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The impact of energy innovation on carbon emissions mitigation: An empirical evidence from OECD countries

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Abstract

Over the past decades, the world has experienced an unprecedented increase in carbon emissions resulting in the emergence of climate change as a significant policy concern. Currently, environmental and energy policymakers are assessing carbon emissions mitigation strategies through the lens of energy innovation. However, research linking energy innovation to carbon emissions remains limited in the literature. In this research, we deploy the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model to investigate the impact of energy innovation on carbon emissions in 26 OECD countries for the period 1974-2017. Our results from the fixed-effect panel quantile regression revealed that energy innovation reduces carbon emission at the lower quantiles (10^{th}, 20^{th}, 30^{th}, 40^{th}, 50^{th}) while it increases carbon emissions at the 70^{th} and 80^{th} quantile. Our results also indicate that population size, energy intensity, service and industrial sectors increase carbon emissions while urbanisation and affluence mitigate carbon emissions. The policy implications are discussed.

Keywords: Carbon emissions; Energy innovation; OECD

1. Introduction

The current research aims to understand the impact of energy innovation R&D on carbon emissions in OECD countries. Over the past decades, the global economy has experienced a persistent increase in carbon emissions. It is well established that carbon emissions have been the principal greenhouse gases responsible for climate change and global warming. It is contended that without ambitious policies, greenhouse gases are expected rise by an extra 50% by 2050, primarily driven by 70% growth in carbon emissions from energy use (Marchal et al., 2011). Thus, without stringent policies, the concentration of greenhouse gases will reach approximately 685ppm CO_2-equivalent by 2050. This scenario compares dangerously with Marchal et al. (2011) finding that greenhouse gas concentration must be kept at 450 ppm or less to have at least 50% chance of limiting the increase in global temperature by 2^o., The authors warned that without limiting greenhouse gases to 450 ppm the global temperature is expected to increase between 3°C to 6°C higher than pre-industrial levels by the end of the century (Marchal et al., 2011). The real concern is that global temperature increases above 3°C might exceed some critical "tipping-points" with the possibility of dramatic natural changes that could have catastrophic or irreversible outcomes for natural systems and society. Therefore, if pragmatic measures are not taken, carbon emissions, which primarily results in climate change and global warming, will stymie both economic and human development.

While it has become policy relevant to understand the factors behind carbon emissions, a vast literature has examined the impact of factors such as economic growth (Apergis & Ozturk, 2015; Shahbaz, Khraief, Uddin, & Ozturk, 2014), energy consumption (Acheampong, 2018; Apergis & Payne, 2009), population (Dong et al., 2018; Yeh & Liao, 2017; Zhu & Peng, 2012; Shi, 2003), urbanisation (Poumanyvong & Kaneko, 2010; Sadorsky, 2014), globalisation (Shahbaz, Mallick, Mahalik, & Loganathan, 2015) on carbon emissions. Current trajectories of development suggest that technological innovation or research and development (R&D) remains critical in the fight against climate change. Shahbaz, Nasir, and Roubaud (2018) argue that technological innovation could moderate the relationship between carbon emissions and its determinants. However, not much is known about the impact of R&D on carbon emissions (Awaworyi Churchill, Inekwe, Smyth, & Zhang, 2019). The high global dependence on fossil energy and the consistent association of fossil energy as a significant source of carbon emissions in the scientific literature cement energy innovation R&D as crucial for influencing carbon emissions. Energy innovation R&D has the appeal and potential for mitigating carbon emissions because of its direct impact on energy consumption but there is paucity in empirical studies that link energy innovation R&D to carbon emissions (Shahbaz et al., 2018; Balsalobre, Álvarez, & Cantos, 2015). Even though fossil energy remains a significant source of carbon emissions, rising voices of descent, especially among the youth demanding carbon mitigation or carbon neutral strategies, are pushing policymakers to include energy innovation R&D in current and future carbon mitigation strategies. The global nature of the climate change problem makes global approach a priority in the fight against globally widespread proven causal factors such greenhouse emissions. While several agreements such as the Kyoto accord and the Paris agreement has been signed, the question is whether nations are contributing their fair share toward solving the greenhouse emission problem? In this research, we deploy the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model to investigate the impact of energy innovation R&D, which is public expenditure on energy innovation R&D, on carbon emissions in 26 OECD countries for the period 1974-2017. The STIRPAT is one of the purpose-built investigation tool incorporating most of the factors theorised as causing the observed rising trend in greenhouse emissions.

We also focused on OECD countries because they have historically been a significant contributor to global carbon emissions (Marchal et al., 2011). Further, carbon emissions from OECD countries have an overall rising trend since 1960 as shown in Figure 1, despite periodic minor declines. The rising carbon emission trend from the OECD countries deserves attention as the OECD countries are at the advanced stage of economic development which means they consume more energy. By their status it is easy to assume that the OECD countries should commit more resources to energy-efficient R&D strategies (Balsalobre et al., 2015). However, the recent OECD (2018, p. 22) report indicates that since 2010, government expenditure on RD in the OECD as a whole incuding the Group of Seven countries (G7) have stagnated or declined. The report indicates that total government spending on R&D has decreased by 4% (from 31% to 27%) between 2009 and 2016. Such a reduction in total R&D expenditure could directly reduce energy innovation R&D, which could worsen their carbon emissions. Finally, the OECD countries contribute significantly to economic growth and remain significant players in achieving the Paris agreement. As depicted in Fig. 1, economic growth in the OECD countries have been trending with carbon emissions; therefore, focusing on the OECD countries to examine the impact of energy innovation R&D will allow policymakers to understand how expenditure on energy technologies are affecting carbon emissions.

