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# Exploring the impact of demand and supply-side interventions on energy decarbonization of freight transportation: a research based on G20 nations

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Through quantitative modeling, the study established a dynamic supply and demand system from freight demand, renewable energy production, alternative new energy, renewable energy consumption and carbon dioxide emissions to assess the impact of demand-side and supply-side changes on energy decarbonization. The results indicate that adjusting the freight volumes of railway and aviation, renewable energy electricity supply, and the use of alternative new energy sources have varying degrees of impact on decarbonization in transportation. Through interventions on the demand side of freight volumes, CO<sub>2</sub> emissions from transportation decrease to levels below those before the intervention-induced fluctuations, while consumption of renewable energy increases to levels above those before the adjustment.

## KEYWORDS

energy decarbonization, freight transportation, time series, PVAR, group of twenty

## 1 Introduction

Freight transportation could be one of the major contributors of global greenhouse gas emissions. Despite the crucial role in maintaining global supply chains and promoting economic development, reducing carbon emissions from freight transportation has become a global challenge in addressing climate change and achieving sustainable development goals. Especially in G20 countries, the carbon emissions from freight transportation are staggering due to the huge economic scale and population size. Therefore, to address climate change and achieve sustainable development goals, G20 countries need to consider various interventions to reduce carbon emissions in transportation. Interventions related to demand and supply are considered important ways to reduce carbon emissions from freight transportation, including demand-side management, the use of electricity sourced from renewable energy and the promotion of alternative new energy applications. However, the impact of the intervention measures could be uncertain, so it could be of significance to explore the impact in the decarbonization process of freight transportation.

Based on panel data covering G20 countries, this research constructs a scenario system by using panel vector autoregressive model (PVAR) to integrate important indicator variables of demand, supply and decarbonized transportation. The aim would be studying the impact of scenario with demand and supply-side intervention measures for freight transport on decarbonized transportation.

## 2 Literature review

The existing research has employed quantitative analysis of panel data to evaluate the dynamic connections and interactions between carbon emissions and interventions related to demand and supply. Arvin et al. (2015) explored the interrelationships and connections between variables such as transportation density, urbanization level, and carbon dioxide emissions by using the PVAR model. The study suggests that the government could encourage research and development in biofuel technology to reduce CO<sub>2</sub> emissions and focus on improving the service efficiency of the transportation system. Habib et al. (2021) estimated the dynamic connections between variables such as transportation intensity, transportation freight volume, and road carbon emissions using panel models. The results indicate a unidirectional relationship between freight transportation and CO<sub>2</sub> emissions. Furthermore, as the largest carbon emitter, the G20 countries should promote environmentally friendly technology and foster the development of renewable technologies. Li et al. (2022) discovered with the PVAR model that transportation efficiency and structure have a mutually reinforcing effect, while interventions could be made by adjusting transportation configurations to reduce energy consumption.

Neves et al. (2019) used PVAR analysis of panel data from OECD countries to suggest that policymakers should encourage the use of alternative energy sources to decarbonize the transportation sector. However, the use of electricity in the transportation sector could not have a significant impact on CO<sub>2</sub> emissions. The study proposes that the possible reason would be the CO<sub>2</sub> emissions saved by the transportation sector through the use of alternative energy sources are compensated by the increase in CO<sub>2</sub> emissions generated in the electricity generation process. Research from Ajanovic and Haas (2016) also support this interpretation, where the environmental benefits associated with the use of electricity in the transportation sector could be only achieved when using renewable energy sources for electricity generation. Carfora et al. (2022) analyzed the PVAR model of EU member states and found that the most effective interventions would be to encourage the abandonment of fossil fuels, while to replace oil and coal with renewable energy sources. Furthermore, Petruška et al. (2022) estimated the short-term relationship between variables such as energy consumption and energy produced from renewable sources using the generalized method of moments (GMM). The results confirm the positive effect of renewable energy production on transport decarbonization, where the increase in the share of renewable energy leads to a reduction for CO<sub>2</sub> emissions.

## 3 Analysis framework and methodology

### 3.1 Dataset construction

For data collection and classification, the WDI (World Development Indicators) database was employed in this study. However, due to objective factors, a significant number of countries had missing data for variables. Therefore, a thorough trade-off between the number of countries and the size of the dataset was made to guarantee a balanced panel data and a long enough

research period. After the extended period of adjustments and attempts, the focus of the study was narrowed down to the G20 nations from 1995 to 2015, during which energy transformation, freight transport innovation, and decarbonized transportation underwent rapid development. The decision to select this time frame was based on careful consideration of the research objectives. The panel data set was chosen for analysis due to the advantages of time-series and cross-sectional data, which allow for the utilization of more information in examining the dynamic relationships of the research.

### 3.2 Proxy measures for variables

After conducting initial research, a pool of 17 indicators were identified as potential variables. However, due to incomplete sequences for some of the indicators, a further screening process was conducted to ensure the balance of the panel data.

#### 3.2.1 Demand side intervention

As the primary methods of freight transportation, railway and air transport offer efficient completion of transport tasks while meeting the diverse requirements of various types and scales of transportation. Both modes of transport exhibit high efficiency in terms of speed and capacity, while also covering a broad range of areas spanning countries and regions. Under the conditions, large-scale cargo transportation undertaken by railway and air transportation predominates due to cost-effectiveness. Therefore, goods transported by railway (*RailTrGood*) and freight transported by aircraft (*AirTrFre*) could be indicative of the demand for freight transportation. Intervention on the demand side could reduce carbon emissions during transportation by adjust freight volumes.

