as a whole had a dramatic decrease in energy intensity between 1991 and 2020. Our rationale for the varying effects is as follows: firstly, high-quantile countries are less developed. As increased attention is paid to carbon dioxide (CO_2) emissions, these countries are turning to technological innovation as they industrialise. This boosts economic growth as technology progresses. Henceforth, because coefficients vary across quantiles, patents can mitigate renewable energy's effects on CO_2 emissions at low quantiles while balancing them at high quantiles. Renewable energy is minimal in high-quantile countries. Renewable energy is extremely advanced. With enough inventions, new electricity generation processes or lower production costs may be possible. Technological innovation can boost the renewable energy sector, reducing CO_2 emissions. Figure 3 shows model results.

5.4. Robustness check results

As a robustness check, we utilised different methodology in order to evaluate the consistency of the estimated parameters that were derived from the quantile regression panel

Table 6. Panel quantile regression and O.L.S. results (with moderating effects).

Model-2: $COE_{i,t} = \beta_i + \alpha_1 GDP_{i,t} + \alpha_2 GDP^2_{i,t} + \alpha_3 REN_{i,t} + \alpha_4 INOV_{i,t} + \alpha_5 GFCF_{i,t} + \alpha_6 (INOV * GDP)_{i,t} + \alpha_7 \ (INOV * REN)_{i,t} + \mu_t$

		Quantiles								
Variables	OLS	10	20	30	40	50	60	70	80	90
GDP	0.3521*	0.7088*	0.7103*	0.3621*	0.3563*	0.2513*	0.2519*	0.2541*	0.2841*	0.3150*
	−0.0601	−0.0184	−0.0160	−0.0276	−0.0291	−0.0210	−0.0200	−0.0115	−0.0110	−0.0231
GDP^2	−0.0061	−0.0256*	−0.0232*	−0.0079*	−0.0075*	−0.0026	−0.0029	−0.0009	−0.0009	0.0015
	−0.0030	−0.0015	−0.0013	−0.0022	−0.0021	−0.0013	−0.0013	−0.0001	−0.0001	−0.0008
REN	− 0.0681*	−0.0921*	−0.0901*	−0.0763*	−0.0770*	−0.0698*	−0.0689*	−0.0798*	−0.0799*	−0.0985*
	−0.0205	−0.0075	−0.0080	−0.0064	−0.0060	−0.0101	−0.0112	−0.0053	−0.0050	−0.0071
INOV	−0.0068	−0.0041	−0.0040	−0.0085*	−0.0080*	0.0009	0.0009	−0.0119*	−0.0120*	−0.0007
	−0.0069	−0.0050	−0.0053	−0.0012	−0.0014	−0.0011	−0.0010	−0.0021	−0.0018	−0.0015
GFCF	−0.0015	−0.0374*	−0.0365*	0.0008	0.0009	0.0298*	0.0291*	0.0031	0.0034	−0.0158**
	−0.0183	−0.0111	−0.0117	−0.0101	−0.0111	−0.0100	−0.0101	−0.0113	−0.0111	−0.0050
INOV * GDP	−0.0014	−0.0005	−0.0004	0.0001	0.0001	0.0001	0.0001	−0.0021*	−0.0026*	−0.0031*
	−0.0011	−0.0003	−0.0003	−0.0002	−0.0002	−0.0004	−0.0003	−0.0008	−0.0009	−0.0004
INOV * REN	0.00074	−0.0008*	−0.0008*	0.0007*	0.0007*	0.0009	0.0009	0.0014*	0.0054*	0.00056*
	−0.00062	−0.0001	−0.0001	−0.0002	−0.0003	−0.0004	−0.0004	−0.0003	−0.0003	−0.00012

Note: * and ** indicate significant at 1% and 5% level. Standard error values are indicated via parenthesis.
Source: Authors' Estimation.

