Impact of Transportation Infrastructure Connectivity on Trade-Embodied Carbon Emissions Transfer: Based on Empirical Analysis of the Belt and Road

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Abstract. This paper first adopts a coupling coordination model to assess the connectivity level of transportation infrastructure (TI) between China and Belt and Road Initiative (BRI) countries. Subsequently, the two-stage instrumental variable regression model is constructed to validate the impact of TI connectivity on the trade-embodied carbon emissions (TECs) transfer. This study reveals that the inter-connectivity of TI plays a certain promoting role in reducing TECs transfer, thereby contributing to overall emissions reduction and fostering the development of a sustainable BRI. Additionally, enhancements in traffic carbon efficiency, imports of goods and services, urbanization levels, and the quality of highway infrastructure all serve to facilitate the decline of TECs. Conversely, increases in per capita GDP exhibit a negative correlation with TECs.

Keywords: Transportation Infrastructure, Trade-embodied Carbon Emissions, Belt and Road Initiative, causal inference.

1 INTRODUCTION

As a fundamental industry supporting national economic and social development, transportation infrastructure (TI) stands as a priority sector for the Belt and Road Initiative (BRI), serving as an essential link and bridge for comprehensive connectivity among countries along the route. With its strong externalities, extensive industrial chains, and potent driving force, TI is deemed crucial for people's livelihoods, economic vitality, and societal stability [1]. It has been demonstrated that the construction of TI can notably enhance both international and domestic road accessibility, facilitate transportation, lower trade transportation costs, expedite logistics, and reduce trade market connection time, thereby propelling the development of sea and land transportation channels and international transportation service networks. In order to strengthen economic and trade cooperation, as well as the exchange of re-

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sources such as personnel and goods with countries along the BRI, it is necessary to further enhance the level of interconnection among regions/countries along the route, gradually forming a TI network connecting China with regions along the BRI [2].

According to the International Energy Agency (IEA), energy consumption and carbon emissions from TI account for approximately one-third of global totals [3]. It is noteworthy that while the construction and expansion of TI promote increased economic and trade activities, while also contribute to greater energy consumption and carbon emissions [4].

Hence it is necessary to fully consider the complexity of both international and domestic trade, analyze the characteristics of TECs transfers through cross-border trade flows, and quantitatively assess the current status of TI connectivity. This assessment should be grounded in a comprehensive understanding of the variations in TECs from trade across different regions. Furthermore, it is crucial to explore the correlation between TI connectivity and the transfer of TECs. Subsequently, tailored emission reduction strategies should be proposed, taking into account local conditions and regional policies.

2 METHODOLOGY AND DATA

2.1 Model Construction and Description

Coupling Coordination Model. The concept of 'coupling' originates from physics and is now commonly applied in the field of social sciences. Coupling models can quantitatively analyze the interactions between multiple systems or subsystems. Furthermore, by employing coupling coordination (CC) analysis, the degree of coordination development between various systems can be assessed, aiming to adjust and optimize the operational status of each subsystem. This paper utilizes a CC model to measure the level of connectivity of transportation infrastructure between China and BRI countries. Based on the research by Yu et al.[5], the coupling degree of the two systems can be expressed as:

$$C=2\times\frac{\sqrt{U_{CHN}\times U_{BRI}}}{\left(U_{CHN}+U_{BRI}\right)} \tag{1}$$

The parameters U_{CHN} *and* U_{BRI} represent the sequence parameters of the TI systems in China and the BRI countries, and they satisfy the condition $C\in[0,1]$. While the coupling model can reflect the degree of interaction between the systems, it may present a challenge when all the systems are at relatively low levels, resulting in a high coupling state and making it difficult to accurately analyze and interpret the computational results. Therefore, building upon the coupling model, the concept of 'coordination' is considered to further enrich formula (1) and establish a coupling coordination model:

$$\begin{cases} T = aU_{CHN} + bU_{BRI} \\ D = \left(C\times T\right)^{\frac{1}{2}} \end{cases} \tag{2}$$

In the equation, D represents the CC index, T is the comprehensive coordination index, and a and b represent weights. Since the importance of TI in China and the BRI countries is consistent, we set a=b=0.5.

Furthermore, utilizing non-parametric estimation methods to construct a kernel density estimation model, this study analyze the overall distribution and evolutionary trends of the connectivity of TI between China and BRI countries.The formula is as follows:

$$f_n(TIC)=\frac{1}{nh}\sum_{i=1}^{n}K\left(\frac{TIC_i-\overline{TIC}}{h}\right) \quad (3)$$

$$K(TIC)=\frac{1}{\sqrt{2\pi}}exp\left(-\frac{TIC^2}{2}\right) \quad (4)$$

Where n is the number of observed units, h is the bandwidth, $\overline{TIC}$ represents the mean CC of TI between China and BRI countries, and $K\left(\frac{TIC_i-\overline{TIC}}{h}\right)$ denotes the kernel density.

