Investigating the Impact of Climate Change Mitigation Technology on the Transport Sector CO$_2$ Emissions: Evidence From Panel Quantile Regression

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Carbon emissions from the transport sector (COE) has witnessed unprecedented growth, which calls for special measures to control these emissions to achieve carbon neutrality by 2050. One of the measures taken to limit these emissions is climate change mitigation technology related to the transport sector (CCMT). However, there exists relatively scant literature that explores the CCMT-COE nexus. Hence, the present study explores whether CCMT curbs COE in the top transport sector carbon-emitting countries. For this purpose, we employ a panel quantile regression (PQR) approach, which probes the impact of CCMT on COE in low-, middle-, and high-emission countries. The result shows that CCMT does not affect COE at the lowest quantile (i.e., 10th quantile) while CCMT plunges the emissions at all other quantiles. In particular, a 1% increase in CCMT curbs COE by 0.13% at the 25th, 50th, and 75th quantile, while a 1% upsurge in CCMT impedes COE by 0.22% at the 90th quantile. In the light of these findings, the carbon policy in the transport sector should invest in climate change mitigating technology in the transport sector and scale it up and out.

Keywords: transport, greenhouse gas, panel quantile regression, climate change mitigation technologies, CO$_2$ emissions

INTRODUCTION

The transport sector is regarded as one of the imperative sectors because it contributes significantly to social and economic development. Improved transport facilities assist the mobilization of the labor force and help to transfer other resources (e.g., coal, machines, other capital goods, etc.). Not only this, the transport sector plays a pivotal role while providing quality education and health services. Further, quality transportation services boost tourism, trade, and effective distribution, thereby upsurging economic growth (EG). Besides, transportation transfers resources from resource-abundant to resource-scarce areas and reduces income inequality. In the US and European Union (EU), the share of the transport sector to GDP is around 8% and 5%, respectively[1]. Thus, the transport sector is undoubtedly inevitable for the socio-economic development of the nation and

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[1]https://joint-research-centre.ec.europa.eu/scientific-activities-z/transport-sector-economic-analysis_en#:~:text=Transport%20plays%20an%20important%20role,gross%20domestic%20product%20(GDP).

the well-being of people (Monioudi et al., 2018; Xu and Lin, 2018; Ülengin et al., 2018; Jiang et al., 2019; Lv et al., 2019; Georgatzi et al., 2020).

However, it is important to note that the transport sector significantly relies on energy. Whether it is road transportation, railways, or air transport services, the use of energy is profound. Both production and consumption/use of transport require a substantial amount of energy. For instance, an enormous amount of energy is used as an input to produce vehicles, ships, and jets, among others. On the contrary, petroleum-based products (e.g., gasoline and jet fuel, etc.) are required to operate vehicles, ships, jets, etc. Such a heavy reliance on energy is responsible for high greenhouse gas (GHG) emissions. According to the World Bank, 16.2% of world energy consumption is associated with the transport sector (Cozzi et al., 2020).

Similarly, the transport sector emits the second-highest level of greenhouse gases (EIA, 2020). Further, according to Energy Information Administration, the transport sector is responsible for almost 22% of global carbon emissions (EIA, 2020). Recently, Tunde et al. (2022) analyzed the trends (i.e., forecasting) of sectoral carbon emissions and concluded that the transport sector emissions experienced the highest trend. Hence proper environmental planning in the transport sector is inevitable for sustainable growth (ibid). Not only this, but the transport sector's emissions also affect EG. Rehman et al. (2022) argued that carbon emissions from various sectors have an asymmetric impact on EG. In particular, the transport sector emissions have an asymmetric effect on both the short- and long-term growth.

Against the backdrop of increasing climate risk resulting from greenhouse gas emissions and a global effort to achieve carbon neutrality by 2050, reducing transport-related carbon emissions (COE) is crucial. Therefore, it is critical to explore the drivers of COE. The literature presents several factors that explain transport-related carbon emissions (COE), such as economic growth (EG) (Arvin et al., 2015; Berg et al., 2017; Nasreen et al., 2020; Godil et al., 2021), non-renewable energy consumption (Nathaniel and Iheonu, 2019; Sharif et al., 2019; Destek and Sinha, 2020; Sharma et al., 2021), renewable energy consumption (Dong et al., 2017; Lee et al., 2017; Hu et al., 2018; Amin et al., 2020; Naderipour et al., 2021), urbanization (Zhang et al., 2020; Hanif, 2018; Liu et al., 2018; Zhou et al., 2021), and environmental policies (Huisingh et al., 2015; Xie et al., 2017; Bhowmik et al., 2020; Chan, 2020; Moran et al., 2020; D'Orazio and Dirks, 2022; Hussain et al., 2022), etc. Parallel to these factors, environmental technologies are the eminent drivers that can help to limit COE (Kwon et al., 2017; Raza et al., 2019; Chen and Lee, 2020; Nguyen et al., 2020; Rissman et al., 2020). Further, climate change mitigation technology related to the transport sector (CCMT) is among the critical factors that play a vital role in curbing COE (Wang et al., 2018; Fan et al., 2019). CCMT is referred to as the technological advancements that escalate the energy efficiency and share of renewables in the transport sector. The literature disregards the CCMT while modeling COE (Lee et al., 2017; Durmaz, 2018), which is necessary to shape policies related to sustainable transportation. CCMT upsurges the energy efficiency, thereby helping to reduce COE. Moreover, CCMT can also escalate the use of renewable energy products, which, in turn, mitigate COE.