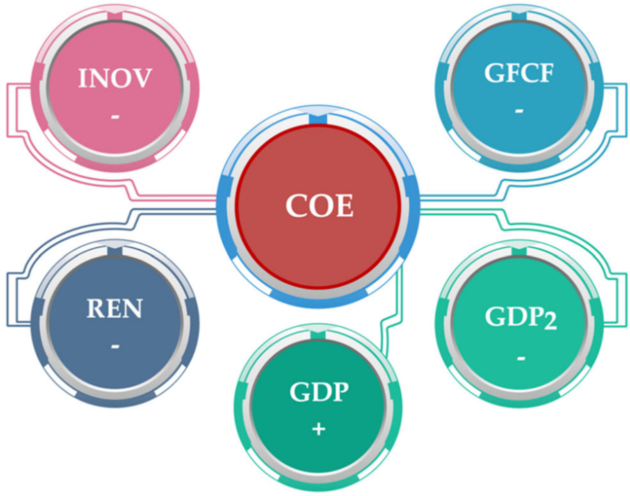

Figure 3. Graphical presentation of empirical findings.
Source: The authors.

data with non-additive fixed effects. To begin, we utilised an alternative panel quantile model that is characterised by additive fixed effects for the purpose of comparison. Koenker (2004) developed this panel quantile model with additive fixed effects, which is currently widely utilised in energy and environmental investigations (Cheng et al., 2018).

Table 7 displays the conclusions drawn from the regression analysis conducted using a panel data model with additive fixed effects. The estimation findings of the robust check are compatible with those of the quantile regression panel data model, as evidenced by the regression results. As a result, we have arrived at the conclusion that the parameters of our model that were gathered via quantile regression panel data are consistent.

6. Conclusion and policy recommendations

6.1. Conclusion

The focus of this research is on the effect that innovation in technology has on carbon dioxide (CO_2) emissions in countries that are members of the O.E.C.D. It is decided to use economic growth, renewable energy, and fixed investment as independent variables. Because the data are not normally distributed, a recently developed

Table 7. Robustness results.

	Quantiles				
Variables	10	30	50	70	90
GDP	0.6126* (0.1231)	0.3941 (0.0244)	0.2733** (0.1024)	0.2795 (0.0090)	0.3314* (0.0701)
GDP^2	−0.0310 (0.0132)	−0.0085 (0.0210)	−0.0035 (0.0070)	−0.0012 (0.0000)	0.0025 (0.0053)
REN	−0.1120** (0.0362)	−0.0954 (0.0053)	−0.0715** (0.0309)	−0.8012 (0.0001)	−0.1214* (0.0302)
INOV	−0.0119 (0.0100)	−0.0096 (0.0000)	0.0021 (0.0063)	−0.0131 (0.0018)	−0.0045 (0.0100)
GFCF	−0.0398 (0.0390)	0.0009 (0.0091)	0.0318 (0.0186)	−0.0027 (0.0006)	−0.0367 (0.0281)

Note: * and ** indicate the significance level at 1% and 5%, respectively.
Standard error values are indicated via parenthesis.
Source: Authors' Estimation.

panel quantile regression method is used to eliminate the possibility of biased results and provide deeper insight into the effects. At various quantiles, the empirical findings are inconsistent. In addition, a comprehensive examination of the factors that drive technological advancement is provided. In this article, we will be talking about the ways in which technological advancement has both a direct and indirect effect on carbon dioxide (CO_2) emissions in O.E.C.D. countries. The main conclusions of this study are listed as follows: (1) The development of new technologies leads to a reduction in CO_2 emissions; (2) Through the reduction in energy intensity, technological innovation has the potential to mitigate the beneficial effects of economic growth on CO_2 emissions; (3) The adoption of new technologies has the potential to amplify the detrimental effects of renewable energy sources on CO_2 emissions by boosting the growth of the renewable energy sector in countries with low quantiles; and (4) In O.E.C.D. countries, the E.K.C. hypothesis is found to be valid.

6.2. Policy recommendations

The following is a summary of policy recommendations that have been suggested on the basis of the results and discussion, graphical trinity policy recommendation presented in Figure 4.

1. One of the major tenets of the Paris Agreement is the need for adaptation. If government and policy makers take strong action to reduce emissions, they can lessen the severity of climate change's impacts and thus the extent to which we need to adapt. Even so, climate change is already having a big impact. This makes it even more important to plan for and invest in adaptation and resilience.

