

Article

Carbon Emission Reduction Drivers and Decoupling Effects in the Transport Industry of the Yangtze River Delta Region

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Abstract

Against the backdrop of global warming, China has set forth its 'dual carbon' goals, striving to achieve carbon neutrality by 2060. As a vital engine of economic development, the Yangtze River Delta region has formulated implementation plans, prioritizing carbon emission reduction. The transport industry, a major source of carbon emissions, plays a crucial role through its transition to clean energy, making it pivotal for advancing regional carbon neutrality. This study categorizes carbon emission drivers based on an assessment of current emissions and dynamic evolution analysis, integrating policy evolution and technological innovation trajectories. These drivers are classified into: transport structure, transport intensity, energy intensity, year-end resident population, per capita GDP, and industrial structure. Using the extended STIRPAT-Ridge model, quantitative analysis of carbon emission drivers is conducted. Employing the Tapio decoupling model, the decoupling state between carbon emissions and economic growth is deconstructed. Empirical findings reveal that carbon emissions from the transport industry in the Yangtze River Delta are influenced by multiple factors, with year-end resident population and industrial structure emerging as primary drivers. The decoupling between carbon emissions and economic growth exhibits fluctuating characteristics, but has been progressively strengthened in recent years by government policy initiatives and market mechanisms.

Keywords: transportation carbon emissions; STIRPAT model; Tapio decoupling

1. Introduction

For a considerable period, substantial global greenhouse gas emissions have precipitated climate warming, with increasingly severe ecological and environmental challenges compelling China to place greater emphasis on advancing a low-carbon economy [1]. The State Council's 'Working Guidance for Carbon Dioxide Peaking and Carbon Neutrality in Full and Faithful Implementation of the New Development Philosophy' issued on 22 September 2021 positions the dual carbon targets (carbon peaking by 2030 and carbon neutrality by 2060) as the core strategic pivot for overcoming rigid resource and environmental constraints and restructuring economic growth drivers [2].

Against the backdrop of the escalating global climate crisis, carbon emissions management in the transportation sector has become a central issue in global academia and policy-making. As a key engine of China's economic growth, the Yangtze River Delta

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region faces particularly significant pressure to reduce carbon emissions in the transportation sector. Accounting for 4% of the country's land area and 17% of its population, the region handles more than 18% of the nation's total passenger traffic and 22% of its total freight traffic; its high-speed rail network has reached 6668 km, and its waterway freight volume stands at 4.45 billion metric tons, accounting for more than half of the national total [3]. Nationally, transportation emissions account for approximately 10% of China's total carbon emissions, with road transport alone accounting for more than 80% of total transportation carbon emissions, making it a priority area for emission reduction [4]. To implement the "dual carbon" goals, the Ministry of Transport's 14th Five-Year Plan for Green Transportation Development proposes that the total number of new energy urban buses, taxis, and urban logistics delivery vehicles reach over 1 million [5]; the Comprehensive Transportation Special Plan for the Yangtze River Delta Ecological and Green Integrated Development Demonstration Zone (2021–2035) further specifies that the proportion of green travel in the demonstration zone should reach over 80%, and that urban transportation carbon emissions should steadily decline after peaking. Given the transportation sector's significant role in regional and national carbon emissions, research on its carbon emission drivers and decoupling effects carries considerable practical significance [6].

The Kaya-LMDI model has been employed to identify the industrial sector as the primary driver of China's coal consumption-related carbon emissions growth [7]. Within agriculture, decomposition analysis has revealed that economic development is the principal positive factor, while efficiency improvements and structural adjustments exert a suppressing effect on emissions [8]. For regional projections, the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model has been applied to identify population, urbanisation, and per capita GDP as core drivers [9,10]. Additionally, structural decomposition analysis has been utilized to reveal the driving mechanisms of final demand and key upstream industries in China's construction sector carbon growth [11]. A PDA-IDA model integrating production theory and index decomposition has been constructed to clarify the pivotal roles of technological progress and energy structure in altering carbon intensity within the transportation sector [12]. Existing research provides a foundation for identifying key pathways and informing policy formulation.

In recent years, the research perspective has gradually shifted from the decomposition of macro-level drivers to micro-level logistics organization and systemic transformation. A road network assignment model has been used to reveal the dominant role of road freight in regional carbon emissions [13]; a vehicle routing optimization algorithm that accounts for carbon footprints has been proposed, emphasizing the critical role of load factors in transportation emissions accounting [14]; circular economy interventions have been found to reduce violent incidents by 48% and increase household income by 20–25%, providing a cross-cutting perspective for assessing the resilience of regional transportation systems [15]; and the enabling mechanisms of digital technologies in circular waste management have been further systematically examined [16].

The aforementioned studies provide an important basis for identifying the critical pathways of transportation carbon emissions. However, existing methods each have their own focus and limitations. The LMDI decomposition method faces challenges when handling large-scale data and is highly dependent on data quality [17]; the STIRPAT model faces econometric challenges related to multicollinearity [18]; the OECD decoupling framework can only distinguish between two states—decoupled and non-decoupled—resulting in relatively crude conclusions, whereas Tapio's elasticity analysis refines decoupling states into eight distinct types, offering greater stability and explanatory power, with its accuracy unaffected by the length of the study period [19]. In

light of this, this study introduces ridge regression within the STIRPAT framework to address multicollinearity among variables and adopts the Tapio decoupling model to refine the classification of decoupling states. This approach enables the simultaneous identification of driving factors and diagnosis of decoupling within a single analytical framework, thereby providing methodological support for the development of region-specific emissions reduction policies.

Although existing research has laid a foundation for identifying the drivers of transportation carbon emissions and measuring decoupling, three key research gaps remain unaddressed. First, at the methodological level, existing studies have either used the STIRPAT model for factor decomposition or the Tapio model for decoupling assessment in isolation, with no attempts to integrate the two into a unified analytical framework. Second, at the technical level, there is severe multicollinearity among the factors influencing transportation carbon emissions; conventional regression estimates can lead to biased coefficients, yet most existing studies have overlooked this econometric issue. Third, at the regional level, the Yangtze River Delta is one of the regions with the densest transportation networks and the highest degree of economic integration in the country; the drivers of its transportation carbon emissions exhibit significant cross-provincial interdependencies, which are difficult to capture effectively in studies focused on a single province or in analyses conducted at the national scale. This study differs from existing STIRPAT-Tapio research in that it introduces Ridge Regression to eliminate multicollinearity while retaining all variables, and applies this integrated framework specifically to the entire Yangtze River Delta region to capture the structural emission characteristics arising from industrial synergy and logistics linkages among the three provinces and one municipality. From a practical perspective, as the “lifeline” of the national economy, the green transition of the transportation sector directly impacts the region’s overall efficiency. Through a systematic analysis involving “carbon emissions quantification—driver analysis—decoupling status diagnosis,” this study reveals key influencing factors and the patterns of decoupling evolution. It promotes the transition of traditional transportation models toward green and intensive development, providing a scientific basis for formulating differentiated emission reduction policies. The research findings will assist the Yangtze River Delta in building a low-carbon transportation network, accelerate the implementation of the region’s “dual carbon” goals, and serve as a model for the carbon neutrality process in the national transportation sector.