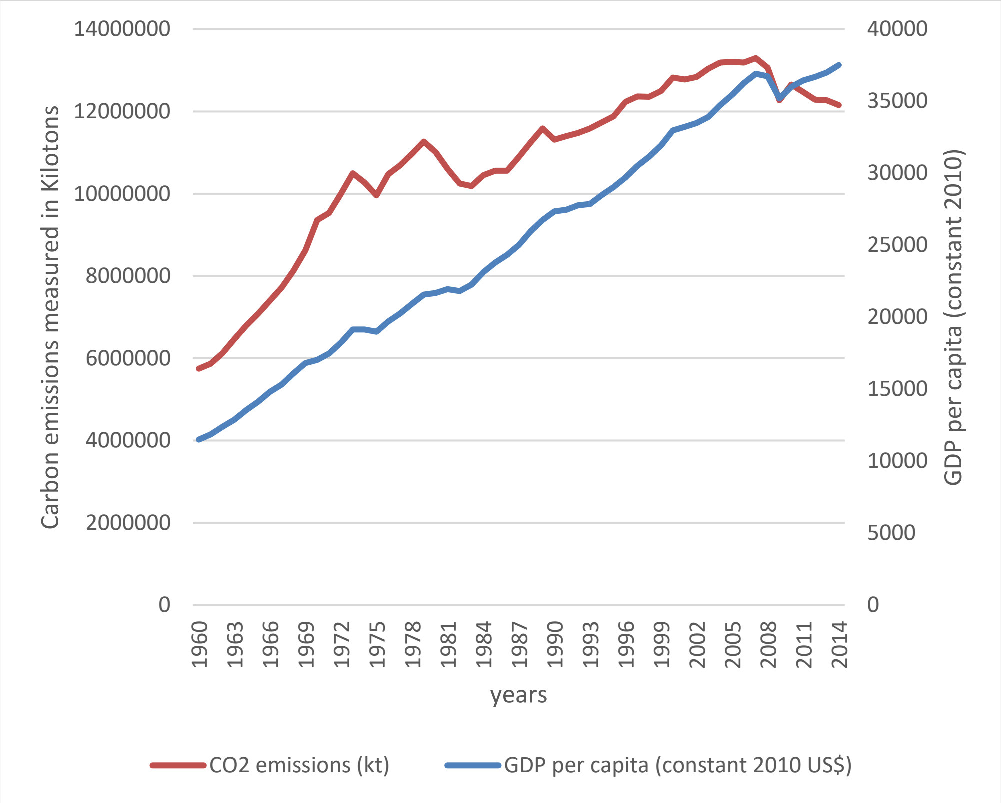

Fig. 1: Carbon emissions and GDP trend in OECD countries
Source: Authors' construct using data from World Development Indicators (WDI) (2019)

This study adds to the literature by providing new empirical evidence on the impact of energy innovation on carbon emissions. Also, unlike the existing empirical studies, our study employs the fixed-effect panel quantile regression as the primary econometric estimation tool. This non-parametric econometric technique is more robust to outliers and heavy tail distributions. Our empirical results revealed that energy innovation reduces carbon emission at the lower quantiles (10^{th}, 20^{th}, 30^{th}, 40^{th}, and 50th) while it increases carbon emissions at the 70^{th} and 80^{th} quantile. The empirical results further indicated other factors such as affluence significantly reduces carbon emissions at the 20^{th}, 30^{th} and 90th while it remains insignificant at the remaining quantiles. It was also found that population size significantly increases carbon emissions at the lower quantiles (the 10^{th}, 20^{th}, 30^{th}, 40^{th}, 50^{th}) while urbanisation substantially reduces carbon emissions at the 10^{th} to 70^{th} quantile. It was further observed that energy intensity significantly increases carbon emissions at all the quantiles. Our findings also revealed that the service sector significantly increases carbon emissions at the 10^{th}, 20^{th}, 30^{th}, 40^{th} and 90^{th}. Also, the industry sector was found to substantially increase carbon emissions at the lower quantiles (10^{th}, 20^{th}, 30^{th}, and 40th) while it significantly reduces carbon emissions at the 70^{th} and 80^{th} quantiles. The remaining sections of the articles proceed in four steps. In section 2, we provide both theoretical and empirical literature on R&D on carbon emissions while methodology and data for the study are described in Section 3. The results and discussions are presented in Section 4, while conclusions and policy recommendations are presented in Section 5.

2. Literature review

The endogenous growth theory asserts that technological innovation is imperative for sustaining higher economic growth because technological innovation through research and development (R&D) could result in higher production efficiency (Romer, 1990, 1994). Higher levels of production have also been associated with the use of energy and natural resources both of which were considered as responsible for greenhouse gas emission (Awaworyi Churchill et al., 2019). Given this, some scholars argue that the impact of R&D on the environment is challenging to ascertain. For instance, efficient technology through R&D could ensure effective environmental management and subsequent reduction of carbon emissions (Awaworyi-Churchill et al., 2019; Shahbaz et al., 2018; Dinda, 2004). The dual effect of R&D greenhouse emissions was highlighted by Awaworyi-Churchill et al. (2019) in their argument that R&D could improve efficiency but it could also boost higher economic growth, which will increase natural resource use and carbon emissions. It could, therefore, be argued that the impact of technological innovation through R&D on carbon emissions is uncertain. This proposition is supported by the conflicting results from empirical studies.