Rudyk et al. (2015) examines the impact of CCMT on COE for European countries and found that CCMT helps in reducing COE. Su and Moaniba (2017) report that CCMT curbs COE for selected 70 countries. In the case of 30 Chinese provinces, Xu and Lin (2015) find similar results. Alatas (2021) reported that CCMT impedes COE in selected OECD economies. Although these studies mentioned above explain the impact of CCMT on COE, no study covers the issue of individual and unobserved heterogeneity. On top of this, no research outlet examines the impact of CCMT on low-, middle-, and higher levels of COE. Therefore, the present study addresses these aforesaid drawbacks of the existing literature.

Based on the above-reported arguments, the objective of this study is to reinvestigate the impact of CCMT on COE for the top five carbon emitters of the transport sector[2] (i.e., China, India, Russia, United States, and Brazil). This set of countries is also the world's leading economy, with a significant rate of EG. Also, these countries consume a major chunk of global energy, thereby emitting a profound quantity of greenhouse gas emissions. Besides, these countries lead the world in terms of population and area. Therefore, they consist of an extensive transportation system that requires tons of energy and produces enormous emissions.

Hence, the current study has three contributions compared to the existing body of knowledge. First, this is the first strive to explore the impact of CCMT on COE for top emitters of the transport sector, namely China, India, Russia, the US, and Brazil. Second, based on our best knowledge, this is the first endeavor that employs the panel quantile regression (PQR) approach to discern the impact of CCMT on COE. The panel quantile regression (PQR) methodology captures the heterogeneous impact of CCMT on various quantiles of COE. Third, we employ Dumitrescu and Hurlin (2012) causality test (henceforth D-H test), which is insusceptible to cross-sectional dependence, slope heterogeneity, and unobserved heterogeneity, and thus provides reliable results (Husnain et al., 2022).

LITERATURE

This section is segregated into two parts. The first part explores the drivers of aggregate/total carbon emissions, while the second section highlights the determinants of emissions in the transport sector. Also, the summary of literature in a smart chart format is depicted in **Figure 1**.

Determinants of Aggregate/Total Carbon Emissions

A plethora of literature related to environmental economics discerns the impact of EG on emissions, with the Environmental Kuznets Curve (EKC) being the most critical hypothesis to test (Grossman and Krueger, 1991). Energy

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[2]https://www.wri.org/insights/everything-you-need-know-about-fastest-growing-source-global-emissions-transport#:~:text=The%2010%20countries%20with%20the,%2C%20Germany%2C%20Mexico%20and%20Iran.
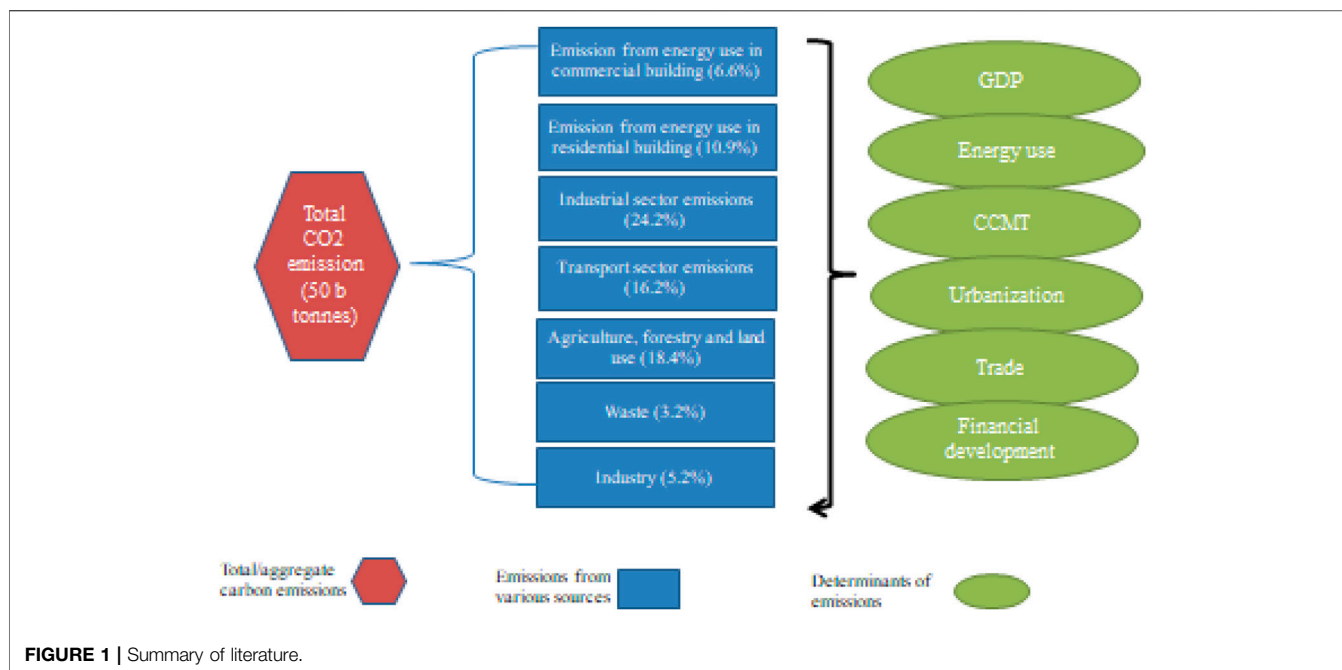
FIGURE 1 | Summary of literature.