#### 3.2.2 Supply side intervention

The utilization of electricity derived from renewable energy sources and the adoption of alternative new energy sources would exert the intervention effect on freight transportation from the supply side. Electricity generated from renewable energy sources (such as wind, solar and hydro power) could reduce carbon emissions significantly during transport. The adoption of alternative new energy sources such as electric locomotives and hydrogen fuel cells could enable more environmentally friendly transportation. Thus, Electricity production from renewable sources (*EleProRe*) and Alternative and new energy (*AltNuE*) would be key factors driving decarbonization of freight transportation and could be used as proxy variables for the supply side intervention.

#### 3.2.3 Decarbonized transportation

To reduce the reliance on fossil fuels, decarbonized transportation necessitates the utilization of renewable energy sources such as wind and solar power. The increase in consumption of renewable energy sources would facilitate the growth and transformation of decarbonized transportation, thereby achieving emission reduction targets. Additionally, carbon dioxide, as a primary greenhouse gas, could be one of the major causes of global climate change. The key to decarbonized transportation would lie in reducing carbon dioxide emissions

during the process. Therefore, Renewable energy consumption (*ReEneCon*) and CO2 emissions from transport (*CO2EmTra*) could be used as important indicators to measure decarbonized transportation.

### 3.3 PVAR model formulation

The Panel Vector Autoregression (PVAR) model was first introduced by Holtz-Eakin et al. (1988). The model could be characterized by elaborate structure and capacity to capture diverse aspects of the data by modeling research variables as endogenous variables while treating each variable as a function of the lag value of all variables in the system. (Holtz-Eakin et al. 1988). Therefore, to examine the dynamic relationship from freight transport demand and supply factors to the context of decarbonized transportation, the PVAR model would be used to investigate and elucidate the research. Moreover, the PVAR presentation format provides the intuitive representation of the interactions between variables in the transport system.

From the theoretical perspective, the PVAR model utilized for the purpose of analysis could be characterized as follows:

$$Y_{it} = C_i + \sum_{p=1}^m A_p Y_{i,t-p} + \Xi_{it}$$

As  $t$  represents the  $t$  th period ( $t = 1, 2, \dots, T_i$ ),  $i$  indicates the  $i$  th nation ( $i = 1, 2, \dots, N$ ) and the lag length would be expressed by  $p = 1, 2, \dots, m$ .

$$Y_{it} = \begin{bmatrix} Y_{1it} \\ Y_{2it} \\ \vdots \\ Y_{6it} \end{bmatrix}, Y_{i,t-1} = \begin{bmatrix} Y_{1i,t-1} \\ Y_{2i,t-1} \\ \vdots \\ Y_{6i,t-1} \end{bmatrix}, \dots, Y_{i,t-p} = \begin{bmatrix} Y_{1i,t-p} \\ Y_{2i,t-p} \\ \vdots \\ Y_{6i,t-p} \end{bmatrix}$$

$Y_{it}$  would be represented by a column vector of dimensions  $6 \times 1$ , incorporating six proxy variables: *RailTrGood*, *AirTrFre*, *EleProRe*, *AltNuE*, *ReEneCon* and *CO2EmTra*. The lag term of  $Y_{it}$ , denoted as  $Y_{i,t-p}$ , reflects the value of variable which  $p$  time periods prior from the  $i$  th nation.

$C_i$  represents a column vector with dimensions of  $6 \times 1$ , which contains the constants as intercept for the model:

$$C_i = \begin{bmatrix} C_{1i} \\ C_{2i} \\ \vdots \\ C_{6i} \end{bmatrix}$$

$$A_1 = \begin{bmatrix} \alpha_{11}^{(1)} & \alpha_{12}^{(1)} & \dots & \alpha_{16}^{(1)} \\ \alpha_{21}^{(1)} & \alpha_{22}^{(1)} & \dots & \alpha_{26}^{(1)} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{61}^{(1)} & \alpha_{62}^{(1)} & \dots & \alpha_{66}^{(1)} \end{bmatrix}, \dots,$$

$$A_p = \begin{bmatrix} \alpha_{11}^{(p)} & \alpha_{12}^{(p)} & \dots & \alpha_{16}^{(p)} \\ \alpha_{21}^{(p)} & \alpha_{22}^{(p)} & \dots & \alpha_{26}^{(p)} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{61}^{(p)} & \alpha_{62}^{(p)} & \dots & \alpha_{66}^{(p)} \end{bmatrix}$$

$A_p$  refers to a matrix with dimensions of  $6 \times 6$ , representing coefficients in the analysis for a lag length of  $p$  periods.

$$\Xi_{it} = \begin{bmatrix} \epsilon_{1it} \\ \epsilon_{2it} \\ \vdots \\ \epsilon_{6it} \end{bmatrix}$$

$\Xi_{it}$  refers to a column vector with dimensions of  $6 \times 1$ , representing the forecast disturbances and errors in the analysis. Each component of  $\Xi_{it}$  would be independent and serially uncorrelated.