For instance, Shahbaz et al. (2018) examined the role of energy innovation research on carbon emissions in France over the period 1955-2016 using Autoregressive Distributed Lag (ARDL) technique and found that energy innovation contributes to carbon emissions mitigation. The authors argue that future environmental policies in France should give priority to energy research and development. Similarly, Awaworyi-Churchill et al. (2019) investigated the impact of R&D intensity on carbon emissions in the Group of Seven (G7) countries for the period of 1870-2014 and found a positive effect of R&D intensity on carbon emissions. Incorporating R&D expenditure in a carbon emissions model, Tamazian, Chousa, and Vadlamannati (2009) revealed that R&D expenditure contributes significantly to carbon emissions reduction in BRIC countries. Using the Common Correlated Effects Mean Group (CCEMG), the study showed that R&D reduces carbon emissions for the three-quarters but increase carbon emissions for a 35-year during the second half of the 20th century. Fernández et al. (2018) found that between 1990 and 2013, R&D expenditure contributes to the decline in carbon emissions in the USA and EU but it increases carbon emissions in China. Similarly

Jiao, Jiang, and Yang (2018) assessed the role of R&D technology on carbon emissions in 29 China provinces for the period between 2000-2013 and found that inter-provincial R&D direct technology with direct spillover limits the growth of carbon emissions in the eastern and central regions of China. The results also revealed that inter-provincial R&D indirect technology and direct spillover reduces carbon emissions in the central region while it increases carbon emissions in the western region of China. Utilising Fully Modified Ordinary Least squares (FMOLS) and Ordinary Least squares (DOLS), the empirical findings of Dauda, Long, Mensah, and Salman (2019) revealed that innovation, measured using trademark application, contributes to carbon emissions reduction in G6 countries while it significantly increases carbon emissions in the Middle East and North Africa (MENA) countries and BRICS. Similarly, Fisher-Vanden and Sue Wing (2008) demonstrated R&D significantly contribute to carbon emission. Garrone and Grilli (2010) examined the impact of public expenditure on energy R&D and carbon emissions for 13 developed countries for the period between 1980-2004. Using dynamic models, the authors empirically argued that government spending on total R&D is not sufficient in itself to drive innovation. The results indicated that expenditure on energy R&D has been adequate to boost energy efficiency but has failed to significantly impact on carbon emissions.

Shahbaz et al. (2018) argue that although technological innovation, in general, is useful for improving the quality of the environment, energy innovation R&D would have rather direct implications on the environment. With the immediate effect energy innovation R&D on carbon emissions, limited empirical studies have linked energy innovation R&D to carbon emissions. We extend the limited empirical studies by investigating the impact of energy innovation on carbon emissions in 26 OECD countries for the period of 1974-2017.

3. Methodology and data

3.1. Theoretical model

Our study adopts the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model to investigate the impact of energy innovation on carbon emissions in the OECD countries. Ehrlich and Holdren (1971) formulated the *IPAT* model and used it to analyse the impact of Population (*P*), Affluence (*A*) and Technology (*T*) on the (*I*) environment (in our case, carbon emissions). The IPAT has been criticised as only a mathematical expression, which cannot be used to test the hypothesis on the impact of the aforementioned factors on the environment Dietz and Rosa (1994). A further criticism of the

IPAT is that it assumes that the impact of population, affluence and technology on the environment has a unitary elasticity (Dietz & Rosa, 1994). Based on these limitations, Dietz and Rosa (1994) reformulated the original *IPAT* model into *STIRPAT* ($I_i = \alpha_i P_i^b A_i^c T_i^d \mu_i$) model. In the *STIRPAT* model, a is the constant term of the model, b, c, d are the respective parameters of Population (P), Affluence (A) and Technology (T) to be estimated, i represents the unit of analysis and μ is the error term. The empirical model to be estimated is obtained after taking the natural logarithm of both sides of the *STIRPAT* model ($I_i = \alpha P_i^b A_i^c T_i^d \mu_i$).

$$\ln{(l)_{it}} = \alpha_0 + b\ln{(P)_{it}} + c\ln{(A)_{it}} + d\ln{(T)_{it}} + \mu_{it} \qquad (1)$$

It is challenging to get the exact proxy for the technology (T) in the model. However, Poumanyvong and Kaneko (2010) and York, Rosa, and Dietz (2003) argue that the T in the STIRPAT model captures multiple factors other than population and affluence that impact per capita of economic activity. Previous studies have used urbanisation (Poumanyvong & Kaneko, 2010; Sadorsky, 2014), energy intensity (Martínez-Zarzoso & Maruotti, 2011; Sadorsky, 2014), and industry and service sector (Martínez-Zarzoso, Bengochea-Morancho, & Morales-Lage, 2007; Martínez-Zarzoso & Maruotti, 2011; Shi, 2003) to capture technology in the STIRPAT model. We augment the empirical STIRPAT model used by Poumanyvong and Kaneko (2010) to investigate the impact of energy innovation on carbon emissions in the OECD countries.

$$\ln{(l)_{it}} = \alpha_0 + b\ln(P)_{it} + c\ln{(A_{it})} + d_1\ln(INNOV_{it}) + d_2\ln{(URB_{it})} + d_3\ln{(INDUS_{it})} + d_4\ln{(SERV_{it})} + d_5\ln{(ENER_{it})} + \mu_{it} \qquad (2)$$