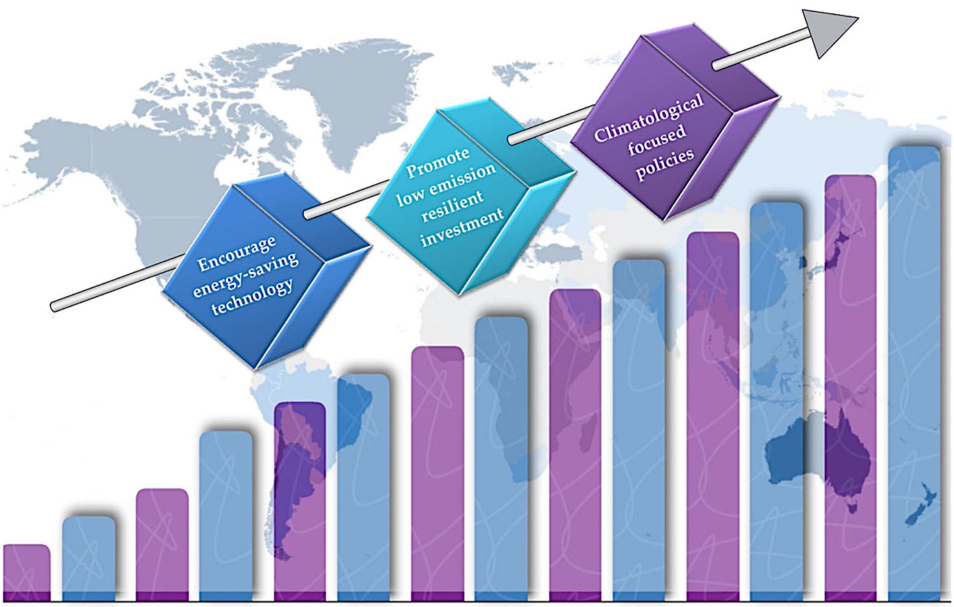

Figure 4. Trinity policy for climate and growth.
Source: The authors.

It is important for the government to support research and development of technology that can reduce overall energy use. The level of energy intensity is one of the ways in which technical innovation can help to moderate the effects of climate change. As a consequence of this, the government ought to foster and stimulate the implementation of this kind of technological advancement. In this manner, it would be possible to realise both the direct affects and the moderating impacts that technological innovation has.

2. To attract the necessary investments for a dramatic transition, governments need to support pro-growth structural reform policies with consistent climate policies and an investment policy environment that is well-aligned. This is necessary in order to attract the necessary investments. The most effective policy combinations to mobilise investment in low-emission infrastructure differ from country to country, including the respective contributions of public and private investment (Yang et al., 2022). In metropolitan settings, inconsistent land-use and transit planning can lock in carbon-intensive infrastructure and behavior. One of the most effective policy combinations is to have a combination of public and private investment. On the other hand in order to facilitate the adoption of new technologies, the government should do away with any obstacles in its way. Alternative energy sources are another moderating effect of technological innovation. The challenges in transferring this technology mean that renewable energy may have unintended consequences, but technological advancement may mitigate these effects. The government should remove these constraints if it is to maximise the benefits of renewable energy and technical innovation. One policy option is to make new rules about the environment, which is seen by many as a good way to speed up the implementation of new patents.
3. Carbon pricing has the potential to be an effective and efficient means of encouraging low-carbon and growth-oriented actions and investments from businesses and people. To date, however, carbon prices have been very modest, especially when 'effective carbon rates' are used as a metric. These rates take into account both explicit carbon pricing and the carbon price equivalent of energy taxes. Where carbon pricing do exist, they have had a muted and indirect effect on infrastructure investment, in part because transitional support packages and exemptions for businesses and families have diluted the price signals. The effectiveness and political acceptability of carbon pricing might also be diminished by misallocating the public revenues generated through carbon price. A better budgetary space and a more inclusive and progressive climate policy are possible with the proceeds from carbon pricing, for instance through the reduction of other taxes and the easing of the burden on the poorest households.