2. Construction of a Carbon Emissions Analysis Model for the Transport Industry

2.1. Selection and Construction of Carbon Emission Driver Models

The STIRPAT model, as an extended stochastic model for environmental pressure analysis, overcomes the theoretical limitations of the traditional Impact = Population × Affluence × Technology (IPAT) identity. It permits the introduction of exponential terms based on specific problems and data availability, enabling flexible adjustment of independent and dependent variables within the model [20]. Moreover, owing to its easily extensible fundamental structure, the STIRPAT model can incorporate additional independent variables influencing environmental development, such as technology, culture, and policy. Computations yield relatively precise results for researchers’ reference, demonstrating particular advantage in analyzing carbon emission determinants. Consequently, this section employs the extended STIRPAT model for research analysis. The STIRPAT model is a stochastic framework developed by Dietz et al. to evaluate environmental impact by human factors, building upon the IPAT model. The fundamental IPAT equation is:

$$I = P \times A \times T \quad (1)$$

where:

I denotes the environmental pressure level of a region;

P denotes the population size of a region;

A denotes the affluence level of a region;

T denotes the technological level of a region.

Due to limitations such as variables P , A , and T only varying proportionally, the IPAT model was expanded by introducing random and exponential terms to flexibly analyze non-proportional environmental impacts of various factors. The formula is as follows:

$$I = a \times P^b \times A^c \times T^d \times e \quad (2)$$

where:

a denotes the regression coefficient of the model;

b denotes the contribution of regional population size;

c denotes the contribution of regional economic level;

d denotes the contribution of regional technological level;

e denotes the random error term.

To facilitate regression analysis, the natural logarithm is typically taken of both sides of the equation to derive a linear regression equation, enabling analysis of each variable's impact on the environment. The formula is as follows:

$$\ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln e \quad (3)$$

This equation reflects the quantitative relationship between environmental impact and population, affluence, and technology, while permitting these factors to influence the environment non-linearly. Through regression analysis, the exponents b , c , and d for each factor can be estimated, thereby revealing their relative importance in environmental impact.

2.2. Construction and Computation of the Extended Stirpat-Ridge Model

(1) Selection of Influencing Factors

Prior to constructing a driving analysis framework for transport carbon emissions in the Yangtze River Delta based on the STIRPAT model, it is necessary to systematically identify and screen potential driving factors, establishing an indicator system significantly correlated with carbon emission intensity. Driving factors for transport system carbon emissions encompass human activities that directly or indirectly cause variations in efficiency values, with their influence permeating all socio-economic subsystems. This paper constructs a dual-analysis framework comprising endogenous sectoral variables and exogenous environmental variables. Specifically, carbon emissions are determined by direct emissions during transport operations, embedded carbon emissions from vehicle manufacturing and infrastructure maintenance, and carbon emission coefficients (which remain constant throughout the study period). Total energy demand is jointly regulated by multidimensional variables, with endogenous factors including: transport mode composition, transport organization efficiency, and energy mix composition. Exogenous variables encompass population concentration, economic output, industrial organization patterns, urbanization levels, and institutional–technological interactions (including low-carbon technology diffusion). Both internal and external factors significantly influence carbon emissions, exhibiting both independent attributes and networked interconnections. The specific causal pathways are illustrated in the mechanism model presented in Figure 1.

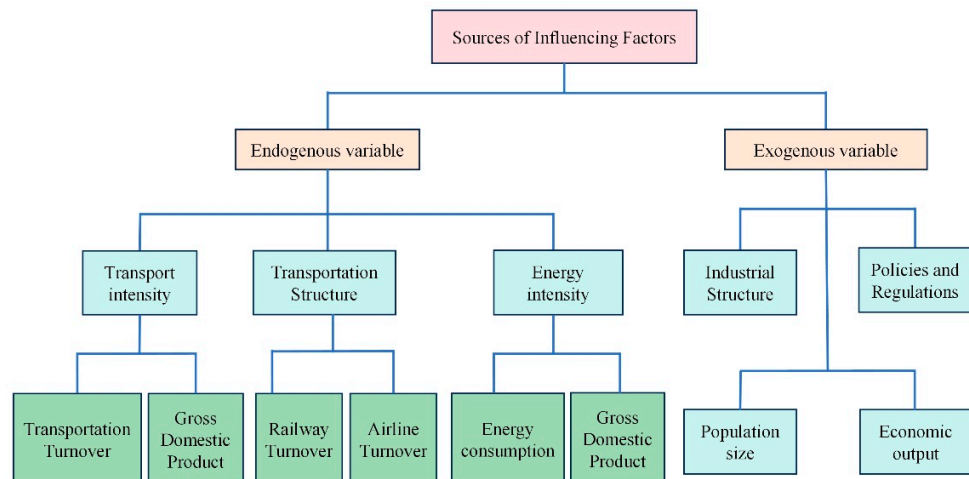


Figure 1. Analysis diagram of influencing factors in the transportation industry.

Based on the mechanism model analysis in Figure 1, from an endogenous industry perspective, transport turnover represents effective output of the industry, with its ratio to GDP directly reflecting transport operation density. Changes in market share for transport modes such as rail and aviation significantly regulate total energy demand. Carbon emission coefficients for different energy types exhibit orders of magnitude differences, with fossil fuels characterized by particularly high carbon intensity. Consequently, the dominant role of energy consumption in total carbon emissions is widely acknowledged. From an exogenous environmental perspective, external variables influence the industry's endogenous system through multiple pathways, primarily manifested as follows: Economic expansion heightens transport demand elasticity; population growth alters travel behaviour patterns; industrial restructuring (such as increased service sector share) reconfigures freight demand profiles and transport network topologies; synergies between policy regulation and technological innovation substantially reshape energy efficiency and fuel mixes, thereby inducing adaptive adjustments in transport organization paradigms and modal composition.