Integrated with the framework of the analysis, the quantification of the freight transportation demand side, supply side, and decarbonized transportation components within the system in the scenario could be expressed as follows:

Demand side:

$$\begin{cases} RailTrGood_{it} = C_i + \sum_{p=1}^m A_p RailTrGood_{i,t-p} + \Xi_{it} \\ AirTrFre_{it} = C_i + \sum_{p=1}^m A_p AirTrFre_{i,t-p} + \Xi_{it} \end{cases}$$

Supply side:

$$\begin{cases} EleProRe_{it} = C_i + \sum_{p=1}^m A_p EleProRe_{i,t-p} + \Xi_{it} \\ AltNuE_{it} = C_i + \sum_{p=1}^m A_p AltNuE_{i,t-p} + \Xi_{it} \end{cases}$$

Decarbonized transportation:

$$\begin{cases} ReEneCon_{it} = C_i + \sum_{p=1}^m A_p ReEneCon_{i,t-p} + \Xi_{it} \\ CO2EmTra_{it} = C_i + \sum_{p=1}^m A_p CO2EmTra_{i,t-p} + \Xi_{it} \end{cases}$$

## 4 Analysis and results

### 4.1 Unit-root tests

Ensuring the stationarity of variables could be crucial before beginning the analysis process. If non-stationarity would be present in the variable sequence, the estimation of the model would deviate from the principles of asymptotic theory, potentially leading to distorted subsequent analysis results. Moreover, non-stationary variables may result in spurious regression estimates. In order to guarantee the dependability of the analysis findings, a Fisher-type examination, predicated on the Augmented Dickey-Fuller test, would be utilized to scrutinize the presence of unit roots in the six variables extracted from the panel data. After undergoing unit-root testing, all the variables (*RailTrGood*, *AirTrFre*, *EleProRe*, *AltNuE*, *ReEneCon*, and *CO2EmTra*) chosen for incorporation into the PVAR model were found to have rejected the null hypothesis. (Please refer to the [Supplementary Appendix](#) for the test results due to space constraints).

### 4.2 Lag order selection

The selection of lag order could be a critical step that impact the estimation outcomes of the model. To determine the reasonable lag

TABLE 1 Lag order selection.

Selection order criteria Sample: 1996–2014				No. of obs	779	
				No. of panels	41	
				Ave. no. of T	19	
Lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	-209.1619	124.2613	0.13563	-594.8039	-91.73872	-285.236
2	-34.6457	79.80007	0.2472966	-399.5767	-64.19993	-193.1981
3	-5.6876	42.86961	0.2002697	-196.8188	-29.13039	-93.62949

order, relevant information criteria would be commonly employed. Based on the 1 to 4 lag values of the variables, the first to third order PVAR models were evaluated and considered as reasonable choices.

Based on the data presented in Table 1, the determination coefficients for each lag were comprehensively evaluated. In accordance with the selection criteria proposed by Andrews and Lu (2001), the first order PVAR model was deemed to be a relatively reasonable choice, given that it had the lowest MBIC, MAIC and MQIC among the criteria for 1 to 3 lags. Therefore, the subsequent analysis and estimation focused on the PVAR model with first order.

### 4.3 PVAR and GMM estimation

In order to estimate the models, the initial four lag periods were utilized as instruments. The outcomes presented in Table 2 suggest that the regression analysis indicates a notable level of significance for the

variables examined. Specifically, the lag term of *EleProRe* and *AltNuE* exhibited a considerable level of significance at the 1% and 5% levels respectively. Moreover, the statistical significance of *RailTrGood*, *AirTrFre*, and *ReEneCon* was demonstrated at a 10% significance level.

The subsequent phase of the analysis involves addressing missing data and enhancing estimation accuracy through the implementation of the Generalized Method of Moments (GMM) instruments recommended by Holtz-Eakin et al. (1988). As noted by Hall (2004), the utilization of GMM facilitates the automatic exclusion of observations without valid instruments and the imputation of missing values. Consequently, the effective sample size could be expanded, thereby improving the estimation efficiency of the model.

Table 3 indicates that the variable parameters estimated through the use of GMM exert a relatively stronger influence compared to the variables presented in Table 2. The lagged term of *RailTrGood* and *AltNuE* has the enhancement of 5% and 1% significance level for CO<sub>2</sub> emissions from transport respectively.

TABLE 2 PVAR estimation.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	RailTrGood	AirTrFre	EleProRe	AltNuE	ReEneCon	CO <sub>2</sub> EmTra
L.RailTrGood	-0.346	-0.00793**	-3.58e-07	1.40e-07	-3.15e-07	2.22e-06*
	(0.329)	(0.00343)	(1.18e-06)	(5.88e-07)	(7.81e-07)	(1.28e-06)
L.AirTrFre	16.75	0.122	3.92e-05	6.71e-05	5.84e-05	-0.000188*
	(18.54)	(0.191)	(7.56e-05)	(4.71e-05)	(3.74e-05)	(0.000106)
L.EleProRe	27,150	861.1***	-0.193*	-0.0207	0.0142	0.464***
	(34,154)	(246.4)	(0.110)	(0.0629)	(0.0752)	(0.162)
L.AltNuE	-81,552*	-325.5	-0.482***	0.130**	-0.0758*	0.653**
	(43,078)	(247.1)	(0.169)	(0.0522)	(0.0397)	(0.262)
L.ReEneCon	-132,850***	-1,155***	0.516***	0.169***	0.532***	-0.184*
	(35,951)	(300.1)	(0.110)	(0.0595)	(0.120)	(0.0954)
L.CO <sub>2</sub> EmTra	-40,482*	-700.1***	-0.0390	0.0243	-0.0909	-0.133
	(24,274)	(239.5)	(0.0616)	(0.0533)	(0.0580)	(0.0831)
Observations	779	779	779	779	779	779

Standard errors in parentheses.