efficiency also plays a pivotal role in curbing COE. For instance, Liobikienė et al. (2019) noted that EG reduces COE in the presence of improved energy efficiency. Contrarily, EN is a key determinant of COE. Several researchers conclude that non-renewable energy is accountable for COE (Erdogan et al., 2020). Since renewable energy is considered low-carbon energy, its use will result in the decline of COE (Lee et al., 2017; Hu et al., 2018). Syed et al. (2022) investigate whether economic policy uncertainty affects emissions in BRICST countries, and the outcomes of the study document that policy uncertainty escalates emissions. Syed and Bouri (2021) apply bootstrap ARDL to examine whether policy uncertainty affects emissions in the United States. The authors find that policy uncertainty has a heterogeneous effect on carbon emissions across the long- and short-run. Similarly, Bhowmik et al. (2022), using a dynamic ARDL approach, shows that monetary policy uncertainty increases emissions, fiscal policy uncertainty impedes emissions, and trade policy uncertainty does not affect the volume of emissions. Like policy uncertainty, geopolitical risk can also affect emissions. Anser et al. (2021a) found that geopolitical risk leads to higher emissions in BRICS countries. Hashmi et al. (2021), using the bootstrap ARDL approach, observed that higher geopolitical risk triggers the use of non-renewables which escalates emissions. Anser et al. (2021b) test the validity of the Environmental Phillips Curve (EPC) in BRICST economies and found that the EPC holds true. Similar findings are reported by Bhowmik et al. (2022) in the United States. Valeria and Giovanna (2022) show that corporate governance strategies reduce firm-level emissions. In the case of India, Irfan et al. (2022) divulge that technological and infrastructural factors, in consort with financial and political factors, are the key barriers to biomass energy, which impedes emissions levels. Tang et al. (2022) validate the financial resource curse hypothesis and also

confirm that business regulations moderate the finance-resources relationship. Gentile et al. (2022) reveal that the CCMT reduces carbon emissions and is cheaper to plunge emissions than the conventional emissions capture system. Khan et al. (2022) argue that energy trilemma and clean energy transition improve the environmental quality. Likewise, Zhang et al. (2022) revealed that ICT decreases emissions while education and EG escalate the levels of emissions in selected developing countries. Parallel to this, Kassouri (2022) uses a quantile-based approach and reports that fiscal decentralization has an asymmetric impact on public energy research development and demonstration in selected developed countries. Muhammad and Khan (2021) noted that EG, FDI, and globalization escalate emissions. Similarly, Murshed et al. (2021) reveal that EG, globalization, urbanization, and renewable electricity are the key drivers of carbon emissions. Hussain et al. (2022) mentioned that environment-related technology can decrease environmental degradation in developing countries by gradually switching from old to modern technologies. Yu and Du (2019) point out that environment-friendly technology or innovation significantly reduces emissions. Wang et al. (2019) noted that the impact of new technological development significantly mitigates emissions. Similarly, Cheng et al. (2021) find that technological innovation significantly mitigates emissions in OECD countries. Moore et al. (2021) also highlight that CCMT has a significant role in decreasing emissions.

Determinants of Carbon Emissions in the Transport Sector

Several studies highlight that economic growth (EG) is an indispensable driver of emissions in the transport sector (Andreoni and Galmarini, 2012; Chandran and Tang, 2013).

Zhang and Nian (2013) use the STIRPAT model to explore transport-related emissions and found that EG, EN, and population increase emissions. Liddle (2015) validates the EKC for the transport sector. In the transport sector, energy is undoubtedly a key driver of emissions. Anwar et al. (2021) showed that public-private investment is also a key driver of emissions. EN is an essential source of transport emissions (Mohsin et al., 2019). Lu et al. (2020) explore the direct and indirect effects of EN on emissions. The study reports that the level of emissions witnessed an upsurge due to the transportation sector development in China. Ahmed et al. (2020) also found similar results in India- that the EN causes an upsurge in emissions.

Recently, Pani et al. (2021) investigated the drivers of transport emissions in India and highlighted that urbanized areas produce higher emissions than the less urbanized regions. Similar findings are reported by Habib et al. (2021) in G20 countries. Robaina and Neves (2021) explore the relationship between the transport sector, EG, and emissions in Europe. The study notes that an upsurge in the number of electric vehicles reduces carbon emissions. Georgatzi et al. (2020) examined whether CCMT affected the transport sector emissions in selected European countries and noted that CCMT significantly plunges emissions. Sajid et al. (2022) highlighted that investment in technology can help to decrease emissions in the transport sector.

MODEL AND DATA

This section briefly presents the empirical model and provides details on the selected dataset. In the literature on environmental economics, the EKC framework is considered a core empirical model to explore the socio-economic drivers of COE (Syed and Bouri, 2021). Therefore, following the study of Hashmi et al. (2021), this study also uses the EKC framework to test the impact of CCMT on COE. The model used in this study is highlighted as follows:

$$COE = FEG, EG2, EN, CCMT \qquad (1)$$

COE denotes carbon dioxide emissions in the transport sector, EG reflects GDP per capita, EG2 represents the square of GDP per capita, EN denotes energy consumption, and CCMT is climate change mitigation technologies related to the transport sector. To validate the EKC hypothesis, EG should be positive, while EG2 needs to be negative. Further, the expected sign for EN is positive, while we expect CCMT to be negative as it has GHG reducing effect. It is worth noting that the EKC[3] is a widely used theoretical and empirical framework in the literature on environmental economics. The theory of EKC argues that EG escalates emissions whereas it decreases emissions once EG exceeds a certain level (Bilgili et al., 2016). The EKC, which is an inverted U-shape relationship between EG and emissions, notes that EG is linked with emissions through scale,

TABLE 1 | Descriptive statistics.