Author contributions

NS: Supervision, Writing – Original draft preparation, Methodology, Software. MU: Data curation, Editing, Literature review, software, validation. HM: Literature review, Visualisation, review & editing. SA & FA: Data curation, Project administration. DM & RSM: Writing – Reviewing and Editing.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Najia Saqib http://orcid.org/0000-0003-2795-2012
Muhammad Usman http://orcid.org/0000-0002-6131-2118
Haider Mahmood http://orcid.org/0000-0002-6474-4338
Shujaat Abbas http://orcid.org/0000-0003-2141-7510
Fayyaz Ahmad http://orcid.org/0000-0001-9038-0817
Daniela Mihai http://orcid.org/0000-0001-7905-0841
Ray Saadaoui Mallek http://orcid.org/0000-0003-0019-7010

References

Ahmad, M., Ahmed, Z., Bai, Y., Qiao, G., Popp, J., & Oláh, J. (2022). Financial inclusion, technological innovations, and environmental quality: Analyzing the role of green openness. *Frontiers in Environmental Science*, *10*, 80. https://doi.org/10.3389/FENVS.2022.851263/BIBTEX

Alam, M. S., Atif, M., Chien-Chi, C., & Soytaş, U. (2019). Does corporate R&D investment affect firm environmental performance? Evidence from G-6 countries. *Energy Economics*, *78*, 401–411. https://doi.org/10.1016/j.eneco.2018.11.031

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

Al-Mulali, U., & Ozturk, I. (2016). The investigation of environmental Kuznets curve hypothesis in the advanced economies: The role of energy prices. *Renewable and Sustainable Energy Reviews*, *54*, 1622–1631. https://doi.org/10.1016/j.rser.2015.10.131

Al-Mulali, U., Weng-Wai, C., Sheau-Ting, L., & Mohammed, A. H. (2015). Investigating the environmental Kuznets curve (EKC) hypothesis by utilizing the ecological footprint as an indicator of environmental degradation. *Ecological Indicators*, *48*, 315–323. https://doi.org/10.1016/j.ecolind.2014.08.029

Álvarez-Herránz, A., Balsalobre, D., Cantos, J. M., & Shahbaz, M. (2017). Energy innovations-GHG emissions nexus: Fresh empirical evidence from OECD countries. *Energy Policy*, *101*, 90–100. https://doi.org/10.1016/j.enpol.2016.11.030

Atici, C. (2009). Carbon emissions in Central and Eastern Europe: Environmental Kuznets curve and implications for sustainable development. *Sustainable Development*, *17*(3), 155–160. https://doi.org/10.1002/sd.372

Banerjee, A. (1999). Panel data unit roots and cointegration: An overview. *Oxford Bulletin of Economics and Statistics*, *61*(S1), 607–629. https://doi.org/10.1111/1468-0084.0610s1607

Chen, J., Cheng, S., & Song, M. (2018). Changes in energy-related carbon dioxide emissions of the agricultural sector in China from 2005 to 2013. *Renewable and Sustainable Energy Reviews*, *94*, 748–761. https://doi.org/10.1016/j.rser.2018.06.050

Cheng, C., Ren, X., Wang, Z., & Shi, Y. (2018). The impacts of non-fossil energy, economic growth, energy consumption, and oil price on carbon intensity: Evidence from a panel quantile regression analysis of EU 28. *Sustainability*, *10*(11), 4067. https://doi.org/10.3390/su10114067

Choi, I. (2001). Unit root tests for panel data. *Journal of International Money and Finance*, *20*(2), 249–272. https://doi.org/10.1016/S0261-5606(00)00048-6

Churchill, S. A., Inekwe, J., Ivanovski, K., & Smyth, R. (2018). The environmental Kuznets curve in the OECD: 1870–2014. *Energy Economics*, *75*, 389–399. https://doi.org/10.1016/j.eneco.2018.09.004

Dong, K., Hochman, G., & Timilsina, G. R. (2020). Do drivers of CO_2 emission growth alter overtime and by the stage of economic development? *Energy Policy*, *140*, 111420. https://doi.org/10.1016/j.enpol.2020.111420

Du, K., Li, P., & Yan, Z. (2019). Do green technology innovations contribute to carbon dioxide emission reduction? Empirical evidence from patent data. *Technological Forecasting and Social Change*, *146*, 297–303. https://doi.org/10.1016/j.techfore.2019.06.010

Erdoğan, S., Çakar, N. D., Ulucak, R., Kassouri, Y., & Danish. (2021). The role of natural resources abundance and dependence in achieving environmental sustainability: Evidence from resource-based economies. *Sustainable Development*, *29*(1), 143–154. https://doi.org/10.1002/sd.2137

Fernández Fernández, Y., Fernández López, M. A., & Olmedillas Blanco, B. (2018). Innovation for sustainability: The impact of R&D spending on CO_2 emissions. *Journal of Cleaner Production*, *172*, 3459–3467. https://doi.org/10.1016/j.jclepro.2017.11.001

Fisher, R. A. (1932). *Statistical methods for research workers*. Oliver and Boyd.