3.2. Econometric estimation strategy

We employ the fixed effect quantile regression[1] to examine the impact of energy innovation on carbon emissions. The quantile regression was developed by Koenker and Bassett Jr (1978) to address the limitations of the Ordinary Least Squares (OLS) method. The quantile regression, which is a conditional median model, is robust to outliers and dense tail distribution, which cannot be captured fully by the conditional mean models. The conditional quantile of y_i given x_i is given as follows:

$$Q_{yi}(\tau|\, \chi_i) = \chi_i^T \beta_T \qquad (3)$$

[1] We follow H. Zhu, Duan, Guo, and Yu (2016) to specify the estimation approach of the fixed effect panel quantile regression.

Although quantile regression is robust to outliers and heavy tail distribution, it does not take into account the unobserved country heterogeneity. We, therefore, utilised the panel quantile regression with fixed effects to estimate the impact of energy innovation and other carbon emissions drivers, which makes it possible to account for the unobserved individual heterogeneity. This generates the panel quantile regression with a fixed-effect model in Eq. (4)

$$Q_{yi}(\tau|\alpha_i\ \chi_{it}) = \alpha_i + \chi_{it}'\beta(\tau_k) \qquad (4)$$

The major problem of Eq. (4) is the inclusion of a considerable amount of fixed effect, which is subjected to the incident parameters problem (Lancaster, 2000; Neyman & Scott, 1948). Thus, the fixed effect panel quantile regression will be inconsistent when the number of individual goes infinity but the number of time is fixed (Galvao & Kato, 2016; H. Zhu et al., 2016). Canay (2011) argues that for quantile regression, it is unfeasible to use the standard approach to eliminate the unobserved fixed effects since these methods rely on the fact that expectations are linear operators, which cannot be satisfied for conditional quantiles[2]. With this inherent problem, Koenker (2004) proposes the shrinkage approach, which treats the unobservable fixed effect as parameters to be jointly estimated with covariate effects for different quantiles. This approach is appropriate since it introduces a penalty term in the minimisation to prevent the computational problem of estimating a mass of paramters (Koenker, 2004; H. Zhu et al., 2016; H. Zhu et al., 2018). Eq. (5) specifies the formular for estimating/calculating the parameter.

$$\underset{(\alpha,\beta)}{min} \sum_{k=1}^{k}\sum_{t=1}^{T}\sum_{i=1}^{N} w_k\, \rho_{\tau_k}\left(y_{it} - \alpha_i - \chi_{it}^{T}\beta(\tau_k)\right) + \lambda \sum_{i}^{N} |\,\alpha_i| \qquad (5)$$

Where i is the number of countries (N), T is the time, k is an index for the quantiles, χ is the matrix of the explanatory covariates/ variables, $\rho_{\tau k}$ is the loss function for the quantiles, which controls for the contribution of the K-th quantile on the estimation of the fixed effect;λ is the tuning parameter that reduces the individual effects to zero to improve the performance of the estimate (β). We, therefore, modify Eq.(2) to specify our empirical model as follows:

$$Q_{yit}(\tau|\alpha_i, \mu_{it}, \chi_{it}) = \alpha_i + b_\tau \ln(P_{it}) + c_\tau \ln(A)_{it} + d_{1\tau}\ln(INNOV_{it}) + d_{2\tau}\ln(URB_{it}) + d_{3\tau}\ln(INDUS_{it}) + d_{4\tau}\ln(SERV_{it}) + d_{5\tau}\ln(ENER_{it}) + \mu_{it} \qquad (6)$$

Where $Q_{yit}(\tau|\alpha_i, \mu_{it}, \chi_{it})$ is the regression parameter of quantile τ^{th} of carbon emissions (CO_2) y in country i at time t conditional on the constant term a_i, error term μ_{it} and

[2] Zhu et al. (2016) and Zhu, Xia, Guo, and Peng (2018) argue that this problem explains why the literature on the fixed effect panel quantile regression is relatively scarce in the literature.

a set of explanatory variables χ. The explanatory variables are population size (P), affluence (A), energy innovation ($INNOV$), urbanisation (URB), industrialisation ($INDUS$), service ($SERV$) and energy intensity ($ENER$). We estimated Eq. (6) using the fixed effect panel quantile regression. In estimating the fixed effect panel quantile regression, we bootstrapped the standard errors of the parameters. Although the mean conditional models are not robust to outliers and heavy tail distribution, we began our analysis with conditional mean models such as OLS, random effect, fixed effect, dynamic fixed effect and system-generalised method of moment (system-GMM).

3.3. Data

This study employs a panel dataset to study the impact of energy innovation on carbon emissions in 26 OECD countries for the period between 1974-2017. The countries included are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hungary Ireland, Italy, Japan, Korea, Rep., Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Spain, Sweden, Switzerland, Turkey, United Kingdom and the United States. As presented in Table 1, the results of the descriptive statistics indicate that the mean of carbon emission is 2.097% with a standard deviation of 0.451. In the OECD countries, affluence (real GDP per capita) has a mean of 27.017% with a standard deviation of 1.249. The service sector and industry sector respectively has a mean of 4.092% and 3.257%. This statistics indicates that the service sector contribution to economy outweighs that of the industry sector in the OECD countries. Furthermore, population size and urbanisation have a mean of 16.731 and 4.281, respectively. The energy intensity has an average growth 8.154 while energy innovation has an average growth of -1.364. Thus, while energy intensity is high, government spending on energy R&D in OECD countries has been weak. The correlation matrix as presented in Table 2 indicates that the correlation coefficient between the explanatory variables is relatively small; hence, multicollinearity is not an issue. Since multicollinearity is not a problem, we included all the explanatory variables in one model to estimate our empirical results.