Statistic	CCMT	COE	EN	EG
Mean	127.72	22.11	3094.39	14704.01
Std. Dev.	249.52	14.06	2644.52	19097.11
Skewness	2.51	0.57	0.68	1.43
Kurtosis	9.32	1.72	1.93	3.20
Jarque-Bera test	(0.06)*	(0.01)**	(0.03)**	(0.35)

(.) is p-value. While *and **represent the level of sig. at 10% and 5%, respectively.
Note: CCMT- mitigation technologies in the transport sector; EN- Energy consumption–measured in kg oil equivalent per capita; EG-GDP per capita–measured in constant \$2015; COE: carbon emission for the transport sector (measured in percentage of total fuel combustion).

composition, and technique effect. Similarly, EN (i.e., a control variable in this study) also theoretically affects emissions as energy sources mostly contain fossil fuels that transmit emissions (Syed et al., 2022). CCMT improves energy efficiency, which in turn plunges emissions. Moreover, CCMT has also been upsurging the use of renewable energy, which is regarded as low carbon energy, and hence emissions witnessed a reduction (Georgatzi et al., 2020).

Regarding the details of the dataset, the present study uses panel data covering 1999–2015 for the top five carbon emitter countries[4], namely China, United States, India, Brazil, and Russia. Next, COE (measured in percentage of total fuel combustion) is used as a dependent variable. While EG (GDP per capita—measured in constant \$2015), EG2 (square of EG), and EN (energy consumption—measured in kg oil equivalent per capita) are employed as control variables. The independent variable of interest is climate change mitigation technologies in the transport sector (CCMT), which is measured as the ratio of environment-related patents in total patents. The data on the COE, EG, and EN are collected from the World Development Indicators (WDI), whereas the OECD database is used to obtain the data on CCMT. It is worth reporting that we converted the entire dataset into a natural logarithmic formation.

The descriptive statistics of the data used in the study is summarized in **Table 1**. EG has the highest mean value, while COE has the lowest mean value. Likewise, EG has the highest variation, and COE contains the lowest deviation. The entire dataset is positively skewed. In contrast, kurtosis confirms that the dataset does not contain the fat tail. Finally, the entire dataset is distributed non-normally except for EG, which has a normal distribution. It is extensively reported in the prior literature that traditional least square-based methodologies can come up with unreliable results if the dataset is non-normally distributed (Khalid et al., 2021; Syed et al., 2022). This motivates the application of the PQR approach, which is reliable even if the dataset follows a non-normal distribution (Li et al., 2022).

This study also uses the q-q plot to explore graphically whether the dataset is normally distributed. **Figures 1–4** depict q-q plots

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[3]For the detailed theortetical understanding on the EKC approach, please see Bibi and Jamil (2021).

[4]In 2015, the per capita carbon dioxide emissions in the selected countries are as follows: 44.75 metric tons per capita (MTPC) in Brazil, 8.60 MTPC in China, 11.47 MTPC in India, 16.24 MTPC in Russia, and 33.39 MTPC in the United States.
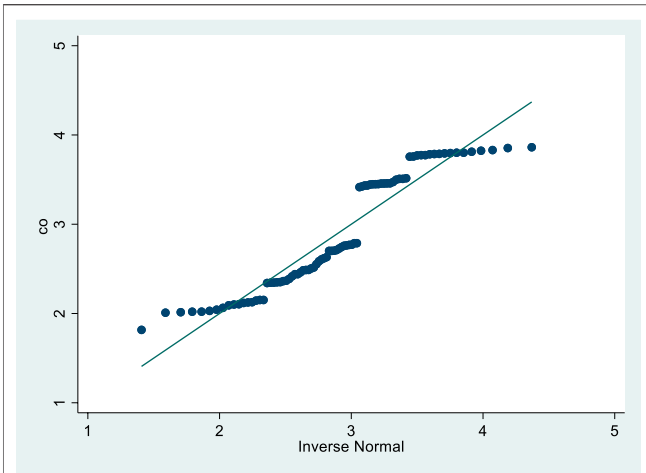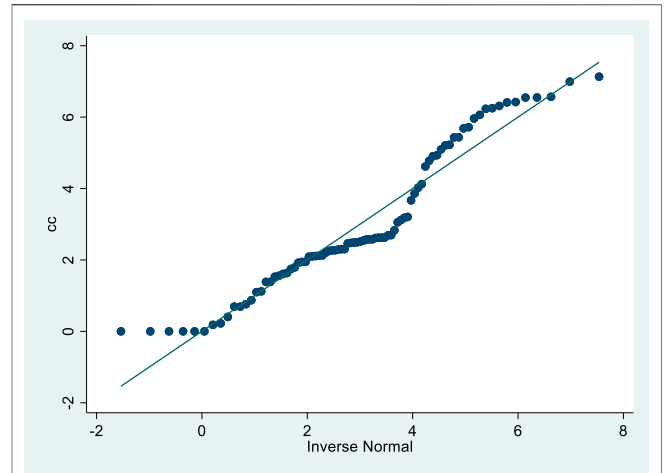
FIGURE 2 | COE.