Galvao, A. F., Montes-Rojas, G., Sosa-Escudero, W., & Wang, L. (2013). Tests for skewness and kurtosis in the one-way error component model. *Journal of Multivariate Analysis*, *122*, 35–52. https://doi.org/10.1016/j.jmva.2013.07.002

Ganda, F. (2019). The impact of innovation and technology investments on carbon emissions in selected organisation for economic co-operation and development countries. *Journal of Cleaner Production*, *217*, 469–483. https://doi.org/10.1016/j.jclepro.2019.01.235

Goulder, L. H., & Mathai, K. (2000). Optimal CO_2 abatement in the presence of induced technological change. *Journal of Environmental Economics and Management*, *39*(1), 1–38. https://doi.org/10.1006/jeem.1999.1089

Gozgor, G., Lau, C. K. M., & Lu, Z. (2018). Energy consumption and economic growth: New evidence from the OECD countries. *Energy*, *153*, 27–34. https://doi.org/10.1016/j.energy.2018.03.158

Grossman, G. M., & Krueger, A. B. (1991). *Environmental impacts of a North American Free Trade Agreement* [Working paper No. 3914]. National Bureau of Economic Research.

Hashmi, R., & Alam, K. (2019). Dynamic relationship among environmental regulation, innovation, CO_2 emissions, population, and economic growth in OECD countries: A panel investigation. *Journal of Cleaner Production*, *231*, 1100–1109. https://doi.org/10.1016/j.jclepro.2019.05.325

Hille, E., & Lambernd, B. (2020). The role of innovation in reducing South Korea's energy intensity: Regional-data evidence on various energy carriers. *Journal of Environmental Management*, *262*, 110293. https://doi.org/10.1016/j.jenvman.2020.110293

Hodson, E. L., Brown, M., Cohen, S., Showalter, S., Wise, M., Wood, F., Caron, J., Feijoo, F., Iyer, G., & Cleary, K. (2018). U.S. energy sector impacts of technology innovation, fuel price, and electric sector CO_2 policy: Results from the EMF 32 model intercomparison study. *Energy Economics*, *73*, 352–370. https://doi.org/10.1016/j.eneco.2018.03.027

Irfan, M., Razzaq, A., Sharif, A., & Yang, X. (2022). Influence mechanism between green finance and green innovation: Exploring regional policy intervention effects in China. *Technological Forecasting and Social Change*, *182*, 121882. https://doi.org/10.1016/j.techfore.2022.121882

Jin, C., Razzaq, A., Saleem, F., & Sinha, A. (2022). Asymmetric effects of eco-innovation and human capital development in realizing environmental sustainability in China: Evidence from quantile ARDL framework. *Economic Research-Ekonomska Istraživanja*, *35*(1), 4947–4970. https://doi.org/10.1080/1331677X.2021.2019598

Kaygusuz, K., Yüksek, Ö., & Sari, A. (2007). Renewable energy sources in the European Union: Markets and capacity. *Energy Sources, Part B: Economics, Planning, and Policy*, *2*(1), 19–29. https://doi.org/10.1080/15567240500400887

Koçak, E., Ulucak, R., Dedeoğlu, M., & Ulucak, Z. Ş. (2019). Is there a trade-off between sustainable society targets in Sub-Saharan Africa? *Sustainable Cities and Society*, *51*, 101705. https://doi.org/10.1016/j.scs.2019.101705

Koenker, R. (2004). Quantile regression for longitudinal data. *Journal of Multivariate Analysis*, *91*(1), 74–89. https://doi.org/10.1016/j.jmva.2004.05.006