\*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

TABLE 3 PVAR with GMM estimation.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	RailTrGood	AirTrFre	EleProRe	AltNuE	ReEneCon	CO2EmTra
L.RailTrGood	-0.171	-0.00569*	-6.32e-07	2.62e-07	-3.52e-07	3.23e-06**
	(0.284)	(0.00293)	(1.12e-06)	(5.66e-07)	(7.45e-07)	(1.29e-06)
L.AirTrFre	10.17	0.000404	2.89e-05	5.39e-05	3.87e-05	-0.000217*
	(15.56)	(0.160)	(7.76e-05)	(4.62e-05)	(3.73e-05)	(0.000111)
L.EleProRe	16,336	909.4***	-0.177	-0.000900	0.0102	0.442***
	(30,063)	(204.0)	(0.113)	(0.0621)	(0.0740)	(0.168)
L.AltNuE	-84,653**	-57.77	-0.527***	0.149**	-0.0683*	0.744***
	(36,918)	(108.0)	(0.174)	(0.0630)	(0.0378)	(0.282)
L.ReEneCon	-120,335***	-1,090***	0.468***	0.167***	0.509***	-0.123
	(32,218)	(259.8)	(0.106)	(0.0630)	(0.114)	(0.106)
L.CO2EmTra	-22,213	-490.6***	-0.0616	0.00232	-0.0664	-0.0850
	(20,958)	(187.2)	(0.0638)	(0.0533)	(0.0560)	(0.0944)
Observations	902	902	902	902	902	902

Standard errors in parentheses.

\*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

TABLE 4 Granger causality.

Equation\Excluded	chi2	df	Prob > chi2
<b>RailTrGood</b>			
AirTrFre	0.427	1	0.513
EleProRe	0.295	1	0.587
AltNuE	5.258	1	0.022
ReEneCon	13.950	1	0.000
CO2EmTra	1.123	1	0.289
ALL	23.617	5	0.000
<b>AirTrFre</b>			
RailTrGood	3.763	1	0.052
EleProRe	19.865	1	0.000
AltNuE	0.286	1	0.593
ReEneCon	17.622	1	0.000
CO2EmTra	6.870	1	0.000
ALL	29.394	5	0.000
<b>EleProRe</b>			
RailTrGood	0.319	1	0.572
AirTrFre	0.139	1	0.709
AltNuE	9.173	1	0.002
ReEneCon	19.609	1	0.000
CO2EmTra	0.932	1	0.334
ALL	25.888	5	0.000

(Continued on following page)

TABLE 4 (Continued) Granger causality.

Equation\Excluded	chi2	df	Prob > chi2
<b>AltNuE</b>			
RailTrGood	0.214	1	0.643
AirTrFre	1.365	1	0.243
EleProRe	0.000	1	0.988
ReEneCon	7.001	1	0.008
CO2EmTra	0.002	1	0.965
ALL	11.388	5	0.044
<b>ReEneCon</b>			
RailTrGood	0.223	1	0.637
AirTrFre	1.075	1	0.300
EleProRe	0.019	1	0.891
AltNuE	3.270	1	0.071
CO2EmTra	1.409	1	0.235
ALL	7.171	5	0.208
<b>CO2EmTra</b>			
RailTrGood	6.217	1	0.013
AirTrFre	3.813	1	0.051
EleProRe	6.908	1	0.009
AltNuE	6.991	1	0.008
ReEneCon	1.355	1	0.224
ALL	19.777	5	0.001

Panel VAR-Granger causality Wald test.

Ho, Excluded variable does not Granger-cause Equation variable.

Ha, Excluded variable Granger-causes Equation variable.

### 4.4 PVAR granger causality wald test

Following the estimation of the aforementioned process, the investigation of the influence of past values of one variable on the identification and prediction of another variable could be performed through Granger causality analysis (Granger, 1969), thereby providing insight into the interdependence between the variables. The examination of the relationship between the variables could serve as a valuable quantitative foundation for the analysis of decarbonized transportation and related proxy variables.

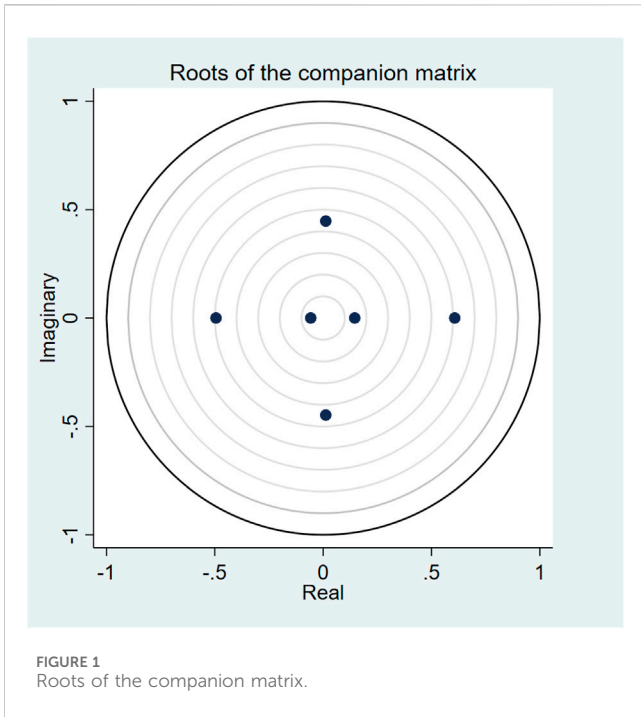
Tables 4, 5 indicate the results that reveal the causal relationships among the variables in the model system.

From the perspective of Demand side: *RailTrGood* could Granger-cause the *CO2EmTra* at 5% significance level while *CO2EmTra* could not be observed Granger-cause the *RailTrGood*. Single direction causality could be existed from the goods transported by railway to CO2 emissions from transport. A two-sided causality could be indicated as *AirTrFre* could Granger-cause *CO2EmTra* at 10% significance level while *CO2EmTra* could be observed Granger-cause the *RailTrGood* at 1% level.