Concurrently, employing bibliometric methodologies and leveraging the CNKI and Wanfang databases, literature screening was conducted using the thematic keyword 'factors influencing carbon emissions from transportation' and the key retrieval term 'STIRPAT'. The screening criteria were limited to journals indexed in CSSCI and Peking University Core Journals, with non-transportation-related articles manually reviewed and excluded. Correlation analyses were performed between high-frequency carbon emission drivers and regional policy innovations alongside technological evolution. During the initial variable screening stage, the urbanization rate was included as a potential influencing factor on transportation carbon emissions. However, Pearson correlation analysis revealed that the correlation coefficient between the urbanization rate and per capita GDP was 0.997, and that between the urbanization rate and industrial structure was 0.972—both far exceeding the threshold of 0.9, indicating a significant risk of multicollinearity. Including the urbanization rate as an independent variable in the STIRPAT model would lead to biased regression coefficient estimates. Therefore, this study did not include the urbanization rate as an independent variable in the model; its effects are reflected through the two variables of per capita GDP and industrial structure. This approach is consistent with the theoretical logic in existing research, which posits that the urbanization rate indirectly influences carbon emissions through economic structure and industrial transformation. Integrating comprehensive analyses of relevant cutting-edge domestic and international literature, following the above screening process,

six driving factors were ultimately identified, and their classifications and definitions are as follows:

① **Transport Structure:** Significant gradient differences exist in energy consumption per unit across different transport modes within the intermodal transport system. Air transport has the highest energy consumption intensity, followed by road transport, while rail transport exhibits moderate energy efficiency, and water transport demonstrates the best energy economy. In line with the strategic orientation of “shifting freight from road to rail” and “shifting freight from road to water” outlined in the 14th Five-Year Plan for Transportation Development, reducing the share of high-energy-consumption transport modes and increasing the modal share of low-carbon alternatives have become the core objectives of regional transport structure adjustment. Based on the aforementioned energy consumption differences and policy orientations, this study defines the quantitative indicator for transport structure as the proportion of road and air transport converted turnover relative to the total converted turnover of the integrated transport system. From the perspective of the Yangtze River Delta region’s actual transport structure, freight transport is predominantly waterborne: in 2022, water transport accounted for approximately 82.7% of freight turnover, rail accounted for approximately 2%, road accounted for approximately 15%, and air accounted for approximately 0.1%, with road and air combined accounting for approximately 15.1%. This indicator effectively reflects the overall proportion of high-energy-consumption transport modes within the regional transportation system; the lower this proportion, the more the regional transport structure tends toward low-carbonization; ② **Transport intensity:** Measures the equivalent transport service demand per unit of economic output, calculated as the ratio of passenger-tonne and freight-tonne equivalent turnover to economic scale. Given the differing carrying capacities of various transport modes, passenger-tonne and freight-tonne conversion coefficients are introduced to calculate equivalent turnover [21]. $\text{Transport industry converted tonne-kilometres} = \text{freight tonne-kilometres} + \text{passenger tonne-kilometres} \times \text{passenger-freight conversion factor}$. The conversion factors for each mode of transportation are: road 0.1, rail 1, water transport 0.33, and air 0.72, in accordance with China’s current statistical system. The conversion factor for air transport is set at 0.72, which is derived by multiplying the domestic factor of 0.072 by 10 according to the conversion standard of “10 passenger-kilometers = 1 ton-kilometer”; ③ **Energy intensity:** Denotes the ratio of transport energy consumption to transport GDP. Within the transport industry, energy intensity levels directly correlate with energy consumption and carbon emissions [22]; ④ **Year-end resident population:** Population growth increases transport demand, thereby driving energy consumption and carbon emissions; ⑤ **Per capita GDP:** As an indicator of economic development, its growth typically coincides with heightened transport activity, subsequently boosting carbon emissions; ⑥ **Industrial structure:** Represented by the share of GDP of tertiary sectors, expansion in this sector—particularly within transport and logistics—further intensifies carbon emission pressures.

The relevant indicators and definitions for each influencing factor are presented in Table 1 below:

Table 1. Relevant indicators of factors influencing carbon emissions in the transportation industry of the Yangtze River Delta region.

Name	Symbol	Unit	Description
Per capita GDP	G	Ten thousand yuan	Gross domestic product/Year-end resident population
Permanent Resident Population at Year-End	P	hundreds of millions	Permanent Resident Population at Year-End
Transport Structure	TS	%	Road and Air Transport Converted Freight Ton-Kilometers/Total Converted Freight Ton-Kilometers
Energy Intensity	EI	Tons of Standard Coal per 10,000 Yuan	Energy Consumption in Transportation Sector/Transportation Sector GDP
Transport Intensity	TI	Ton-kilometers per Yuan	Transportation-Adjusted Freight Volume/Gross Transportation Output Value
Industrial Structure	IS	%	Tertiary Industry Output Value/Total Output Value
Total Carbon Emissions	C	Billion tons	Transportation Sector Carbon Emissions

The data calculations for each influencing factor are shown in Table 2 below:

Table 2. Calculation data for each influencing factor.

Year	Per Capita GDP (10,000 Yuan)	Total Population (Billion)	Transport Structure (%)	Energy Intensity (Tonnes of Standard Coal/10,000 Yuan)	Transport Intensity (Ton-Kilometers/Yuan)	Industrial Structure (%)
2003	1.671	1.994	8.899	1.102	6.878	40.832
2004	1.961	2.016	8.159	1.145	6.945	40.612
2005	2.278	2.020	7.685	1.402	9.281	40.713
2006	2.635	2.036	7.511	1.341	9.142	40.968
2007	3.183	2.056	7.574	1.318	9.135	41.514
2008	3.681	2.073	19.187	1.222	9.324	41.993
2009	4.021	2.087	21.866	1.286	9.415	43.561
2010	4.788	2.088	21.892	1.135	8.844	43.650
2011	5.537	2.113	20.939	1.023	9.446	44.090
2012	5.998	2.130	22.589	1.024	9.287	45.313
2013	6.547	2.146	20.385	1.002	9.008	46.787
2014	7.065	2.160	21.242	1.009	9.312	47.954
2015	7.641	2.166	17.928	1.044	8.548	49.655
2016	8.296	2.179	18.734	1.032	8.037	51.562
2017	9.170	2.190	17.345	1.011	8.602	52.176
2018	10.057	2.200	16.864	0.838	7.609	54.458
2019	10.686	2.208	14.183	0.789	7.493	55.763
2020	11.045	2.214	14.852	0.766	7.890	56.460
2021	12.523	2.220	15.814	0.667	7.174	55.683
2022	13.059	2.223	15.091	0.596	6.925	55.205