Lantz, V., & Feng, Q. (2006). Assessing income, population, and technology impacts on CO_2 emissions in Canada: Where's the EKC? *Ecological Economics*, *57*(2), 229–238. https://doi.org/10.1016/j.ecolecon.2005.04.006

Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics*, *108*(1), 1–24. https://doi.org/10.1016/S0304-4076(01)00098-7

Li, H., Jiang, H.-D., Dong, K.-Y., Wei, Y.-M., & Liao, H. (2020). A comparative analysis of the life cycle environmental emissions from wind and coal power: Evidence from China. *Journal of Cleaner Production*, *248*, 119192. https://doi.org/10.1016/j.jclepro.2019.119192

Li, Q., Sharif, A., Razzaq, A., & Yu, Y. (2022). Do climate technology, financialization, and sustainable finance impede environmental challenges? Evidence from G10 economies. *Technological Forecasting and Social Change*, *185*, 122095. https://doi.org/10.1016/j.techfore.2022.122095

Lindman, Å., & Söderholm, P. (2016). Wind energy and green economy in Europe: Measuring policy-induced innovation using patent data. *Applied Energy*, *179*, 1351–1359. https://doi.org/10.1016/j.apenergy.2015.10.128

Liu, Y., Hao, Y., & Gao, Y. (2017). The environmental consequences of domestic and foreign investment: Evidence from China. *Energy Policy*, *108*, 271–280. https://doi.org/10.1016/j.enpol.2017.05.055

Maddala, G. S., & Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics*, *61*(S1), 631–652. https://doi.org/10.1111/1468-0084.0610s1631

Markewitz, P., Kuckshinrichs, W., Leitner, W., Linssen, J., Zapp, P., Bongartz, R., Schreiber, A., & Müller, T. E. (2012). Worldwide innovations in the development of carbon capture technologies and the utilization of CO_2. *Energy & Environmental Science*, *5*(6), 7281–7305. https://doi.org/10.1039/c2ee03403d

Mensah, C. N., Long, X., Boamah, K. B., Bediako, I. A., Dauda, L., & Salman, M. (2018). The effect of innovation on CO_2 emissions of OCED countries from 1990 to 2014. *Environmental science and Pollution Research International*, *25*(29), 29678–29698. https://doi.org/10.1007/s11356-018-2968-0

Mensah, C. N., Long, X., Dauda, L., Boamah, K. B., Salman, M., Appiah-Twum, F., & Tachie, A. K. (2019). Technological innovation and green growth in the Organization for Economic Cooperation and Development economies. *Journal of Cleaner Production*, *240*, 118204. https://doi.org/10.1016/j.jclepro.2019.118204

Munir, Q., Lean, H. H., & Smyth, R. (2020). CO_2 emissions, energy consumption and economic growth in the ASEAN-5 countries: A cross-sectional dependence approach. *Energy Economics*, *85*, 104571. https://doi.org/10.1016/j.eneco.2019.104571

OECD. (2020). *Patents on environment technologies (indicator)*. https://doi.org/10.1787/cc8a7b7a-en

Ozcan, B. (2013). The nexus between carbon emissions, energy consumption and economic growth in Middle East countries: A panel data analysis. *Energy Policy*, *62*, 1138–1147. https://doi.org/10.1016/j.enpol.2013.07.016

Özokcu, S., & Özdemir, Ö. (2017). Economic growth, energy, and environmental Kuznets curve. *Renewable and Sustainable Energy Reviews*, *72*, 639–647. https://doi.org/10.1016/j.rser.2017.01.059

Pao, H. T., & Tsai, C. M. (2011). Multivariate Granger causality between CO_2 emissions, energy consumption, FDI (foreign direct investment) and GDP (gross domestic product): Evidence from a panel of BRIC (Brazil, Russian Federation, India, and China) countries. *Energy*, *36*(1), 685–693. https://doi.org/10.1016/j.energy.2010.09.041

Peng, G., Meng, F., Ahmed, Z., Ahmad, M., & Kurbonov, K. (2022). Economic growth, technology, and CO_2 emissions in BRICS: Investigating the non-linear impacts of economic complexity. *Environmental science and Pollution Research International*, *29*(45), 68051–68062. https://doi.org/10.1007/s11356-022-20647-7