Multi-scale Input-output Model. Given that the multi-regional input-output model can TECs through inter-industry linkages, cross-border supply chains, and trade flows, it is suitable for analyzing the implicit environmental flows of production/consumption and imports/exports caused by trade activities [5, 6]. Based on the input-output equilibrium, the following matrix is constructed:

$$X=AX+Y \quad (5)$$

This study references the research by Zheng et al. [7] and Lu et al.[8] to nested the Chinese MRIOT into the Eora MRIOT, obtaining a multi-scale input-output (MSIO) model nested within Eora for China. By utilizing the Environmental-expand IO model in combination with the existing environmental account in the China-BRI nested MSIO, it can be used to observe the CO_2 flows between regions due to trade inflows and outflows, also known as 'carbon footprint'. The calculation formula is as follows (Eq. (6)) :

$$\hat{e}LY=\begin{bmatrix}\hat{e}^1 & 0 & \cdots & 0\\ 0 & \hat{e}^2 & \cdots & 0\\ \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & \cdots & \hat{e}^n\end{bmatrix}\begin{bmatrix}L^{11} & L^{12} & \cdots & L^{1n}\\ L^{21} & L^{22} & \cdots & L^{2n}\\ \vdots & \vdots & \ddots & \vdots\\ L^{n1} & L^{n2} & \cdots & L^{nn}\end{bmatrix}\begin{bmatrix}Y^{11} & Y^{12} & \cdots & Y^{1n}\\ Y^{21} & Y^{22} & \cdots & Y^{2n}\\ \vdots & \vdots & \ddots & \vdots\\ Y^{n1} & Y^{n2} & \cdots & Y^{nn}\end{bmatrix}$$

$$=\begin{bmatrix}\hat{e}^1\sum_{R=1}^{n}L^{1R}Y^{R1} & \hat{e}^1\sum_{R=1}^{n}L^{1R}Y^{R2} & \cdots & \hat{e}^1\sum_{R=1}^{n}L^{1R}Y^{Rn}\\ \hat{e}^2\sum_{R=1}^{n}L^{2R}Y^{R1} & \hat{e}^2\sum_{R=1}^{n}L^{2R}Y^{R2} & \cdots & \hat{e}^2\sum_{R=1}^{n}L^{2R}Y^{Rn}\\ \vdots & \vdots & \ddots & \vdots\\ \hat{e}^n\sum_{R=1}^{n}L^{nR}Y^{R1} & \hat{e}^n\sum_{R=1}^{n}L^{nR}Y^{R2} & \cdots & \hat{e}^n\sum_{R=1}^{n}L^{nR}Y^{Rn}\end{bmatrix} \quad (6)$$

Construction of Two-Stage Instrumental Variable Regression Models. This study referred to the research of Sajons [9] and constructed a regression equation using instrumental variables (IV), as shown below (Eq. (7) and Eq. (8)):

$$TIC_{it}^{BRI}=\gamma_0+\gamma_1 lnIV_{it}+\gamma_2 Control_{it}+\mu_i+\lambda_t+\varepsilon_{it} \quad (7)$$

$$lnTEC_i^{BRI}=\alpha_0+\beta_1\hat{TI}_{it}^{BRI}+\beta_2 Control_{it}+\mu_i+\lambda_t+\varepsilon_{it} \quad (8)$$

Where *TIC* is the endogenous variable, the fitted values obtained from equation (7) are substituted into equation (8) for instrumental variable regression.

2.2 Data Sources

The Dependent Variable. I. t calculated by the author, and comprises panel data reflecting the TECs from China's exports to BRI countries between 2010 and 2017.

The Explanatory Variable. It is the level of connectivity in transportation infrastructure (TIC) between China and BRI countries, and the data is calculated by the author.

The Control Variables. (i) Carbon efficiency of transportation infrastructure (TCE), and the data sourced from the study of Du et al. [10]; (ii) Imports of Goods and Services (GSI), data retrieved from the World Bank database; (iii) Per Capita GDP (PGDP) and Urbanization Level (UR), data obtained from the World Bank database; (iv) Road Infrastructure (Road) and Port Infrastructure (Port), and the data is sourced from the Global Competitiveness report. This study also utilizes the geographical distance between China and BRI trade partners, as well as the level of TI connectivity that lags behind a certain phase, as the instrumental variables.