As shown in Table 2, various influencing factors in the Yangtze River Delta region underwent significant changes from 2003 to 2022. Per capita GDP grew steadily from 16.71 thousand yuan to 130.59 thousand yuan, with an average annual growth rate of approximately 11.3%, reflecting the rapid improvement in the region's economic level; the year-end resident population grew steadily from 199.4 million to 222.3 million, with an average annual growth rate of only 0.57%. The transport structure—defined as the combined share of road and air transport—jumped from approximately 7.5% in 2007 to 19.19% in 2008, peaked at 22.59% in 2012, and then fluctuated downward to 15.09% in 2022, following an inverted U-shaped trajectory of first rising and then falling. This aligns

with the historical process of gradually implementing policy adjustments to shift freight from road to rail and from road to water transport following the large-scale construction of expressways in the Yangtze River Delta region. Energy intensity peaked at 1.402 in 2005 and has since generally fluctuated downward, falling to 0.596 by 2022—a cumulative decrease of 57.5%. This indicates a systematic improvement in the region's energy efficiency, though the decline has been accompanied by periodic fluctuations. Transportation intensity fluctuated widely within the range of 6.8 to 9.5. After 2018, it generally trended downward; following a brief rebound in 2020, it continued to decline. The tertiary industry's share of the economy fluctuated upward from 40.83% in 2003, peaked at 56.46% in 2020, and then declined slightly to 55.21% in 2022, reflecting the service sector's increasingly dominant role in the regional economy.

(2) Model Construction

Based on the six influencing factors selected in (1), an STIRPAT model for the expansion of the transport industry in the Yangtze River Delta region is constructed, with the formula as follows:

$$C = a \times G^b \times P^c \times TS^d \times EI^e \times TI^f \times IS^g \times k \quad (4)$$

where:

C denotes carbon emissions from the transport industry in the Yangtze River Delta region;

a denotes the constant term;

G, P, TS, EI, TI, IS , respectively, denote per capita GDP, year-end resident population, transport structure, energy intensity, transport intensity, and industrial structure;

b, c, d, e, f, g represent the contribution levels of the corresponding influencing factors;

k denotes the error term.

To facilitate subsequent regression analysis, taking the logarithm of both sides of the equation yields:

$$\ln C = \ln a + b \ln G + c \ln P + d \ln TS + e \ln EI + f \ln TI + g \ln IS + \ln k \quad (5)$$

(3) Correlation Analysis

As demonstrated in (1), the selected influencing factors exhibit strong correlations with carbon emissions in the Yangtze River Delta region. Consequently, potential interrelationships exist among these factors. This study therefore employs Pearson correlation analysis to systematically evaluate linear dependencies between the six driving factors. Pearson correlation analysis requires fulfillment of two conditions: ① data must be quantitative; ② data must follow a normal distribution. Given that all required data are quantitative, we now test for normality. Due to substantial numerical variations among the influencing factors, data compression was applied to stabilise calculations. The data in Table 2 underwent logarithmic transformation, followed by Shapiro–Wilk tests using SPSS 26.0 software to verify normality for each variable. Table 3 indicates that the significance p -values for $\ln P$, $\ln G$, $\ln P$, and $\ln EI$ all yielded significance p -values greater than 0.05. The null hypothesis could not be rejected, indicating compliance with normality. For $\ln TS$, $\ln TI$, and $\ln IS$, although the significance p -values were less than 0.05, the absolute values of the kurtosis were below 10 and the skewness below 3. By plotting Q-Q charts, these variables were deemed broadly acceptable as normally distributed.

Table 3. Results of normal distribution test for each influencing factor from 2003 to 2022.

Variable	Median	Mean	Standard Deviation	Skewness	Kurtosis	Statistic	S-W Test	
							Degrees of Freedom	Significance
lnG	1.835	1.714	0.638	−0.457	−0.952	0.942	20.000	0.265
lnP	0.760	0.754	0.036	−0.339	−1.251	0.926	20.000	0.130
lnTS	−1.766	−1.890	0.412	−0.761	−0.804	0.861	20.000	0.008
lnEI	0.028	0.013	0.231	−0.795	0.211	0.928	20.000	0.143
lnTI	2.149	2.111	0.122	−0.386	−1.571	0.850	20.000	0.005
lnIS	−0.776	−0.753	0.123	0.240	−1.586	0.883	20.000	0.020

Subsequently, Pearson correlation analysis was conducted. Table 4 presents the correlation coefficients between pairs of influencing factors after taking logarithms. Elasticity analysis of these coefficients reveals that the following relationships passed the 1% significance level test: lnP with lnG, lnEI, and lnIS; lnG with lnEI and lnIS; lnTI with lnEI; and lnIS with lnG. This indicates strong correlations, suggesting the potential for multicollinearity among the influencing factors.

Table 4. Pearson correlation test results.

	lnG	lnP	lnTS	lnEI	lnTI
lnP	0.995 (0.000) ***	/	/	/	/
lnTS	0.393 (0.086) *	0.378 (0.101)	/	/	/
lnEI	−0.818 (0.000) ***	−0.823 (0.000) ***	−0.033 (0.890)	/	/
lnTI	−0.215 (0.364)	−0.254 (0.280)	0.261 (0.266)	0.611 (0.004) ***	/
lnIS	0.947 (0.000) ***	0.964 (0.000) ***	0.221 (0.348)	−0.873 (0.000) ***	−0.407 (0.075) *

*** At the 0.01 level (two-tailed), the correlation is significant. * At the 0.10 level (two-tailed), the correlation is significant.

- (4) Multicollinearity testing is grounded in econometric model specification theory. Multicollinearity specifically denotes non-orthogonal relationships among explanatory variables, which distort model parameters and cause significant bias in parameter estimates. To diagnose multicollinearity, this paper constructed regression models using ordinary least squares (OLS) and conducted diagnostic analyses based on indicators such as the variance inflation factor (VIF). Detailed results are presented in Table 5 below:

Table 5. OLS regression analysis results for each influencing factor.

	Regression Coefficient B	Significance	VIF	R ²	F
(Constant)	−2.95	0.31	/		
lnG	0.53	0.012 **	198.116		
lnP	2.785	0.467	257.474		
lnTS	0.022	0.406	2.051	0.991	F = 245.13 p = 0.000 ***
lnEI	0.57	0.000 ***	10.498		
lnTI	−0.077	0.561	3.683		
lnIS	−0.238	0.555	34.237		

Dependent variable: lnC

Note: *** and ** represent significance levels of 1% and 5%, respectively.

Based on the data in the table above, the regression coefficients for all variables are non-zero, indicating a significant regression relationship exists between the variables.