TABLE 5 Stability condition.

Eigenvalue stability condition		
Eigenvalue		
Real	Imaginary	Modulus
0.6073936	0	0.6073936
-0.4,945,063	0	0.4,945,063
0.0121,435	-0.4,474,897	0.0121,435
0.0121,435	-0.4,474,897	0.0121,435
0.1,457,892	0	0.1,457,892
-0.0572,217	0	0.0572,217

From the perspective of Supply side: A single way causality could be observed from electricity production from renewable sources to CO2 emissions from transport, which *EleProRe* could Granger-cause the *CO2EmTra* at 1% significance level. Similarly, *AltNue*

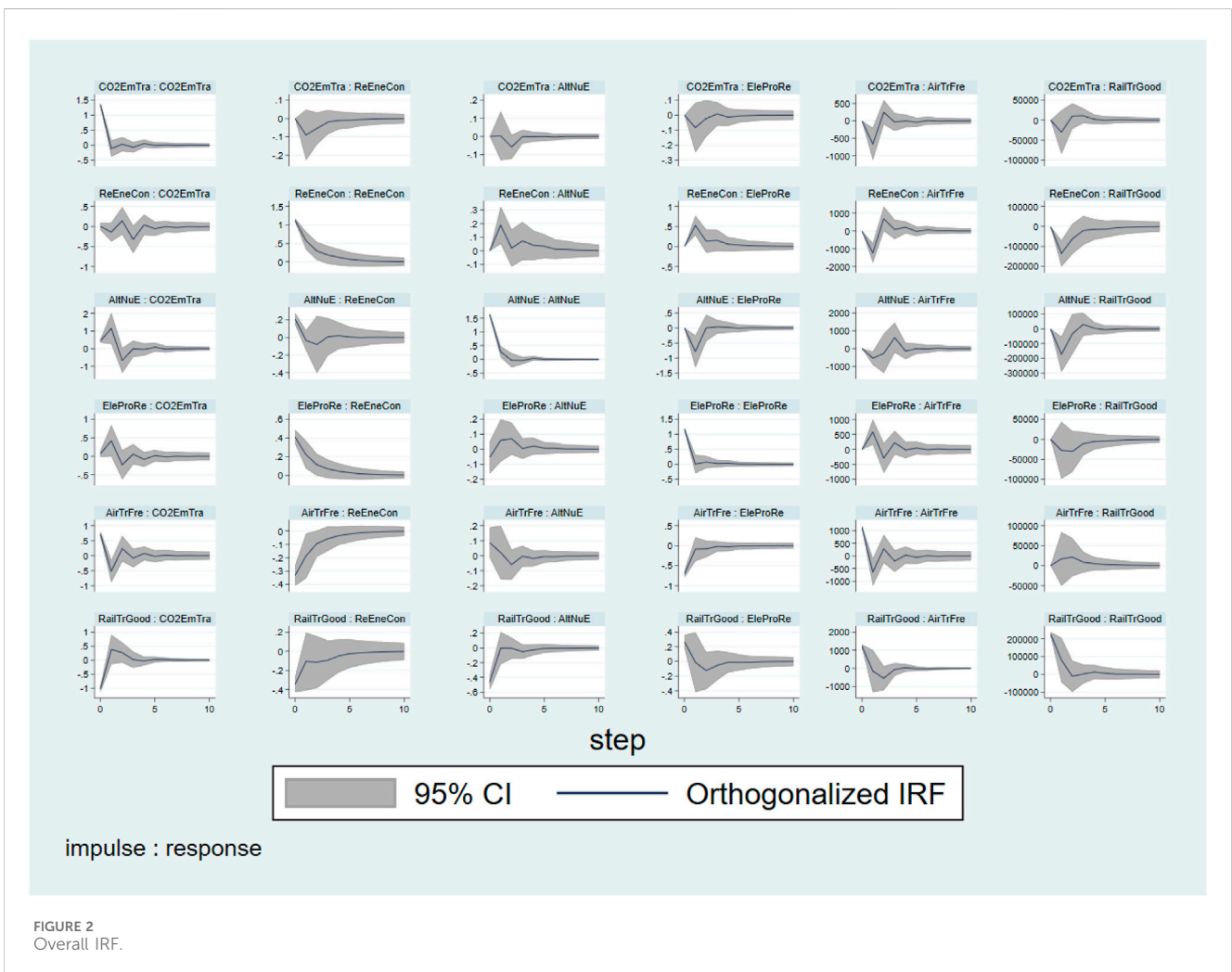


could Granger-cause the *CO2EmTra* at 1% significance level while *CO2EmTra* could not be observed Granger-cause *AltNue*. Moreover, *AltNue* could Granger-cause the *ReEneCon* at 10% significance level while *ReEneCon* could relatively more significantly Granger-cause the *AltNue* at 1% level.

### 4.5 Stability condition

As noted by [Abrigo and Love \(2016\)](#), the causal effects that explain the relationship among PVAR variables could not be elucidated without identifying the constraints on the parameters. Consequently, it would be of considerable importance to assess the stationarity of the PVAR model prior to conducting procedures such as IRF and FEVD analysis. By satisfying the stationarity condition, it would become possible to derive meaningful interpretations for IRF and FEVD analysis in the following stage.