The descriptive statistics and correlation analysis of the panel dataset are shown in Table 1.

Table 1. Descriptive statistics and correlation analysis.

Descriptive statistics	$lnTEC^{BRI}$	*TIC*	*TCE*	*GSI*	*lnPGDP*	*UR*	*Road*	*Port*
Mean-vaule	7.314	0.414	0.344	0.493	8.778	0.600	3.929	4.003
Max-vaule	16.008	1.000	1.000	1.758	11.205	1.000	6.646	6.765
Min-vaule	-3.585	0.007	0.017	0.000	6.588	0.168	1.200	0.962
Sd.	2.412	0.219	0.257	0.255	1.110	0.210	1.223	1.201
Obs.	280	280	280	280	280	280	280	280
Correlation analysis								
$lnTEC^{BRI}$	1.000							
TIC	0.524***	1.000						
TCE	-0.018	0.269***	1.000					
GSI	-0.082	-0.226***	0.427***	1.000				
lnPGDP	0.208***	0.645***	0.541***	0.275***	1.000			
UR	0.159***	0.535***	0.381***	0.285***	0.833***	1.000		
Road	0.289***	0.799***	0.230***	0.217***	0.594***	0.464***	1.000	
Port	0.363***	0.806***	0.362***	0.258***	0.639***	0.549***	0.819***	1.000

Note: *, ** and *** respectively indicate significance at the 10%, 5%, and 1% levels. The same below.

3 RESULT

3.1 The Connectivity of Transportation Infrastructure Between China and BRI Countries

By calculating the CC of TI connectivity from 2010 to 2017, this study obtained the time trend of the average level of CC between China and BRI countries (Table 2). Overall, the average level of transport infrastructure coupling coordination between China and BRI countries has increased significantly, rising from a mere 0.11 (indicating imbalance and recession) in 2010 to 0.51 (reflecting basic coordination) in 2017. Moreover, the coupling degree has exhibited fluctuations and overall growth, with several years demonstrating high coupling levels.

Table 2. Average value of CC between China and BRI countries.

Year	Coupling degree	Coupling stage	Coupling coordination degree	Coordination level
2010	0.21	Low Coupling	0.11	Decline dysregulation
2011	0.79	Break in Period	0.37	Near coordination
2012	0.84	High coupling	0.42	Near coordination
2013	0.86	High coupling	0.45	Near coordination
2014	0.86	High coupling	0.49	Near coordination
2015	0.86	High coupling	0.51	Basic coordination
2016	0.77	Break in Period	0.48	Near coordination
2017	0.79	Break in Period	0.51	Basic coordination

The non-parametric test method of kernel density estimation (Eq. (3) and Eq. (4)) is employed to examine the dynamic evolution characteristics of the CC between the TI systems of China and the BRI countries. As depicted in Figure 1, the distribution of the curves indicates a rightward shift from 2010 to 2017, suggesting a gradual improvement in the overall level of connectivity of TI between China and the BRI countries.

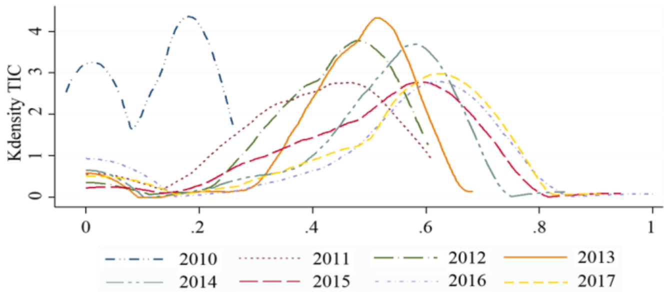

Fig. 1. The kernel density estimation of TI connectivity between China and BRI countries.

As shown in Figure 1, it is noteworthy that the 2010 curve exhibited a 'bimodal' pattern, highlighting the increased polarization of data in that particular year. Analyzing the changes in the wave crest and wave width, the peak of the curve in 2013 was positioned at a high level with a narrow crest width, suggesting a minimal gap between China and the BRI countries in terms of TI connectivity. Contrasting with 2013, the peak of the kernel density curve decreased from 2014 to 2017, accompanied by an increase in peak width. This indicates a significant gap remains in the coordination level among the systems sampled, with this disparity widening over time.