Analysis via the F-test yields a p -value of 0.000 ***, demonstrating high statistical significance under the stringent two-tailed testing criteria. Consequently, the null hypothesis that all explanatory variables collectively exert a significant effect is rejected. This validates the construction of this model, confirming that the selected variables effectively account for the variation in the dependent variable.

Among these, the variance inflation factor (VIF) represents the severity of multicollinearity. VIF should ideally be less than 10, strictly less than 5. Here, except for $\ln TS$ and $\ln TI$, the VIF values of other variables exceed 10. This indicates severe multicollinearity within the model. The variance estimates obtained using ordinary least squares (OLS) would be significantly biased, leading to discrepancies between the actual influence of each independent variable on the dependent variable (carbon emissions) and the estimated effects. Such bias could even produce opposite conclusions. Therefore, to avoid this scenario, multicollinearity must be eliminated to ensure the relative accuracy of the computational results.

(5) Addressing Multicollinearity

Multivariate regression models addressing multicollinearity primarily employ two methods: stepwise regression and ridge regression. Stepwise regression mitigates multicollinearity by eliminating collinear independent variables; however, this approach excludes factors highly correlated with the dependent variable (carbon emissions), thereby diminishing the interpretability of results.

Ridge regression, also termed L2 regularized regression, is a regression method specifically designed to address high inter-variate correlations [23]. This approach introduces an L2 norm penalty term to reduce excessively large feature weights within the model, thereby decreasing model complexity and effectively mitigating overfitting risks. Consequently, this study employs the ridge regression method, utilizing SPSSAU 24.0 software to eliminate multicollinearity. The resulting ridge trace plot is illustrated in Figure 2:

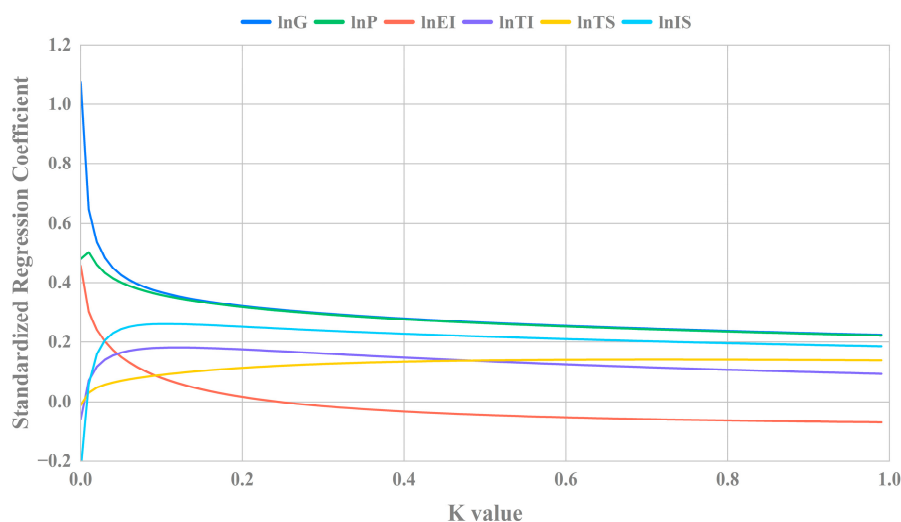


Figure 2. Ridge trace plot.

The principle for selecting the K value is that the VIF should be less than 10 and the standardised regression coefficients of each independent variable should stabilize. A smaller K value indicates less bias; when K is set to 0, it corresponds to ordinary linear OLS regression. Based on the ridge trace plot, it is determined that when $K = 0.05$, the regression coefficients of the independent variables begin to stabilize. To further

numerically confirm the optimal value of K, this study compared the model performance for five candidate values of K: 0.01, 0.03, 0.05, 0.07, and 0.10. The results are shown in Table 6.

Table 6. Comparison of ridge regression results for different K values.

K	lnG	lnP	lnEI	lnTI	lnTS	lnIS	R ²	VIF Range
0.01	0.323 **	4.476 **	0.419 **	0.196	0.025	0.155	0.988	2.167–13.627
0.03	0.241 **	3.866 **	0.278 *	0.386 *	0.046	0.532 *	0.984	1.801–4.567
0.05	0.235 ***	3.773 ***	0.221 **	0.273 **	0.080 **	0.436 **	0.981	1.089–3.292
0.07	0.198 **	3.396 **	0.160	0.478 **	0.064	0.666 **	0.979	0.689–2.517
0.10	0.184 **	3.208 **	0.111	0.494 **	0.072	0.679 **	0.976	0.443–1.801

Dependent variable: lnC

Note: ① ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively. ② The VIF range is the interval between the minimum and maximum VIF values for each variable.

As shown in Table 6, when K = 0.01, the model's R² is highest, reaching 0.988; however, the VIF value for lnG remains as high as 13.627, exceeding the critical value of 10, indicating that multicollinearity has not yet been fully eliminated. When K is increased to 0.05, the VIF values for all variables fall to between 1.089 and 3.292, well below the critical value of 10, indicating that multicollinearity has been effectively eliminated; at the same time, all variables are statistically significant, and the model's R² remains at 0.981, showing that the model's explanatory power has not been significantly weakened by the introduction of the penalty term. When K is increased to 0.07 and 0.10, the coefficients for lnEI and lnTS are no longer significant, indicating that an excessively high K value leads to increased bias in the estimates, causing some variables to lose their statistical significance. Furthermore, for all values of K, the regression coefficients for all six variables are positive. The coefficient for the year-end permanent resident population (lnP) is consistently much higher than those of the other variables across all K values, ranging from 3.208 to 4.476, and remains the most significant influencing factor for carbon emissions, indicating the robustness of the core conclusion. Based on the above analysis, K = 0.05 represents the optimal balance between eliminating multicollinearity and preserving the model's explanatory power. Therefore, this study selected K = 0.05 for ridge regression estimation, with the results shown in Table 7. When K = 0.05, the model's R² is 0.981, and the *p*-value of the F-test is 0.000, indicating that the model as a whole is statistically significant.

Table 7. Ridge regression analysis results.

	Regression Coefficient B	Significance <i>p</i> -Value	R ²	F
(Constant)	−3.306	0.000 ***		
lnG	0.235	0.000 ***		
lnP	3.773	0.000 ***		
lnTS	0.08	0.017 **	0.981	112.131 (0.000)
lnEI	0.221	0.038 **		***
lnTI	0.273	0.041 **		
lnIS	0.436	0.030 **		

Dependent variable: lnC

Note: *** and ** represent significance levels of 1% and 5%, respectively.