Table 1: Data description and variables descriptive statistics

Variables	**Description**	**Mean**	**SD**	**Min**	**Max**	**Source**
Carbon emissions	CO2 emissions (metric tons per capita)	2.097	0.451	0.466	3.090	WDI
Affluence	GDP per capita (constant 2010 US$)	27.017	1.249	24.430	30.485	WDI
Service	Services, value added (% of GDP)	4.092	0.121	3.651	4.351	WDI
Population size	Population, total	16.731	1.178	14.922	19.600	WDI
industry	Industry, value added (% of GDP)	3.257	0.190	2.616	3.696	WDI
Energy intensity	Energy use (kg of oil equivalent per capita)	8.154	0.488	6.487	9.043	WDI
Urbanisation	Urban population (% of total population)	4.281	0.168	3.698	4.585	WDI
Energy innovation	Energy technology RD&D budgets per thousand units of GDP[3]	-1.364	1.088	-6.215	0.395	IEA

Note: All the variables are expressed in natural logarithms; WDI = World Development Indicators (2019); IEA = International Energy Agency

Table 2: Correlation matrix

	CO_2	*A*	*SERV*	*P*	*INDUS*	*ENER*	*URB*	*INNVO*
CO_2	1							
A	0.318^{***}	1						
SERV	0.242^{***}	0.576^{***}	1					
P	0.121^{**}	0.919^{***}	0.425^{***}	1				
INDUS	0.0194	-0.191^{***}	-0.724^{***}	-0.167^{***}	1			
ENER	0.757^{***}	0.220^{***}	0.212^{***}	-0.0597	0.0734	1		
URB	0.371^{***}	0.200^{***}	0.305^{***}	0.0362	-0.212^{***}	0.529^{***}	1	
INNVO	0.395^{***}	0.170^{***}	0.112^{**}	-0.0491	0.220^{***}	0.618^{***}	0.371^{***}	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[3] http://wds.iea.org/WDS/TableViewer/tableView.aspx

4. Results and discussions

We expressed all the variables in the natural logarithms; therefore, our estimates should be interpreted as elasticity. To make our results comparable, we estimate our model using the OLS, random effect, fixed effect, dynamic fixed effect and system-GMM techniques. The results from these models are presented in Table 3. Affluence reduces carbon emissions in all the models but significant only the random effect, fixed effect and the dynamic fixed-effect models. Population contributes significantly to carbon emissions but insignificant only in the system-GMM model. The service sector substantially reduces carbon emissions in the random effect, fixed effect and the dynamic fixed-effect models. Industrialisation contributes significantly to the increases in carbon emissions in the system-GMM model. Energy intensity also increases carbon emissions in all the models. Urbanisation contributes significantly to carbon emissions only in the OLS model. The results indicate that energy innovation contributes significantly to carbon emissions only in the OLS and the system-GMM model. It is likely that these estimators are not robust to outliers and heavy tail distributions. Therefore, we employ the panel quantile regression technique to account for outliers and heavy tail distributions.

Table 3: Static and dynamic results

	Model 1	Model 2	Model 3	Model 4	Model 5
	OLS	Random effect	Fixed effect	Dynamic fixed effect	Dynamic system-GMM
Lagged carbon emissions				0.497***	0.961***
				(0.057)	(0.022)
Affluence	-0.011	-0.393***	-0.436***	-0.238***	-0.006
	(0.025)	(0.061)	(0.072)	(0.048)	(0.008)
Population size	0.058**	0.468***	0.656***	0.259**	0.011
	(0.025)	(0.084)	(0.183)	(0.114)	(0.008)
Service sector	0.231	-0.508**	-0.533*	-0.386*	-0.034
	(0.193)	(0.257)	(0.288)	(0.192)	(0.046)
Industry sector	0.082	-0.007	0.012	-0.031	0.046**
	(0.102)	(0.117)	(0.130)	(0.087)	(0.023)
Energy intensity	0.832***	1.255***	1.267***	0.749***	0.057**
	(0.033)	(0.063)	(0.062)	(0.089)	(0.025)
Urbanisation	-0.143**	0.242	0.267	0.139	0.004
	(0.071)	(0.176)	(0.191)	(0.114)	(0.023)
Energy innovation	-0.040***	0.006	0.006	0.002	-0.012***
	(0.010)	(0.011)	(0.011)	(0.005)	(0.003)
Constant	-6.088***	-4.300**	-6.444**	-1.887	-0.442*
	(0.965)	(1.856)	(2.561)	(1.714)	(0.262)
Observations	596	596	596	593	593
r2	0.611	0.743	0.745	0.844	
rho		0.944	0.975	0.930	
rmse	0.238	0.061	0.059	0.046	
Sargan					467.563

P(Sargan)	0.862
AR(1)	0.009
AR(2)	0.737

Heteroskedastic robust standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 presents the panel quantile regression results. The panel quantile regression result is reported for 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th and 90th percentile of the conditional carbon emissions distribution. The results indicate that at 10th quantile affluence worsens carbon emissions; however, from the 20th to 40th quantile, affluence reduces carbon emissions. Additionally, from 50th to 80th quantile affluence increase carbon emission while at the 90th to 99th quantile affluence reduce carbon emissions. These patterns depict the polynomial relationship between economic growth and carbon emissions, which has been found in previous studies (see Balsalobre et al., 2015; Friedl & Getzner, 2003). However, the results indicate that the impact of affluence on carbon emissions is significant only at the 20th, 30th and 90th. The implication is that economic growth in the OECD countries is environmentally friendly and could be attributed to the technique and composition effect associated with higher economic growth. Thus, as the OECD countries are at the advanced stage of economic development, there are better environmental technologies, increased in environmental awareness and strict enforcement of environmental policies, which have contributed to the decline or improvement in environment pollution (Stern, 2004).