3.2 The Regression Results and Correlation Tests

The following Table 3 gives regression results and correlation tests. The findings indicate that the estimated TECs growth resulting from TI connectivity between China and the BRI countries is not statistically significant when using ordinary OLS regression estimation. This confirms that the original explanatory variable, the level of TI connectivity, is endogenous and leads to biased results in OLS estimation. Furthermore, the regression coefficient of TI connectivity is negative and statistically significant at the 1% level. This suggests that an increase in TI connectivity between China and the BRI countries will lead to a reduction in TECs from China's exports to these countries. It is possible that the lack of significance in the growth effect of TECs resulting from China's TI connectivity with BRI countries can be attributed to the enhanced inter-connectivity between regions. This enhanced connectivity provides more convenient and efficient physical infrastructure support for cross-regional trade, thereby promoting the development of bilateral trade activities. Additionally, the calculation of TECs is not solely linked to the volume of trade transferred between regions but is also closely associated with the carbon intensity of each region. When the carbon emissions output remains constant, the economic growth resulting from trade development will lead to a reduction in carbon intensity, thus explaining the overall trend of decreasing TECs transfer.

Imports of goods and services, urbanization levels, and the quality of road infrastructure are significant promoters of increased TECs at the 1% level. Moreover, GDP per capita and TECs exhibit a significant negative relationship at the 1% level. Additionally, transportation carbon efficiency has a positive impact on TECs, with the regression coefficients showing a reversal between OLS and 2SLS. Notably, the estimated regression coefficients for port infrastructure instrumental variables are all found to be insignificant.

The regression results have passed the necessary tests, as demonstrated in the lower section of Table 3. Additionally, the stability and effectiveness of the model estimation have been verified.

Table 3. The regression results and correlation tests.

	OLS	IV regression		
		2SLS	IV-GMM	IV-LIML
TIC	-0.187	-0.097***	-0.128**	-0.097***
	(0.287)	(0.646)	(1.678)	(0.646)
TCE	-0.189	0.053*	-0.232*	0.053*
	(0.466)	(0.613)	(1.262)	(0.613)
GSI	1.171**	1.283**	3.838**	1.283**
	(0.541)	(0.523)	(1.841)	(0.523)
lnPGDP	-0.776***	-0.447*	-6.005***	-0.447*

	(0.287)	(0.280)	(1.950)	(0.280)
UR	4.096***	0.369	16.216***	0.369
	(1.275)	(1.028)	(5.240)	(1.028)
Road	0.322*	1.153***	2.910***	1.153***
	(0.174)	(0.289)	(1.038)	(0.289)
Port	0.420***	-0.221	0.082	-0.221
	(0.127)	(0.310)	(0.350)	(0.310)
Constant	9.114***	5.969***		5.969***
	(1.652)	(1.502)		(1.502)
F-statistic in first stage of TI		104.36	16.28	104.36
		[0.000]	[0.000]	[0.000]
F-statistic for weak instrumental variable testing		25.482	10.131	25.482
		{16.38}	{16.38}	{16.38}
Basmann statistics for over identification testing		3.603	10.027	3.603
		[0.058]	[0.001]	[0.059]
Sargan statistic		3.730	3.729	3.805
		[0.053]	[0.054]	[0.051]

Note: (i) The (·) represents the T-statistic corresponding to the coefficients; (ii) [·] represents the P-value of the statistic; {·} represents the critical value of the Stock Yogo test at the 10% level; (iii) The weak instrumental variable test shows that there is no weak instrumental variable; (iv) Over-identification test and Sargan test all prove that the selected IV are valid.

4 CONCLUSION AND POLICY IMPLICATION

This paper revealed fluctuations and overall growth in the average level of TI coupling and coordination between China and BRI countries. Furthermore, the regression results demonstrated that the connectivity of TI (explanatory variable) has a causal effect on China's TECs to BRI countries (dependent variable), and the connectivity of TI between China and BRI countries has notably decreased TECs. This study can provide a reference for the low-carbon development of the TI in BRI.

Based on the above conclusions, this study proposes the following policy recommendations: (1) Actively promote the optimization of the export trade structure in key regions and industry sectors, focusing on leveraging the advantages of various export industries across China; (2) Continue to actively promote the implementation of the BRI, creating an enabling environment for achieving high-quality development of infrastructure construction and operation across all regions of China. This will unlock the 'dividend' of transportation economic structure, facilitate the upgrading of traditional infrastructure construction technology, and fundamentally enhance environmental efficiency; (3) It is essential to increase investment and policy support for transportation infrastructure in BRI regions, while also strengthening the interconnection of transportation infrastructure between countries and regions. This should be guided by optimizing industrial layout, enhancing transportation convenience, promoting optimized resource allocation, accelerating the cross-regional flow of production factors, and thereby improving the economic development environment across various regions.

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