According to the findings presented in [Table 5](#); [Figure 1](#), it could be concluded that the PVAR model meets the criterion for stability. The result could be supported by the observation that all of the eigenvalues are situated within the interior of the unit circle, as well as the fact that the modulus of the companion matrix for the variables is less than 1.



### 4.6 Impulse response function (IRF)

The Impulse Response Function (IRF) plot depicts the response pattern and trajectory of the delayed impact of the target variable under the assumption of independent shocks with a standard deviation of one from other variables (Abrigo and Love, 2016). Thus, the analysis could reveal the influence and directionality of the effects from demand-side and supply-side interventions on the decarbonization of the transportation through the impact on proxy variables.

#### 4.6.1 Scenario of supply side intervention

Figure 2 illustrates the Impulse Response Function (IRF) analysis that applies 200 Monte Carlo simulations and spans a time horizon of 10 periods, thereby providing the overview of the interplay and response patterns of the six variables in the simulated scenario system. In the next stage, indicators to measure decarbonized transportation (*CO2EmTra* and *ReEneCon*) would be used as the response variable, while the intervention impact of the other four variables from demand and supply side on decarbonising transport would be focused on.

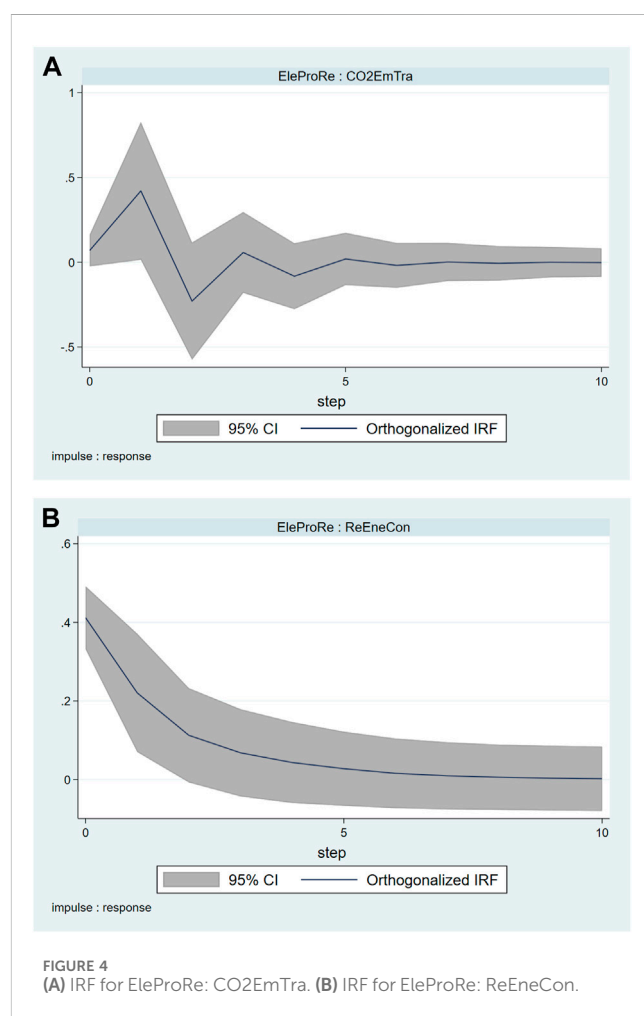
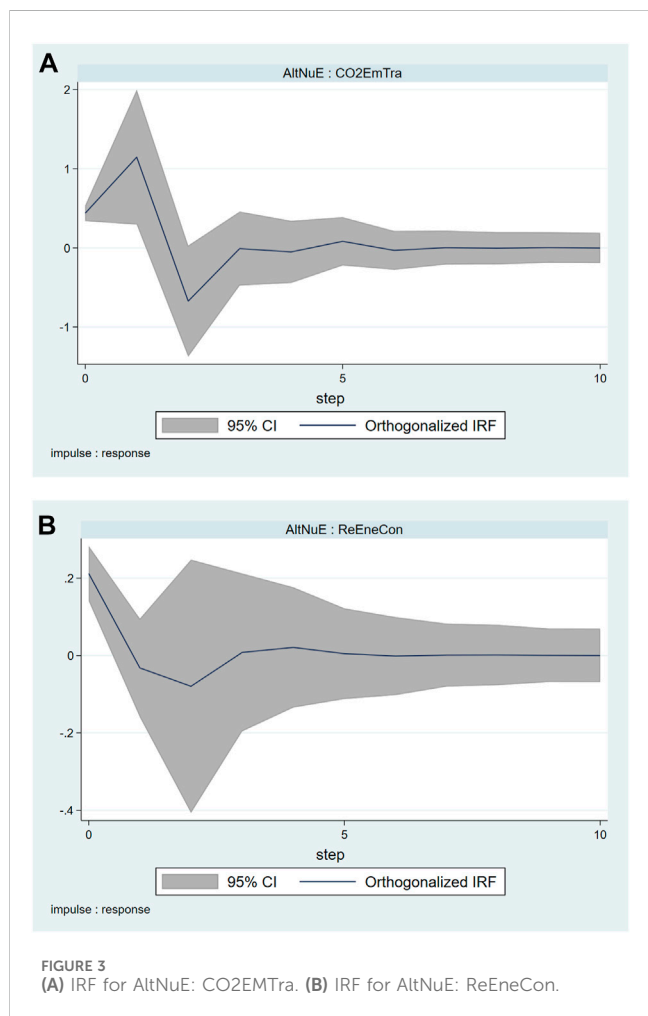
According to the results of Figures 3A, B above, following the impact of one standard deviation of *AltNuE*, a positive impact to *CO2EMTra* could be observed during the first period.