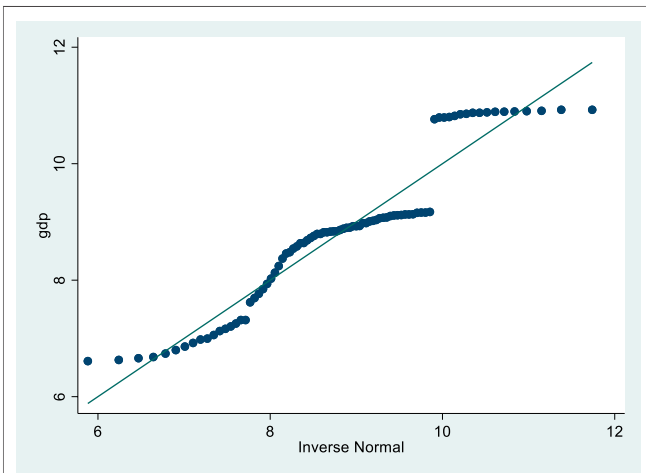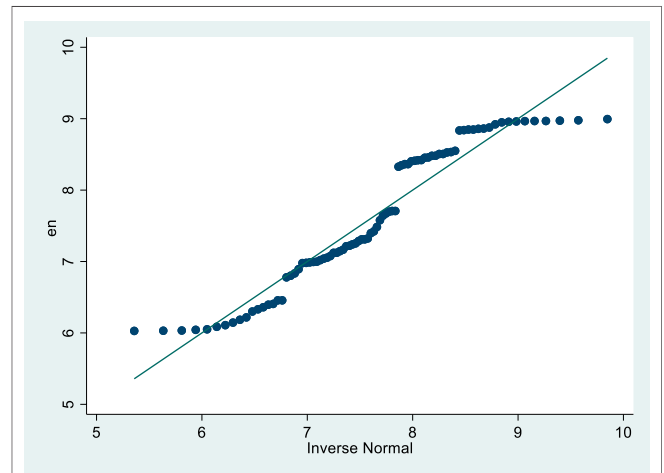

FIGURE 4 | CCMT.

FIGURE 3 | EG.

FIGURE 5 | EN.

for the considered variables. In the q-q plots, the diagonal line represents the normality of data, while the blue dotted line shows the actual distribution of the variable. The deviation of the blue dotted line from the diagonal line expresses that the data are non-normally distributed. In **Figures 2–5**, the blue dotted line diverges from the diagonal line for all variables, indicating that the dataset used in the study is distributed non-normally.

METHODOLOGY

In the prior literature, it is well-cited that OLS regression gives an unbiased estimator with a minimum variance if: 1) disturbance term in OLS regression contains zero mean, and it follows an identical distribution (iid); and 2) disturbance term is normally distributed. Da Silva et al. (2016) noted that these assumptions mentioned above are not satisfied most of the time, leading to

unreliable results. To avoid the deficiency of OLS regression, Koenker and Bassett (1978) put forward the quantile regression (QR) approach. Quantile regression (QR) has certain merits, for instance, 1) the QR does not use any assumption related to the occurrence of moment function (Zhu et al., 2016); 2) QR gives relatively truthful and robust outcomes if outliers and fat tail distribution occur in the dataset (Bera et al., 2016); 3) Quantile regression (QR) does not establish any assumption related to the distribution (Sherwood and Wang, 2016). Based on these properties of Quantile regression (QR), this study employs this methodology.

$$Q_{yi} \ (\varnothing|x_i) = \ x_i' \alpha_\varnothing \qquad (2)$$

Equation 2 yields the conditional quantile Y_i in a given x_i, however, $\varnothing$ is the quantile. While applying the Quantile regression (QR) approach in the panel dataset, unobserved heterogeneity is taken into account, which compels us to use

the Panel Quantile Regression (PQR) approach with a fixed effect. The Panel Quantile Regression (PQR) approach allows to control for the unobserved individual heterogeneity. The Panel Quantile Regression (PQR) model with fixed effect is reported as follows.

$$Q_{y_{it}} \left(\varnothing_k | \varphi_i, \, x_{it} \right) = \varphi_i + x_{it}' \alpha \left(\varnothing_k \right) \qquad (3)$$

In **Eq. 3**, φ_i expresses the fixed effect that also brings the incidental parameter problem (Lancaster, 2000). In the case of fixed time-series observations for each cross-sectional unit, the estimator is found to be inconsistent if the cross-sectional unit approaches infinite value (Galvao and Kato, 2016). So, traditional linear approaches cannot be applied in the Panel Quantile Regression (PQR) model. Therefore, Koenker (2004) put forward a method, recognized as the shrinkage method, to resolve the aforesaid issue of the Panel Quantile Regression (PQR). The method develops a penalty term to abolish the unobserved fixed effects. The parameters of the model are estimated as follows.

$$\left(\hat{\alpha} \left(\varnothing_k, \eta \right), \, \left\{ \varphi_i \left(\eta \right) \right\} Ni = 1 \right)$$
$$= \arg \min \sum_k^K \sum_t^T \sum_i^N \Omega_k \rho_{\varnothing k} \left(y_{it} - \varphi_i \right.$$
$$\left. - x_{it}' \alpha \left(\varnothing_k \right) \right) + \eta \sum_i^N \left| \varphi_i \right| \qquad (4)$$

In **Eq. 4**, i and t respectively note country and year. k shows the quantile while $\rho_{\varnothing k}$ notes the quantile loss functions. Ω_k is the assigned weight that is provided to kth quantile. Ω_k delineates the contribution of different quantiles. Following Lamarche (2011), we also set $\Omega_k = 1/k$. η is tunning term/parameter that is used to decrease the individual effect to zero for better estimation of slope coefficients in the model. Following the studies of Li et al. (2022), this study set $\eta =$.

EMPIRICAL FINDINGS

The current section presents the empirical findings, and the steps we follow are depicted in **Figure 6**. While handling the panel dataset, the occurrence of cross-sectional dependence (CSD) can be critical for the reliability of the results. The CSD holds if the shock in any of the cross-sections has a spillover effect to other cross-sections. Hence, it is indispensable to test for the CSD to check for the reliability of the findings. Various CSD testing approaches have been developed in econometrics literature, Pesaran (2007) CSD test other being the most extensively used test. Hence, including Pesaran (2007) CSD test, we use the other three tests, namely, i.e., Pesaran test, Frees test, and the Friedman test, to discern the presence of CSD in this study.