The results further depict that population size significantly increases carbon emissions at the lower quantiles (the 10th, 20th, 30th, 40th, 50th) and remains insignificant at the higher quantiles (60th, 70th, 80th and 90th). The significant positive effect of population size at the lower quantiles of carbon emissions and the insignificant effect at the higher quantiles indicate that at lower carbon emissions, individual or households' consumption are unstainable and are willingly pay for the cost of a clean environment. However, when carbon emissions become substantially higher, people care most for the environment, thereby increasing environmental awareness, sustainable consumption and demand stringent environmental regulation. Consistently, Baldwin (1995) argues that people opt for a higher standard of living and willingness to pay for a cleaner environment as income level grows, but subsequently people become intuitively crave for quality and care more for the environment at higher income level.

Consistent with the ecological modernisation and urban transition theories, our results indicate that urbanisation significantly reduces carbon emissions at the 10th to 70th quantile while it insignificantly increases carbon emissions at the 80th to 90th quantile. The implication of this results could be that rapid urbanisation in the OECD countries is facilitating the economies of scale for public infrastructure and these economies of scale limit the growth of carbon emissions (Poumanyvong & Kaneko, 2010; Sadorsky, 2014). Also, as urbanisation increases in the OECD countries coupled with their advanced economic development, cities/urban planners become more environmentally conscious and sought to decouple environmental challenges (carbon emissions) from economic growth through urban agglomeration, technological innovation and shift towards knowledge-based economy (Poumanyvong & Kaneko, 2010). Notwithstanding this, urban planners in OECD countries should continue to expand urban infrastructure facilities that are energy efficient and environmentally friendly, as there is a likelihood that urbanisation could worsen the environment, by increasing carbon emissions.

Although the OECD countries are regarded as energy-efficient countries; however, our results suggest that energy intensity significantly contributes to the rise in carbon emissions, but the estimated elasticity is very high in the lower quantiles (the 10th, 20th, 30th, 40th, 50th). This result is against our priori expectation, as we expect energy intensity to reduce carbon emissions in the OECD countries. This results could be explained using the Jevon's paradox. Jevon's paradox argues that technological innovation that improves energy efficiency could induce higher energy consumption; thereby contributing to the rise in CO_2 emissions (Jevons, 1866). Thus, more technological innovation in the OECD countries and the desire of these countries to boost economic activities could induce higher energy demand, thereby causing carbon emissions.

Table 4: Panel quantile regression results

Variables	**Quantiles**								
	10th	20th	30th	40th	50th	60th	70th	80th	90th
Affluence	0.007	-0.138***	-0.082**	-0.034	0.007	0.021	0.006	0.008	-0.114*
	(0.085)	(0.029)	(0.033)	(0.023)	(0.026)	(0.037)	(0.041)	(0.048)	(0.065)
Population size	0.135**	0.223***	0.163***	0.110***	0.060**	0.042	0.040	0.007	0.063
	(0.067)	(0.024)	(0.033)	(0.024)	(0.027)	(0.036)	(0.043)	(0.045)	(0.065)
Service sector	1.011**	0.839***	0.408**	0.331**	0.191	-0.019	0.047	-0.084	0.426*
	(0.407)	(0.251)	(0.161)	(0.145)	(0.153)	(0.190)	(0.209)	(0.226)	(0.227)
Industry sector	1.055***	0.689***	0.246***	0.198***	0.051	-0.129	-0.196*	-0.399***	-0.038
	(0.082)	(0.220)	(0.091)	(0.071)	(0.077)	(0.089)	(0.101)	(0.120)	(0.179)
Energy intensity	1.048***	1.091***	0.985***	0.946***	0.900***	0.866***	0.832***	0.805***	0.924***
	(0.042)	(0.024)	(0.030)	(0.018)	(0.022)	(0.023)	(0.026)	(0.030)	(0.063)
Urbanisation	-1.057***	-0.256***	-0.130**	-0.202***	-0.201***	-0.191***	-0.213**	0.022	0.149
	(0.198)	(0.077)	(0.061)	(0.045)	(0.057)	(0.068)	(0.094)	(0.174)	(0.174)
Energy innovation	-0.110***	-0.093***	-0.049***	-0.042***	-0.028***	-0.002	0.016*	0.029*	-0.013
	(0.012)	(0.019)	(0.010)	(0.006)	(0.007)	(0.010)	(0.009)	(0.018)	(0.030)
Constant	-12.512***	-11.746***	-8.570***	-7.846***	-6.628***	-4.948***	-4.099***	-3.118***	-5.474***
	(1.474)	(1.667)	(0.862)	(0.721)	(0.795)	(0.854)	(0.949)	(1.201)	(1.680)
Observations	596								