Subsequently, the positive impact turn to negative from 2nd to 3rd period, the impact increase slightly at 4th period then reached a stable state which below the starting level. In addition, a downward trend of positive influence for *ReEneCon* could be observed in the first two periods. In subsequent periods, *ReEneCon* recovered and increased from 2nd to 4th period approximately, followed by a slight decline after the fourth period then returned to a steady state.

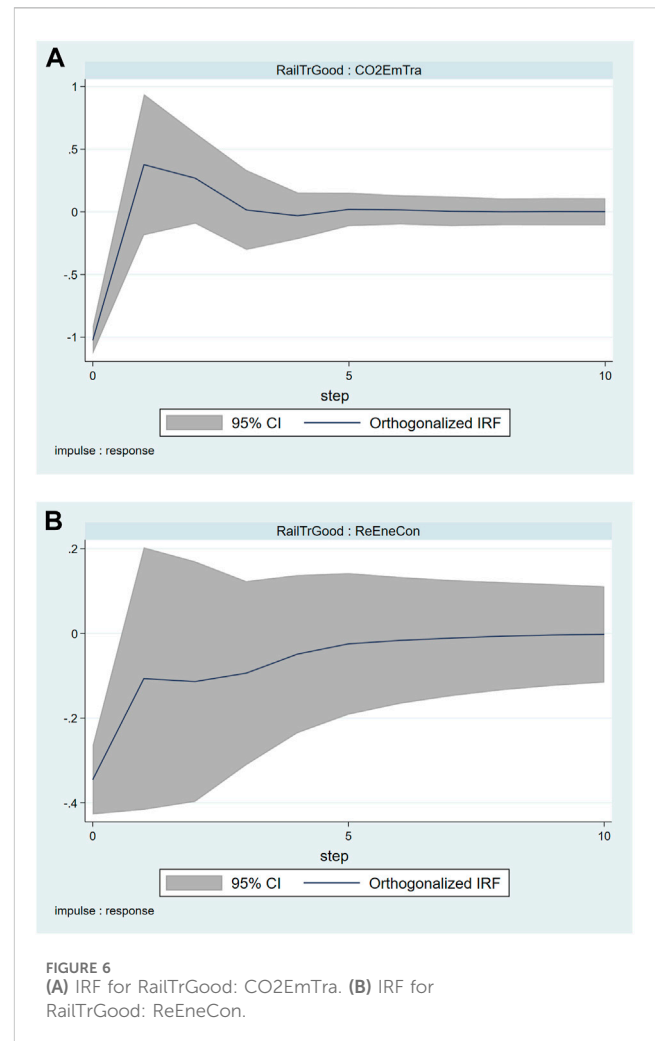
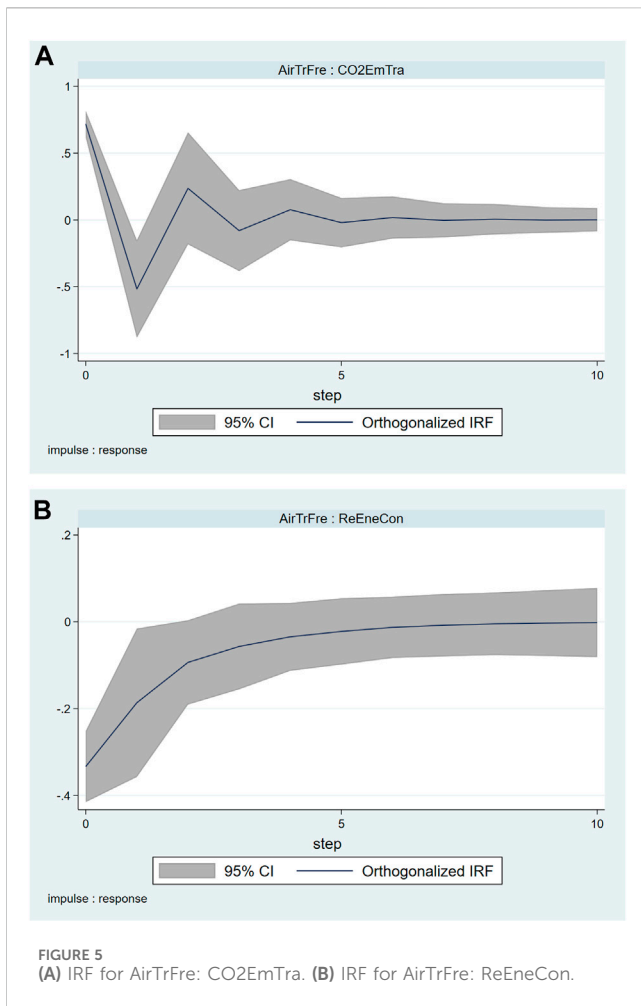
As the result from Figures 4A, B, for a standard deviation impact from *EleProRe*, *CO2EmTra* could be observed positively affected at the first period then fall back and turns to negative impact from 2nd to 3rd period. The impact tends to stabilize lower than the initial level after experiencing slight fluctuations between 3rd to 6th period. The impact of *EleProRe* on *ReEneCon* exhibits a singular declining trend, with a gradually decreasing rate observed from the first to the 5th period, followed by the tendency towards stability.

#### 4.6.2 Scenario of demand side intervention

Based on the results presented in Figures 5A, B, it could be observed that *CO2EmTra* exhibited a notable decline during the first time period subsequent to the influence of *AirTrFre*. However, in the following time periods spanning from the second to the fifth, fluctuations were observed. The fluctuations gradually diminished beyond the fifth time period,







eventually stabilizing at a level lower than the initial state. *ReEneCon* was observed to have been continuously affected by negative impacts, despite the decreasing intensity of the influence over time, which eventually reached a stable state higher than the beginning level.