Table 2 highlights the findings from the CSD tests. The *Ho* of these tests mentioned above is the absence of CSD where the alternate hypothesis assumes vice versa. As shown in **Table 2**, we can reject the *Ho* for all tests. Hence, it could be noted that there is an occurrence of CSD in our case.

After testing the CSD, we perform the unit root test. It is crucial to test for the unit root as disregarding it could lead the

pseudo findings. In panel data econometrics, second-generation unit root tests have been extensively used because of their ability to handle the CSD. Therefore, we also apply the second-generation unit root test (i.e., the CIPS test). The findings from the CIPS test are provided in **Table 3**. The *Ho* of the CIPS test assumes of the absence of unit root where the alternate hypothesis vice versa. As depicted in **Table 3**, we cannot reject *Ho* at level, indicating that the dataset contains the unit root at the level. Contrarily, we can reject the *Ho* at the first difference for the entire dataset, implying that the dataset is stationary at the first difference.

The next step is to discern the cointegration, which notes whether there is a long-run relationship among the chosen variables. To this end, we employ Westerlund (2007) test, which can handle the CSD. The *Ho* of this test mentioned above expounds no cointegration while the alternate hypothesis notes vice versa. The outcomes from Westerlund (2007) test are presented in **Table 4**. We can reject the *Ho* in the case of all four statistics of the Westerlund test. Thus, it confirms that cointegration holds among the chosen variables of this study.

Thereafter, we report the findings from the panel quantile regression (PQR) approach at 10th, 25th, 50th, 75th, and 90th quantiles. We also estimate the fixed effect model to compare its results with the panel quantile regression (PQR) approach and included the results in **Table 5**. With regard to the findings from the fixed-effect model, the EG is statistically significant with a positive coefficient, while EG2 is insignificant. Therefore, we conclude that the Environment Kuznets Curve (EKC) hypothesis does not hold in the case of the top five transport emitter countries as it requires both EG and EG2 to be statistically significant with a positive and negative coefficient, respectively. Next, EN–in kg oil equivalent per capita is negative and statistically significant, implying that the use of renewable energy mitigates COE. Finally, CCMT is negative and statistically significant, indicating that CCMT reduces emissions. The value of CCMT is 0.136, indicating that a 1% increase in CCMT reduces emissions by 0.136%. It is worth mentioning that the fixed-effects model assumes the normality assumption, and some of the findings from this model (e.g., results of the EKC and EN) are not in line with the theory. Thus, applying the quantile regression (QR) approach is inevitable if the normality assumption violates.

In the case of the panel quantile regression (PQR) approach, the 10th and 25th quantiles are regarded as the lower quantiles, the 50th quantile is considered the middle quantile, while 75th and 90th quantiles are considered are the higher quantiles. EN is statistically significant and positive across the quantiles, whereas EG2 is negative and statistically significant across all quantiles. This implies that EG escalates COE, and after a certain level, it curbs the COE. Thereby, we conclude that the EKC holds in this analysis. The results are also backed by the studies of Bilgili et al. (2021), Anser et al. (2021a), Anser et al. (2021b), and Bilgili et al. (2022). The sign of EN is positive with statistical significance at a 1% level across the distribution. This indicates that energy use escalates transport-related carbon
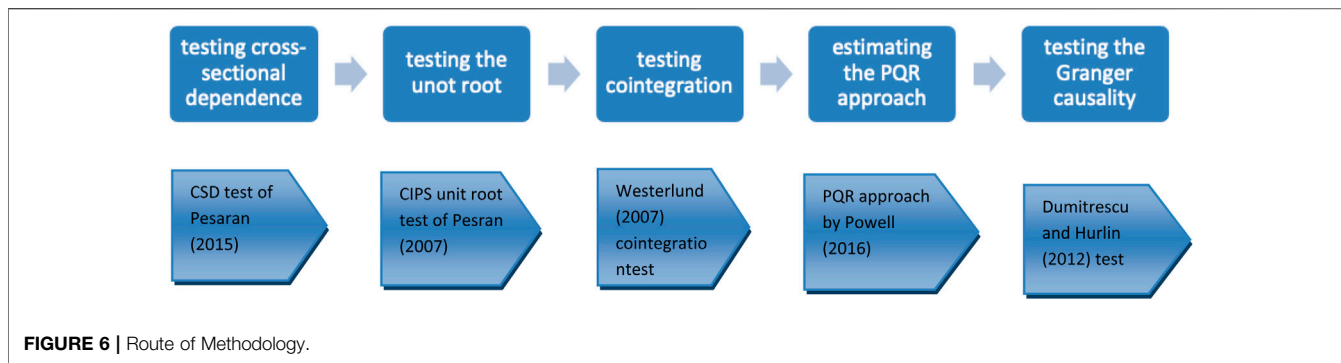
FIGURE 6 | Route of Methodology.

TABLE 2 | Testing CSD.

	CSD tests		
	Pesaran CSD test	**Friedman CSD test**	**Frees CSD test**
COE= f (EG, EG2, EN, CCMT)	[0.00]***	[0.00]***	[0.00]***

*[.] is p-value while ***p < 0.01.*

TABLE 3 | CIPS test.

Indicator	**CIPS test**	
	Level	**1st difference**
COE	−1.02	−2.97***
EG	−1.91	−2.99***
EN	−1.02	−3.96***
CCMT	−1.37	−3.71***

***p < 0.01

Note: COE: carbon emission for the transport sector (measured in percentage of total fuel combustion); EG-GDP per capita–measured in constant $2015; EN- Energy consumption–measured in kg oil equivalent per capita; CCMT- mitigation technologies in the transport sector.