Standard errors in parentheses* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Our results reveal that energy innovation reduces carbon emission at the lower quantiles (10^{th}, 20^{th}, 30^{th}, 40^{th}, 50^{th}); however, the estimated elasticity declines. At the 70^{th} and 80^{th} quantile, energy innovation contributes significantly to an increase in carbon emissions. Thus, investment in energy innovation initially contributes to carbon emissions reduction as it increases energy efficiency; however, a rise in such technological innovation induce carbon emissions as it fuels energy consumption and economic growth. This result is firmly grounded in the endogenous growth theory, which argues that technological progress resulting from research and development (RD) could lead to greater efficiency in production and the use of natural resources and energy, thereby increasing carbon emissions. Additionally, the positive effect of energy innovation on carbon emissions at higher quantiles could be attributed to the decline or stagnation of government expenditure on RD in the OECD countries. The OECD (2018, p. 22) report indicates that since 2010, government expenditure on RD in the OECD as a whole and almost all the Group of Seven countries (G7) have stagnated or declined. For instance, the report indicates that total government spending on RD has decreased by 4% (from 31% to 27%) between 2009 and 2016.

Table 5: Wald test for equality of slopes

	F-statistics	*P-value*
Affluence	6.46***	0.000
Population size	9.35***	0.000
Service sector	5.97***	0.000
Industry sector	71.27***	0.000
Energy intensity	42.81***	0.000
Urbanisation	2.79***	0.005
Energy innovation	14.83***	0.000

From our results, the service sector significantly increases carbon emissions at the 10^{th}, 20^{th}, 30^{th}, 40^{th} and 90^{th} while it remains insignificant from the 50^{th} to 80^{th} quantile. Thus, the continued growth of the service sector, which has become a more significant part of the OECD countries' economy consumes more energy and release more carbon emissions. Previous empirical studies have indicated that the service sector contributed massively to carbon emissions (Nansai et al., 2009; Poumanyvong & Kaneko, 2010; Sohag, Al Mamun, Uddin, &

Ahmed, 2017; Suh, 2006). Additionally, the industry sector further contributes significantly to carbon emissions at the lower quantiles (10th, 20th, 30th, 40th) while it substantially reduces carbon emissions at the 70th and 80th quantiles. The significant positive impact of industrialisation on the lower quantiles indicates the scale effect, while the significant reduction at higher quantiles reflects the composition and the technique effect. Thus, as there is a need for structural transformation, industrialisation initially fuels higher energy consumption, economic growth and the use of energy and carbon-intensive production techniques, which exacerbates carbon emissions. However, at a higher level of carbon emissions, there is a stringent environmental regulatory policy that compels industries to find innovative ways of production such as deploying energy-efficient techniques of production, using less environmental damage inputs, implementing and enforcing standard corporate social responsibilities (environmental sustainability). Additionally, while the OECD countries are at the later stage of economic development, there is a change in *output mix*, where there is a shift from the more resource-intensive extractive and heavy industries to service and light manufacturing, which are argued to emit less carbon (Stern, 2004).