The corresponding ridge regression formula for the extended STIRPAT model is:

$$\begin{aligned} \ln C = & -3.306 + 0.235 \times \ln G + 3.773 \times \ln P \\ & + 0.08 \times \ln TS + 0.221 \times \ln EI \\ & + 0.273 \times \ln TI + 0.436 \times \ln IS \end{aligned} \quad (6)$$

2.3. Development of Carbon Emissions Decoupling Models

Carbon decoupling, as the practical extension of decoupling theory within environmental research, fundamentally seeks to achieve effective control over total carbon emissions through the synergistic effect of sustained economic expansion coupled with a gradual reduction in energy consumption intensity. The mainstream decoupling measurement methodologies within the international academic community comprise two major frameworks: the OECD framework and the Tapio model. The OECD framework employs a comparative approach between baseline and terminal period values to dynamically analyse the correlation strength between environmental pressure factors and economic driver factors. This method typically uses carbon emissions to represent environmental pressure indicators and GDP to represent economic driver indicators, determining the degree of decoupling through growth rate comparisons. The mathematical expression for the decoupling factor is:

$$D_f = 1 - \frac{(EP/DF)_{end}}{(EP/DF)_{start}} \quad (7)$$

where:

D_f denotes the decoupling factor;

EP represents environmental pressure, typically expressed as carbon emissions;

DF signifies driving force, generally measured by GDP.

The OECD decoupling formula, whilst widely employed to measure the impact of economic growth on environmental pressures across different countries or regions, exhibits limitations due to its sensitivity to base period selection and insufficient result stability. To overcome these constraints, Tapio innovatively introduced the concept of ‘decoupling elasticity’ within the OECD framework in 2005, establishing the Tapio decoupling index analytical framework. Compared to traditional models, this framework offers enhanced explanatory power and practical applicability. By employing elasticity coefficients to refine the characterization of decoupling states, it categorizes decoupling into three broad types: decoupling, negative decoupling, and coupling. These are further subdivided into eight distinct sub-states, including weak decoupling, strong decoupling, and regressive decoupling, as illustrated in Figure 3 (where T denotes decoupling elasticity):

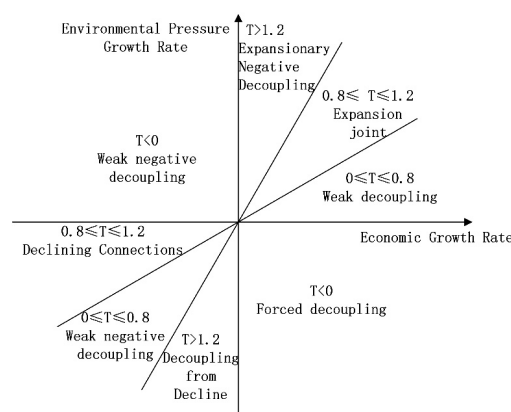


Figure 3. Distribution of eight states in the Tapio decoupling model intervals.

Compared to the OECD decoupling framework, the Tapio decoupling index methodology offers superior stability and measurement precision. This model not only effectively mitigates dimensional interference but also exhibits low sensitivity to base period selection. Consequently, this study employs the Tapio decoupling index as its analytical tool to systematically reveal the synergistic evolution patterns between carbon emissions and economic growth within the Yangtze River Delta urban cluster from 2003 to 2022. To accurately reflect decoupling trends over the period [24], the 2002 data serves as the base period. For the 2003–2022 observation period, carbon emissions from the transport industry represent environmental pressure changes, while the sector's gross value added (GVA) indicates economic development levels. The specific formula is as follows:

$$T = \frac{\Delta C / C^0}{\Delta TG / TG^0} \quad (8)$$

where:

T denotes the Tapio decoupling index;

ΔC denotes the change in carbon emissions from the transport industry during the observation period;

ΔTG denotes the change in transport industry output value during the observation period;

C^0 denotes the carbon emissions from the transport industry during the base period;

TG^0 denotes the transport industry output value during the base period.

To investigate the contribution of various driving factors to the decoupling index of carbon emissions from GDP in the Yangtze River Delta region, this paper adopts the additive decomposition method from the LMDI decomposition mode [25], performing the following decomposition based on Equation (8):

$$\Delta C = \Delta C_G + \Delta C_P + \Delta C_{TS} + \Delta C_{EI} + \Delta C_{TI} + \Delta C_{IS} \quad (9)$$

$$\Delta C_G = \sum_{i=1} \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} (\ln G_t - \ln G_0) \quad (10)$$

$$\Delta C_P = \sum_{i=1} \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} (\ln P_t - \ln P_0) \quad (11)$$

$$\Delta C_{TS} = \sum_{i=1} \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} (\ln TS_t - \ln TS_0) \quad (12)$$

$$\Delta C_{EI} = \sum_{i=1} \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} (\ln EI_t - \ln EI_0) \quad (13)$$

$$\Delta C_{TI} = \sum_{i=1} \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} (\ln TI_t - \ln TI_0) \quad (14)$$

$$\Delta C_{IS} = \sum_{i=1} \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} (\ln IS_t - \ln IS_0) \quad (15)$$

Substituting Equations (10)–(15) into (8) yields the extended Tapio decoupling model formula:

$$T = \frac{\frac{\Delta C}{\Delta TG}}{\frac{C}{TG^0}} = a \frac{C}{C^0} \frac{TG^0}{\Delta TG} = \frac{\Delta C_G TG^0}{C^0 \Delta TG} + \frac{\Delta C_P TG^0}{C^0 \Delta TG} + \frac{\Delta C_{TS} TG^0}{C^0 \Delta TG} + \frac{\Delta C_{EI} TG^0}{C^0 \Delta TG} + \frac{\Delta C_{TI} TG^0}{C^0 \Delta TG} + \frac{\Delta C_{IS} TG^0}{C^0 \Delta TG} = T_G + T_P + T_{TS} + T_{EI} + T_{TI} + T_{IS} \quad (16)$$

where:

ΔC_G , ΔC_P , ΔC_{TS} , ΔC_{EI} , ΔC_{TI} , ΔC_{IS} , respectively, denote the change in transport carbon emissions attributable to per capita GDP, year-end resident population, transport structure, energy intensity, transport intensity, and industrial structure;

T_G , T_P , T_{TS} , T_{EI} , T_{TI} , T_{IS} respectively denote the contribution values of per capita GDP, year-end resident population, transport structure, energy intensity, transport intensity, and industrial structure to the transport carbon emissions decoupling index.