The results of Figures 6A, B demonstrate that, following the influence of *RailTrGood*, *CO2EmTra* exhibited a gradually diminishing negative impact during the first period and gradually shifted to a positive influence. During the second to fourth periods, the positive impact gradually weakened and turned into negative, eventually stabilizing at the end of the period. Also, *ReEneCon* was observed to continuously experience negative impacts, which persisted over time and stabilized at a level higher than the initial state.

#### 4.7 Forecast error variance decomposition (FEVD)

The FEVD technique could be used to determine how much each variable in the created scenario system contributes to the forecast for the target variable. As a result, the technique emphasises the matching levels of importance associated with each variable. The FEVD would concentrate on the implications

from variables of demand and supply side interventions for decarbonizing transportation.

Based on the results shown in Figure 7, in terms of *CO2EmTra*, the largest contribution could be attributed to the supply-side technology *AltNuE*, accounting for approximately 31%. The contribution from *EleProRe* would be relatively lower, at approximately 3.8%. The demand-side technologies *RailTrGood* and *AirTrFre* have contributions of approximately 20% and 13%, respectively. As for *ReEneCon*, the largest contribution could be derived from the own lagged values, which remains at 74.08% from the first period to the tenth period, only slightly decreasing to 73.84%. The supply-side technology *EleProRe* has the highest contribution among the remaining variables, accounting for approximately 10%. The lowest contribution could be observed from *AltNuE*, at around 2.2%. The demand-side variables *RailTrGood* and *AirTrFre* both have contributions of approximately 6.5%.

## 5 Discussion and conclusion

This study explores the panel data of G20 countries during 1995–2015 using the PVAR model. By establishing scenarios

Response variable and Forecast horizon	Impulse variable					
	RailTrGood	AirTrFre	EleProRe	AltNuE	ReEneCon	CO2EmTra
<b>ReEneCon</b>						
0	0	0	0	0	0	0
1	.0695595	.0648354	.0986475	.0261871	.7407704	0
2	.0608388	.0679433	.1013866	.0213908	.7447078	.0037328
3	.0630374	.0679055	.1011625	.0229455	.7401446	.0048045
4	.0653883	.067756	.1008641	.0224547	.7386699	.0048668
5	.0658092	.0676454	.10074	.0224357	.7385013	.0048683
6	.0658674	.0676497	.1007607	.0223777	.7384524	.0048921
7	.0659127	.0676472	.1007595	.0223549	.7384241	.0049015
8	.0659377	.0676458	.1007576	.0223464	.738409	.0049036
9	.065945	.0676447	.1007566	.0223437	.7384059	.0049042
10	.0659471	.0676446	.1007566	.0223426	.7384046	.0049045
<b>CO2EmTra</b>						
0	0	0	0	0	0	0
1	.2933056	.1438285	.0013374	.0535112	3.07e-06	.5080144
2	.2162698	.1418657	.0329882	.2730654	.0035089	.332302
3	.2049675	.135852	.0380002	.3175689	.0064921	.2971194
4	.2011016	.1342806	.0378063	.3115366	.0230187	.2922563
5	.2005903	.1347647	.0387576	.3109254	.0232132	.2917488
6	.2003027	.1345935	.0387497	.3114588	.0236518	.2912433
7	.2002794	.1346048	.0387925	.3115214	.0236447	.2911572
8	.2002617	.1345922	.0387889	.3114902	.0237386	.2911284
9	.2002584	.134595	.0387944	.3114881	.0237388	.2911252
10	.2002572	.1345938	.0387941	.311488	.0237443	.2911226

FIGURE 7  
FEVD for ReEneCon and CO2EmTra.

involving demand and supply-side interventions and decarbonization of transportation, the research analyzes the effects of adjusting railway and air freight volume, renewable energy electricity supply and alternative new energy use on decarbonization of transportation.

The results suggest that adjusting railway and air freight volume, renewable energy electricity supply and alternative new energy use could have varying degrees of impact on decarbonization of transportation. By intervening in demand-side freight volume, the CO<sub>2</sub> emissions from transportation decrease below the pre-adjustment level after a fluctuation caused by the intervention, while renewable energy consumption increases above the pre-adjustment level. The result supports the findings of [Li et al. \(2022\)](#) and similar to the results of [Habib et al. \(2021\)](#). Combining supply-side interventions, renewable energy electricity supply could

continuously have a positive effect on consumption of renewable energy and reduce CO<sub>2</sub> emissions from transportation below the pre-adjustment level, confirming the views of [Petruška et al. \(2022\)](#). Alternative new energy use causes more fluctuations in CO<sub>2</sub> emissions from transportation, although the emissions could be observed lower than before the intervention in the later stages, while this fluctuation could be explained by the views of [Neves et al. \(2019\)](#). The intervention of alternative new energy on renewable energy consumption has a positive impact for most of the period, stimulating the use of renewable energy and further reflecting the measures mentioned by [Carfora et al. \(2022\)](#).

Due to the difference in research focus, this study explores factors concentrate on demand and supply-side interventions. Future research could further investigate and consider additional external factors such as urbanization

and population growth to provide a more comprehensive evaluation of the impact and effectiveness of decarbonized transportation.

## Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

## Author contributions

BZ: Investigation, Writing—original draft.

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## Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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## Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fenrg.2024.1341010/full#supplementary-material>

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