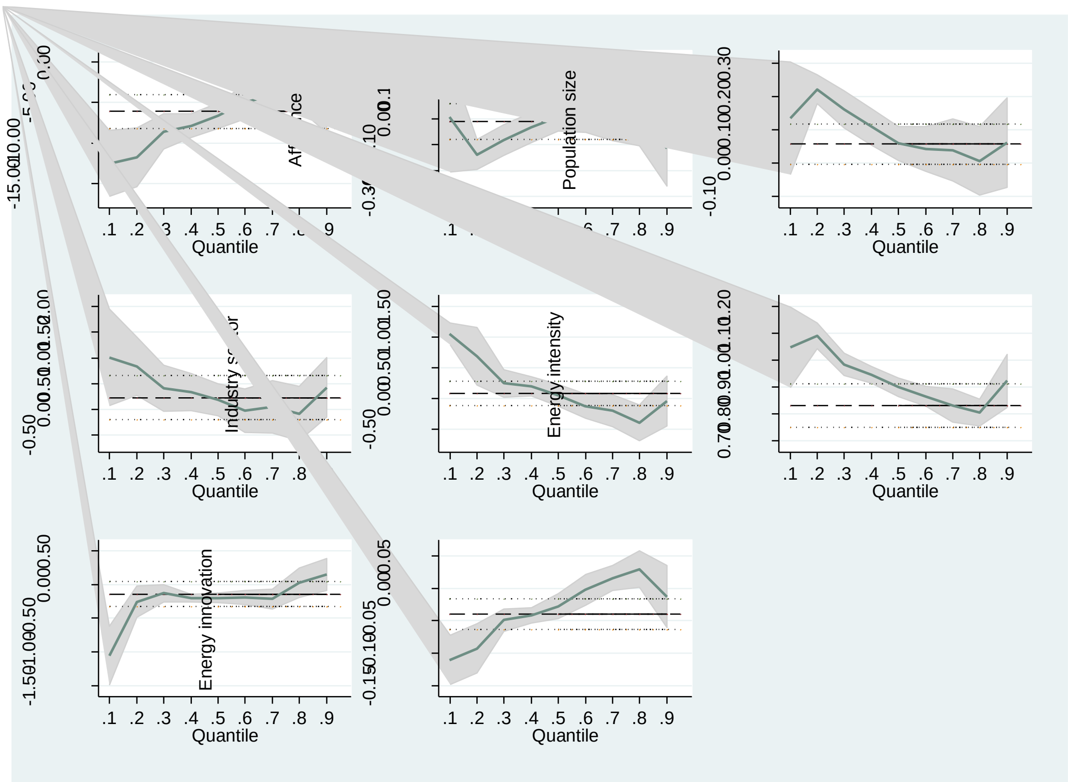

Fig. 2: Quantile distribution of the variables

Table 5 tests for the equality of slopes. We test the 10th quantile against the remaining quantiles, and the *F*-statistics rejects the hypothesis of parameter homogeneity. Thus, the slopes are heterogeneous; therefore, the results from the panel quantile regression crucial for policy. Similarly, Fig. 2 suggests that the impact of population size, economic growth (affluence), energy innovation, urbanisation, industrial sector, service sector and energy intensity on carbon emissions in OECD countries are heterogenous; therefore, using panel quantile regression is the best approach compared to conditional mean models such as OLS.

5. Conclusions and policy implications

Over the past decades, the world has experienced an unprecedented increase in carbon emissions. The rise in carbon emissions has raised significant concern among researchers and policymakers. It is argued that if pragmatic measures are not taken, carbon emissions, which is a significant cause of climate change and global warming, would devastate social, economic, political and cultural development. Currently, environmental and energy policymakers are assessing carbon emissions mitigation strategies through the lens of energy innovation. However, research linking energy innovation to carbon emissions remains limited in the literature. In this research, we deploy the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model to investigate the impact of energy innovation on carbon emissions in 26 OECD countries for the period 1974-2017. In addition to population and affluence variables in the STIRPAT model, we also accounted for other variables such as energy intensity, urbanisation, the industrial and the service sectors in our empirical model to reduce variable omissions bias. In estimating our empirical models, we began the analysis using a conditional mean model such as OLS, random effect, fixed effect, dynamic fixed effect and system-generalised method of moment (system-GMM), which reveal some impressive preliminary results. However, to account for slope heterogeneity, we employed the fixed effect panel quantile regression, which is a non-parametric model, as the primary econometric technique for this study.

Interestingly, our results revealed that energy innovation reduces carbon emission at the lower quantiles (10^{th}, 20^{th}, 30^{th}, 40^{th}, 50^{th}) while it increases carbon emissions at the 70^{th} and 80^{th} quantile. The empirical results further indicated that affluence significantly reduces carbon emissions at the 20^{th}, 30^{th} and 90^{th} while it remains insignificant at the remaining quantiles. It was also found that population size significantly increases carbon emissions at the lower quantiles (the 10^{th}, 20^{th}, 30^{th}, 40^{th}, 50^{th}) while urbanisation substantially reduces carbon emissions at the 10^{th} to 70^{th} quantile. It was further observed that energy intensity significantly increases carbon emissions at all the quantiles, but the estimated elasticity is very high in the lower quantiles (the 10^{th}, 20^{th}, 30^{th}, 40^{th}, 50^{th}). Our findings also revealed that the service sector significantly increases carbon emissions at the 10^{th}, 20^{th}, 30^{th}, 40^{th} and 90^{th}. Also, the industry sector was found to substantially increase carbon emissions at the lower quantiles (10^{th}, 20^{th}, 30^{th}, 40^{th}) while it significantly reduces carbon emissions at the 70^{th} and 80^{th} quantiles. These results have important policy implications for OECD countries.

One of the policy implications of these empirical findings is that public investment in energy technology RD&D is critical for mitigating carbon emissions in OECD countries.

Although energy innovation is associated with an increase in carbon emissions at higher quantiles, we argue that such impact is a reflection of weak growth or decrease in R&D investment in the OECD countries (see OECD, 2018). The OECD reports suggest that lower public R&D poses a treat to innovation at a time when global challenges such as climate change demand solution. This indicates that to reduce carbon emissions substantially, governments in the OECD countries should increase their budget spending on total R&D, and more specifically, energy innovation R&D. Additionally, future environmental policy in the OECD countries should give priority to energy innovation as one of the pragmatic strategies to mitigate carbon emissions and further help to fulfil the Paris agreement.

Another implication of our results is that urbanisation contributes to carbon emissions reduction. Thus, urbanisation in OECD countries facilitates the economies of scale for public infrastructure, and these economies of scale are limiting the growth of carbon emissions. Therefore, omitting urbanisation will have a critical impact on environmental strategies to mitigate carbon emissions and to achieve a sustainable development policy. On the other hand, as there is a likelihood for urbanisation to induce carbon emissions at higher quantiles, urban planners should be environmentally conscious and continue to expand urban infrastructure facilities that are energy efficient and environmentally friendly. One of the critical strategies for OECD countries to curb carbon emissions is to sustain higher economic growth. Thus, sustaining higher economic growth will not conflict with carbon emissions mitigation strategies but will instead complement it to halt the carbon emissions growth. Another direct way for the OECD countries to control carbon emissions is to reduce population by incentifying and to strengthen family planning policies. The rapid expansion of the service and the industrial sectors of the OECD countries puts an extra demand for energy and contributes to carbon emissions. Therefore, improving energy efficiency or reducing energy intensity by making a sharp transition from fossil energy use to renewable energy use remains imperative for curbing carbon emissions. Additionally, future environmental policy in OECD countries should entice as well as compelling the industrial and service sectors of the economy to decouple environmental pollutions from their production activities.

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