3. Analysis of Factors Influencing Carbon Emissions in the Transport Industry

3.1. Data Sources

This study is based on combined energy consumption data for the transport, warehousing, and postal sectors in Shanghai Municipality, Jiangsu Province, Zhejiang Province, and Anhui Province from 2003 to 2022. The study period ends in 2022 primarily because the China Energy Statistical Yearbook no longer provides provincial-level physical volume data by energy type for subsequent years, making it impossible to continue using the IPCC emission factor method for calculating carbon emissions by energy type; therefore, data from 2023 and beyond were not included. This data scope is derived from the industry classification standards of the China Energy Statistical Yearbook and represents the official statistical data currently available that most closely approximates the actual energy consumption of the transportation sector. However, since the current statistical yearbook combines transportation with warehousing and postal services, it is impossible to isolate energy consumption data for the transportation sector alone [26]; therefore, these aggregated data are used as a proxy for the energy consumption of the transportation sector. This approach has been widely adopted in similar studies. This same aggregated dataset was used to decompose carbon emission drivers and simulate peak emission pathways for China's transportation sector [27].

It should be noted that the use of this aggregated data inevitably includes energy consumption from the warehousing and postal sectors, which may lead to a systematic overestimation of total carbon emissions. However, in terms of the energy mix, within the combined carbon emissions for the transportation, warehousing, and postal sectors calculated in this study, carbon emissions from petroleum products—such as gasoline, diesel, kerosene, and fuel oil—account for more than 99% of the sector's total carbon emissions, while electricity and heat combined account for less than 0.5%. As fixed facilities, the warehousing and postal sectors rely primarily on electricity for energy consumption—such as warehouse lighting, ventilation, cold storage refrigeration, and sorting equipment—and emissions from the direct combustion of fossil fuels are extremely limited. Even if all electricity and heat emissions were attributed to the warehousing and postal sectors, their combined share within this consolidated scope would still be less than 0.5%. This structural characteristic indicates that the share of the warehousing and postal sector within this consolidated scope is extremely limited, and any changes in this sector would not have a substantial impact on the ranking of the standardized regression coefficients of the various driving factors. Furthermore, since the energy consumption of the warehousing and postal sector consistently maintained this low proportion throughout the 20-year study period, it would not alter the time-series trend of carbon emissions. Therefore, this data scope would also not affect the direction

of annual changes in the Tapio decoupling index. Following the China Energy Statistical Yearbook [28] and IPCC guidelines, a consumption matrix covering multiple energy types was constructed. Using standard coal conversion factors and carbon emission accounting methods, annual carbon emissions from the transport industry in the Yangtze River Delta region were systematically calculated.

The CO₂ emission factors for each energy source were calculated using default parameters—such as carbon content, carbon oxidation rate, and average lower heating value—provided in the IPCC 2006 Guidelines. The results are presented in Table 8.

Table 8. CO₂ emission factors for major energy types.

Energy Type	Carbon Emission Factor (tCO ₂ /t)
Raw coal	1.9003
Gasoline	2.9251
Kerosene	3.0334
Diesel oil	3.0959
Fuel oil	3.1705
Liquefied petroleum gas	3.1013
Natural gas	2.1650

The IPCC 2006 Guidelines note that emission factors calculated using default parameters are subject to a certain degree of uncertainty (typically $\pm 5\%$ to $\pm 10\%$). This study focuses on the time-series trends of carbon emissions and the relative relationships among various driving factors, rather than on absolute emission values. Additionally, the same emission factor parameters were consistently applied for estimates throughout the study period; therefore, parameter uncertainty does not have a substantial impact on the core conclusions.

3.2. Analysis of the Degree of Influence of Relevant Factors

As can be seen from the expanded STIRPAT-Ridge model formula derived in the previous section, after controlling for multicollinearity among the variables, the magnitudes of the standardized regression coefficients for each factor reflect the degree of partial correlation with changes in carbon emissions; they should not be overinterpreted as causal contribution rates. The regression coefficients, ranked from highest to lowest, are: year-end resident population (P) > industrial structure (IS) > transport intensity (TI) > per capita GDP (G) > energy intensity (EI) > transport structure (TS). The following sections will analyze the conditional associations between each variable and carbon emissions.

Among the six influencing factors, the year-end resident population (P) exhibits the strongest conditional association, with a regression coefficient of 3.773. When controlling for other variables, a 1% increase in the region's population corresponds to a 3.773% increase in carbon emissions from the transportation sector. There is a positive correlation between population growth and carbon emissions; as the population expands, residents' travel demand rises significantly, particularly the use of private transportation such as private cars and taxis, which is closely linked to rising carbon emissions. On the other hand, the diversification of daily needs resulting from population growth is accompanied by an increase in logistics demand, which has an indirect association with carbon emissions from transportation. The year-end resident population in the Yangtze River Delta region grew from 199.4 million to 222.3 million between 2003 and 2022, with an average annual growth rate of approximately 0.57%. Combined with its relatively large regression coefficient, the conditional association between population and carbon emissions is the most pronounced.

The conditional association strength for industrial structure (IS) is second only to that of population, with a regression coefficient of 0.436. This means that, holding other variables constant, a 1% increase in the share of the tertiary sector corresponds to a 0.436% increase in carbon emissions from the transportation sector. In 2022, the tertiary sector's share in the Yangtze River Delta region reached 55.2%, surpassing the primary and secondary sectors and accounting for more than half of the region's total output value. With the rapid development of the tertiary sector, growth in industries such as services, finance, and information technology has been accompanied by increased demand for passenger and freight transportation, which is positively correlated with the overall activity level and carbon emissions of the transportation sector.

The regression coefficient for transport intensity (TI) is 0.273, meaning that, holding other variables constant, a 1% increase in transport intensity leads to a 0.273% increase in carbon emissions from the transportation sector. In 2022, transport intensity was 6.925, a 3.5% decrease from the same period the previous year, indicating that the increase in transport turnover in the Yangtze River Delta region was smaller than the increase in the transportation sector's GDP. As transport turnover increases, the operating time of transport vehicles and equipment correspondingly lengthens, leading to a rise in energy consumption and carbon emissions. Road transport, in particular, exhibits a stronger positive correlation between increased turnover and carbon emissions due to its high energy consumption and carbon emission levels. A decrease in transport turnover is typically associated with improved transport efficiency, scientific and technological progress, and the emergence of more environmentally friendly, low-energy-consumption modes of transport. The positive correlation between transport intensity and carbon emissions suggests that reducing transport intensity contributes to lowering carbon emission levels.