TABLE 4 | Testing cointegration.

Statistic	**Value**
G_t	−12.21 [0.00]***
G_a	−7.31 [0.00]***
P_t	−12.23 [0.00]***
P_a	−6.09 [0.00]***

*[.] denotes p-value. ***p < 0.01.*

emission COE in low-, middle-, and higher- emitters. Moreover, the impact of EN is relatively high at lower quantiles. Similar outcomes are reported by Bilgili et al. (2016) and Bashir et al. (2022).

Regarding CCMT, the coefficient is negative and statistically significant at all quantiles except the 10th quantile, which is insignificant. This implies that an increase in CCMT mitigates COE in top emitter countries at the 25th, 50th, 75th, and 90th quantile. At the 10th quantile (countries with lower levels of transport sector emissions), CCMT is found to be ineffective. The latent reasons could be that these CCMT are not properly used in

the transport sector. The high cost of CCMT, complex procedure to adopt CCMT, and lack of bindings from the government to use CCMT could hinder inappropriate usage of CCMT in the low emitter countries. At the 25th, 50th, and 75th quantile, CCMT is 0.013. This indicates that a 1% upsurge in CCMT decreases the COE by 0.013%. These results highlight that CCMT improves energy efficiency and exacerbates renewables use. As a result, the proper usage of the CCMT curbs emissions. Next, the CCMT is −0.022 at the 90th quantile, reporting that a 1% growth in CCMT decreases the COE by 0.22%. It is worth reporting that the impact of CCMT is heterogeneous across the quantiles, which could not be captured using conventional methodologies (e.g., fixed effect model, etc.). These results are almost similar to Alatas (2021), which argues that environment-related technologies curb transport-related emissions in OECD countries. The key findings from the PQR approach are graphically delineated in **Figure 7**.

Next, we employ a pooled mean group-auto regressive distributed lags (PMG-ARDL) approach as a sensitivity analysis to see whether our baseline findings from the PQR approach are consistent with a dynamic regression approach (i.e., PMG-ARDL model). The findings are reported in **Table 6**.

As depicted in **Table 6**, all coefficients are statistically significant in both the short- and long-run, which implies that EG, EN, and CCMT affect COE. In the long-run, the coefficient of CCMT is -0.13, expressing that a 1% increase in CCMT plunges the COE by 0.13%. While EG and EG2 are positive and negative, respectively, and this shows that the EKC holds in the long-run. Further, the coefficient on EN is positive, indicating that energy consumption leads to higher COE. Similarly, in the short-run, the coefficient of CCMT is −0.06, which illustrates that a 1% increase in CCMT fosters a 0.06% reduction in COE. We also validate the existence of the EKC in the short-run. Further, the positive coefficient of EN indicates that energy use contributes to COE. It is worth reporting that the key findings

TABLE 5 | Empirical findings from the panel quantile regression (PQR) approach.

Indicator	Fixed effects	Panel quantile regression				
		10th	25th	50th	75th	90th
GDP per capita–in constant $2015 (EG)	1.011***	0.532***	0.503***	0.512***	0.502***	0.561***
GDP per capita Square- in constant $2015 (EG2)	0.001	−0.001***	−0.001***	−0.0001***	−0.005***	−0.003***
Energy consumption–measured in kg oil equivalent per capita (EN)	−0.002***	0.021***	0.009***	0.04***	0.003***	0.003***
Mitigation technologies in the transport sector (CCMT)	−0.136***	−0.010	−0.013***	−0.013***	−0.013***	−0.022***

***p-value < 0.01.

Note: COE: carbon emission for the transport sector (measured in percentage of total fuel combustion) is the dependent variable; EG-GDP per capita - measured in constant $2015; EN-Energy consumption - measured in kg oil equivalent per capita; CCMT- mitigation technologies in the transport sector.
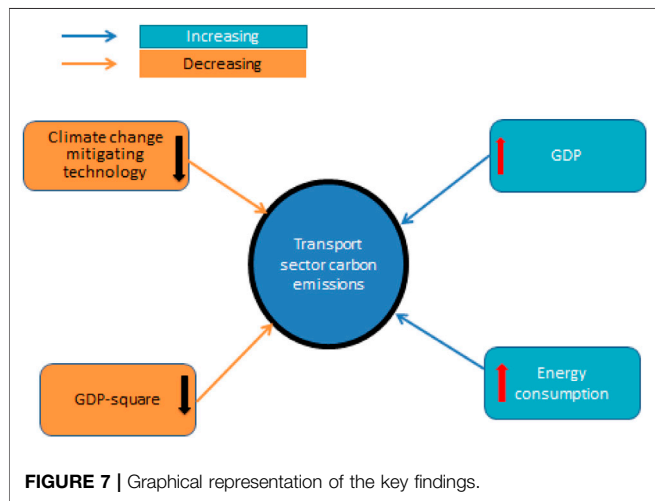

FIGURE 7 | Graphical representation of the key findings.

TABLE 6 | Findings from PMG-ARDL model.

Coefficient	p-value
Long-run estimates	
EG	0.04***
EG2	−0.01***
CCMT	−0.13***
EN	0.16***
Short-run estimates	
EG	0.05***
EG2	−0.01***
CCMT	−0.06***
EN	0.11***

Note: The value of the error correction term (ECT) is -0.08

***We just report the coefficients on the current time "t". The detailed findings in consort with the diagnostics are available upon request.

from the PMG-ARDL approach are supported by the findings of the PQR approach, which divulges that CCMT impedes COE.