Petrović, P., & Lobanov, M. M. (2020). The impact of R&D expenditures on CO_2 emissions: Evidence from sixteen OECD countries. *Journal of Cleaner Production*, *248*, 119187. https://doi.org/10.1016/j.jclepro.2019.119187

Powell, D. (2022). Quantile regression with nonadditive fixed effects. *Empirical Economics*, *63*(5), 2675–2691. https://doi.org/10.1007/s00181-022-02216-6

Rauf, A., Liu, X., Amin, W., Ozturk, I., Rehman, O. U., & Hafeez, M. (2018). Testing EKC hypothesis with energy and sustainable development challenges: A fresh evidence from belt and road initiative economies. *Environmental science and Pollution Research International*, *25*(32), 32066–32080. https://doi.org/10.1007/s11356-018-3052-5

Requate, T., & Unold, W. (2003). Environmental policy incentives to adopt advanced abatement technology: Will the true ranking please stand up? *European Economic Review*, *47*(1), 125–146. https://doi.org/10.1016/S0014-2921(02)00188-5

Saqib, N. (2018). Greenhouse gas emissions, energy consumption and economic growth: Empirical evidence from gulf cooperation council countries. *International Journal of Energy Economics and Policy*, *8*(6), 392–400. https://doi.org/10.32479/IJEEP.7269

Saqib, N. (2022a). Green energy, non-renewable energy, financial development and economic growth with carbon footprint: Heterogeneous panel evidence from cross-country. *Economic Research-Ekonomska Istraživanja*, *35*(1), 6945–6964. https://doi.org/10.1080/1331677X.2022.2054454

Saqib, N. (2022b). Nexus between the renewable and nonrenewable energy consumption and carbon footprints: Evidence from Asian emerging economies. *Environmental science and Pollution Research International*, *29*(38), 58326–58340. https://doi.org/10.1007/s11356-022-19948-8

Saqib, N. (2022c). Asymmetric linkages between renewable energy, technological innovation, and carbon-dioxide emission in developed economies: Non-linear ARDL analysis. *Environmental science and Pollution Research International*, *29*(40), 60744–60758. https://doi.org/10.1007/s11356-022-20206-0

Saqib, N., Duran, I. A., & Sharif, I. (2022). Influence of energy structure, environmental regulations and human capital on ecological sustainability in EKC framework; evidence from MINT countries. *Frontiers in Environmental Science*, *10*, 1–15. https://doi.org/10.3389/fenvs.2022.968405

Saqib, N., Sharif, A., Razzaq, A., & Usman, M. (2022). Integration of renewable energy and technological innovation in realizing environmental sustainability: The role of human capital in EKC framework. *Environmental Science and Pollution Research*, 1–14. https://doi.org/10.1007/s11356-022-23345-6

Sarkodie, S. A., & Strezov, V. (2019). Effect of foreign direct investments, economic development and energy consumption on greenhouse gas emissions in developing countries. *The Science of the Total Environment*, *646*, 862–871. https://doi.org/10.1016/j.scitotenv.2018.07.365

Shahbaz, M., Raghutla, C., Song, M., Zameer, H., & Jiao, Z. (2020). Public-private partnerships investment in energy as new determinant of CO_2 emissions: The role of technological innovations in China. *Energy Economics*, *86*, 104664. https://doi.org/10.1016/j.eneco.2020.104664

Sharif, A., Saqib, N., Dong, K., & Khan, S. A. R. (2022). Nexus between green technology innovation, green financing, and CO_2 emissions in the G7 countries: The moderating role of social globalisation. *Sustainable Development*, *30*(6), 1934–1946. https://doi.org/10.1002/sd.2360

Socolow, R., Hotinski, R., Greenblatt, J. B., & Pacala, S. (2004). Solving the climate problem: Technologies available to curb CO_2 emissions. *Environment: Science and Policy for Sustainable Development*, *46*(10), 8–19. https://doi.org/10.1080/00139150409605818

Song, M., Fisher, R., & Kwoh, Y. (2019). Technological challenges of green innovation and sustainable resource management with large scale data. *Technological Forecasting and Social Change*, *144*, 361–368. https://doi.org/10.1016/j.techfore.2018.07.055