Finally, we employ the D-H causality test to inspect the direction of causality, and the result is presented in **Table 7**. As shown in **Table 6**, there is unidirectional causality from CCMT to COE, indicating that a change in CCMT will affect COE, whereas any change in COE will not alter CCMT. Further, there is unidirectional causality from CCMT to EN, which implies that CCMT affects the use of energy, but vice versa is not valid. We observe the bidirectional causality between EG and CCMT. This

TABLE 7 | D-H causality test.

Ho	p-value
COE ≠> CCMT	0.86
CCMT ≠> COE	0.00***
EN ≠> CCMT	0.62
CCMT ≠> EN	0.00***
EG ≠> CCMT	0.00***
CCMT ≠> EG	0.00***
EG ≠> EN	0.07*
EN ≠> EG	0.21

≠> denotes does not Granger cause. * and *** represent the level of sig. at 10% and 1%, respectively.

Note: COE: carbon emission for the transport sector (measured in percentage of total fuel combustion) is the dependent variable; EG-GDP per capita - measured in constant $2015; EN- Energy consumption–measured in kg oil equivalent per capita; CCMT-mitigation technologies in the transport sector.

notes that economic growth leads to higher CCMT, and CCMT also impacts economic growth. Next, we find a unidirectional causality from EG to EN, which shows that economic growth leads to higher energy use. Thus, we validate the conservation hypothesis in top emitters in the transport sector.

Future research should apply dynamic panel data methods to explore the long- and short-run impact of CCMT on emissions. Further, the asymmetric impact of CCMT on emissions can also be discerned in the future.

CONCLUSION AND POLICY RECOMMENDATIONS

The transport sector is a leading sector in terms of energy consumption, thereby emitting tons of carbon, especially in the last few decades. The emission from transport sectors is likely to increase due to increasing demand for transport. Therefore, policymakers, environmental scientists, and economists have been questing to explore the drivers of the transport sector emissions in consort with the factors that can curb emissions. Climate change mitigation technology (CCMT) is considered an option that can plunge emissions. However, there is scant empirical evidence on the nexus between CCMT and greenhouse gas (GHG) emissions. Hence, the present study explored whether CCMT impedes transport sector emissions (COE) in the top five transport sector emitters countries. We

used the panel quantile regression (PQR) approach, which examines the heterogeneous impact of CCMT on low-, middle-, and high-level emissions. We found the validity of the environmental Kuznets curve (EKC) hypothesis. The findings revealed that at the lowest quantile (i.e., 10th quantile), CCMT does not affect emissions. Next, CCMT mitigated emissions at all other quantiles. Also, the impact of CCMT on emissions is the strongest at the highest quantile (i.e., 90th quantile). Next, EN upsurged the COE at all quantiles.

Additionally, the D-H causality test findings reported that unidirectional causality runs from CCMT to COE and EN. In contrast, bidirectional causality was observed between EG and CCMT. Finally, unidirectional causality runs from EG to EN. We propose few policy recommendations. First, the validity of the EKC hypothesis confirms that EG is an avenue to curb COE. Therefore, the selected countries need to focus on improving EG by initiating policies that help achieve higher EG. Next, to achieve a higher EG without deteriorating the environmental quality, the selected countries need to use renewable energy resources. Further, there should be an investment in human capital, R&D, and innovations that might lead to sustainable EG. Since EN upsurges the COE, policies should be initiated to discourage non-renewable energy sources. For this purpose, environmental/carbon taxes should be introduced on non-renewables, while renewable energy usage should be encouraged. The positive impact of CCMT in curbing COE in all quantiles, except the 10th quantile, implies that there should be more and more utilization of CCMT in the lower-, middle-, and high-emission countries. To escalate the use of CCMT, these countries should invest in R&D related to environmental technology. The high-emission countries need to pay attention to increase the number of CCMT since the role of CCMT is the strongest for the high-emission countries.

Next, to increase CCMT, there should be social awareness programs. To get benefit from the CCMT, countries should share their technologies with each other. Not only this, countries should collaborate to produce efficient CCMT. Also, there should be incentives for individuals (e.g., tax exemptions, etc.) for the individuals who use products having high levels of CCMT. The governments of selected countries should escalate subsidized public transport services which will decrease the privately-owned transportation (e.g., vehicles, ships, jets, etc.). Not only this, governments should introduce public transportation with high CCMT, which will reduce COE. The causality analysis shows that EG and CCMT cause each other; therefore, achieving higher levels of CCMT can be an option to escalate EG, and vice versa. Next, the validity of the conservation hypothesis notes that policies to conserve energy will not adversely impact EG; therefore, the selected countries should initiate energy conservation policies.

Regarding the limitations of this study, the data on CCMT is unavailable for most developing countries, which hinders exploring the CCMT-COE nexus in the aforesaid countries. Also, a relatively small dataset does not allow for incorporating several control variables because, by doing so, the model could be comprised of a low degree of freedom. Next, a relatively small panel dataset discourages us from using several recent methodologies, such as the dynamic panel quantile regression approach by Harding et al. (2020). Regarding future research directions, researchers can employ dynamic panel methodologies such as CS-ARDL, AMG, and CCMG estimators. Moreover, the CCMT-COE nexus could be explored for other sectors, such as the industrial and commercial sectors, among others.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://stats.oecd.org/Index.aspx?DataSetCode=EPS.

AUTHOR CONTRIBUTIONS

RB: led the conceptualization of the research idea, data cleaning, analysis, write up, editing and structuring, revision. QS: led and contributed in conceptualization of the research idea, data cleaning, analysis, write up, editing and structuring, revision. DR: contributed in conceptualization of the research idea, data cleaning, analysis, write up, editing and structuring, revision.

FUNDING

ACKNOWLEDGMENTS

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.