Su, H.-N., & Moaniba, I. M. (2017). Does innovation respond to climate change? Empirical evidence from patents and greenhouse gas emissions. *Technological Forecasting and Social Change*, *122*, 49–62. https://doi.org/10.1016/j.techfore.2017.04.017

Tang, T., Shahzad, F., Ahmed, Z., Ahmad, M., & Abbas, S. (2022). Energy transition for meeting ecological goals: Do economic stability, technology, and government stability matter? *Frontiers in Environmental Science*, *10*, 1146. https://doi.org/10.3389/fenvs.2022.955494

Ulucak, R., Koçak, E., Erdoğan, S., & Kassouri, Y. (2020). Investigating the non-linear effects of globalization on material consumption in the EU countries: Evidence from PSTR estimation. *Resources Policy*, *67*, 101667. https://doi.org/10.1016/j.resourpol.2020.101667

Ulucak, R., Yücel, A. G., & Koçak, E. (2019). The process of sustainability: from past to present. In *Environmental Kuznets Curve (EKC)* (pp. 37–53). Academic Press. https://doi.org/10.1016/B978-0-12-816797-7.00005-9

UNFCCC. (2015). *United Nations Framework Convention on Climate Change. INDC submission*. http://unfccc.int/focus/indc_portal/items/8766.php

Usman, M., & Balsalobre-Lorente, D. (2022). Environmental concern in the era of industrialization: Can financial development, renewable energy and natural resources alleviate some load? *Energy Policy*, *162*, 112780. https://doi.org/10.1016/j.enpol.2022.112780

Wang, J., Dong, X., Qiao, H., & Dong, K. (2020). Impact assessment of agriculture, energy and water on CO_2 emissions in China: Untangling the differences between major and non-major grain-producing areas. *Applied Economics*, *52*(60), 6482–6497. https://doi.org/10.1080/00036846.2020.1796920

Wang, S., Zeng, J., & Liu, X. (2019). Examining the multiple impacts of technological progress on CO_2 emissions in China: A panel quantile regression approach. *Renewable and Sustainable Energy Reviews*, *103*, 140–150. https://doi.org/10.1016/j.rser.2018.12.046

Wang, X., & Lin, B. (2016). How to reduce CO_2 emissions in China's iron and steel industry. *Renewable and Sustainable Energy Reviews*, *57*, 1496–1505. https://doi.org/10.1016/j.rser.2015.12.131

Wang, Z., Yang, Z., Zhang, Y., & Yin, J. (2012). Energy technology patents–CO_2 emissions nexus: An empirical analysis from China. *Energy Policy*, *42*, 248–260. https://doi.org/10.1016/j.enpol.2011.11.082

Wurlod, J. D., & Noailly, J. (2018). The impact of green innovation on energy intensity: An empirical analysis for 14 industrial sectors in OECD countries. *Energy Economics*, *71*, 47–61. https://doi.org/10.1016/j.eneco.2017.12.012

Yang, Q., Huo, J., Saqib, N., & Mahmood, H. (2022). Modelling the effect of renewable energy and public-private partnership in testing EKC hypothesis: Evidence from methods moment of quantile regression. *Renewable Energy*, *192*, 485–494. https://doi.org/10.1016/j.renene.2022.03.123

Yin, J., Zheng, M., & Chen, J. (2015). The effects of environmental regulation and technical progress on CO_2 Kuznets curve: An evidence from China. *Energy Policy*, *77*, 97–108. https://doi.org/10.1016/j.enpol.2014.11.008

Zhang, J., Liu, Y., Saqib, N., & Waqas Kamran, H. (2022). An empirical study on the impact of energy poverty on carbon intensity of the construction industry: Moderating role of technological innovation. *Frontiers in Environmental Science*, *10*, 732. https://doi.org/10.3389/fenvs.2022.929939

Zhang, N., Wang, B., & Liu, Z. (2016). Carbon emissions dynamics, efficiency gains, and technological innovation in China's industrial sectors. *Energy*, *99*, 10–19. https://doi.org/10.1016/j.energy.2016.01.012

Zhao, X., Zhang, X., & Shao, S. (2016). Decoupling CO_2 emissions and industrial growth in China over 1993–2013: The role of investment. *Energy Economics*, *60*, 275–292. https://doi.org/10.1016/j.eneco.2016.10.008