The regression coefficient for per capita GDP (G) is 0.235, meaning that, holding other variables constant, a 1% increase in per capita GDP results in a 0.235% increase in carbon emissions. According to data from the Statistical Yearbook, the per capita GDP in the Yangtze River Delta region reached 130,600 yuan in 2022, a year-on-year increase of 4.29%, with Shanghai recording the highest figure at 179,900 yuan. Growth in per capita GDP is accompanied by increases in consumer demand, investment demand, and foreign trade demand, which are positively correlated with the development of the transportation sector. Although the regression coefficient for per capita GDP is relatively small, its conditional association with carbon emissions should not be overlooked.

The regression coefficient for energy intensity (EI) is 0.221, meaning that, holding other variables constant, a 1% increase in energy intensity results in a 0.221% increase in carbon emissions. Energy intensity reflects the level of energy efficiency, and there is a positive correlation between it and carbon emission levels. The energy intensity of the transportation sector in the Yangtze River Delta region followed a trend of first rising and then falling between 2003 and 2022, with the consumption of raw coal showing the most significant decline. This is, to some extent, associated with improvements in energy efficiency and the transition of the energy structure. Through the application of new energy sources, the transportation sector can reduce its reliance on non-clean resources such as petroleum, achieve sustainable use of energy resources, and establish a corresponding trend with the decline in carbon emissions.

The transport structure (TS) has the weakest conditional correlation, with a regression coefficient of 0.08; holding other variables constant, a 1 percentage point increase in the transport structure corresponds to a 0.08 percentage point increase in total carbon emissions. In this study, the transport structure is defined as the ratio of road and air transport tonne-kilometers to total transport tonne-kilometers; the volume of road and air transport tonne-kilometers directly influences the level of the transport structure. Road

transport primarily relies on petroleum fuels, such as gasoline and diesel, and the combustion of these fuels produces large amounts of carbon dioxide; air transport consumes significant amounts of jet fuel, particularly for long-haul flights and large passenger aircraft, which have enormous fuel consumption and exhibit a positive correlation with carbon emissions. Statistical data show that the transport structure has been declining year by year in recent years, with freight transport shifting toward water transport. In 2022, water transport accounted for 82.7% of freight tonne-kilometers, and the increase in waterway freight tonne-kilometers between 2003 and 2022 was 45,998.8 billion tonne-kilometers. Waterway transport offers the advantages of high capacity, low cost, and low energy consumption; there is a corresponding trend between the optimization of the transport structure and the reduction in carbon emissions.

3.3. Analysis of Fitting Results

Based on the above analysis, all six influencing factors exhibit a positive correlation with the transport sector in the Yangtze River Delta region, meaning that an increase in any variable leads to higher carbon emissions. To more intuitively demonstrate the fitting performance of the extended STIRPAT model, historical data for the end-of-year permanent resident population, industrial structure, transport intensity, per capita GDP, energy intensity, and transport structure from 2002 to 2022 were input into the Formula (6) to obtain simulated values. These simulated values were then compared with actual values to observe the magnitude of discrepancy between the two. The comparison results are presented in Table 9 below:

Table 9. Comparison of actual and predicted carbon emissions in the transportation industry of the Yangtze River Delta region from 2003 to 2022.

Year	Actual Value	Forecast Value (Billion Tons)	Error Rate
2003	1.618	1.715	−5.99%
2004	1.821	1.796	1.40%
2005	1.944	1.991	−2.46%
2006	2.126	2.064	2.96%
2007	2.337	2.200	5.86%
2008	2.472	2.458	0.54%
2009	2.524	2.667	−5.68%
2010	2.736	2.665	2.61%
2011	2.823	2.876	−1.88%
2012	3.085	3.077	0.26%
2013	3.246	3.046	6.15%
2014	3.394	3.507	−3.34%
2015	3.573	3.566	0.20%
2016	3.794	3.773	0.54%
2017	4.132	4.072	1.47%
2018	4.244	3.955	6.81%
2019	4.190	3.997	4.62%
2020	3.930	4.195	−6.74%
2021	4.002	4.092	−2.25%
2022	3.514	3.574	−1.72%

As observed in Table 9, from 2003 to 2022, discrepancies existed between the actual and predicted carbon emissions for the transport industry in the Yangtze River Delta region. However, these differences were relatively minor, with the maximum error rate reaching 6.81%—a figure within reasonable parameters. Furthermore, the trends depicted in Figure 4 show consistent alignment between actual and predicted values. This indicates

that the model exhibits high predictive accuracy and favourable fitting performance. Consequently, the derived results possess practical significance and may be utilized for subsequent carbon emission forecasting.

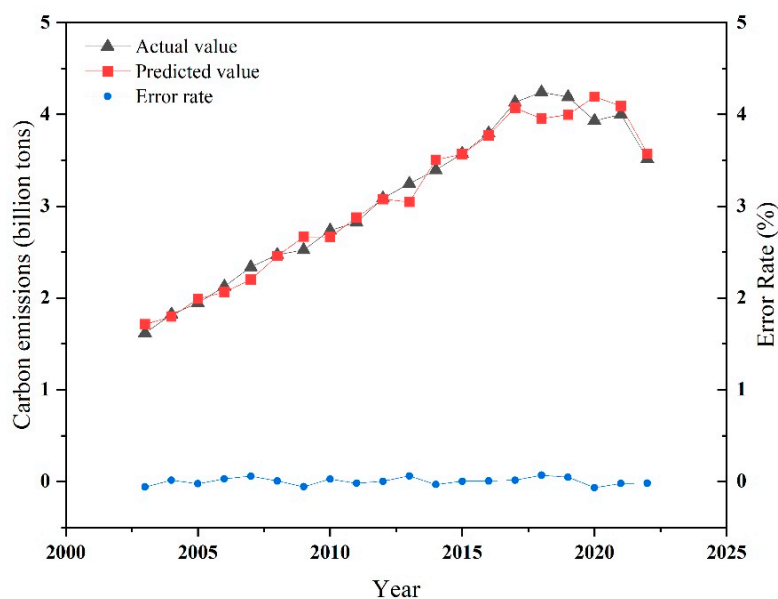


Figure 4. Fit effect of actual and predicted carbon emissions in the transportation industry of the Yangtze River Delta region from 2003 to 2022.

4. Analysis of the Decoupling Status of Carbon Emissions in the Transport Sector

4.1. Carbon Emissions Decoupling Analysis

Table 10 data reveals that the Yangtze River Delta urban cluster exhibited a distinct dynamic evolution of carbon-economic relations between 2003 and 2022. This decoupling trajectory can be deconstructed into six characteristic phases: expansive negative decoupling, expansive linkage, strong negative decoupling, weak decoupling, strong decoupling, and recessionary decoupling. Between 2003 and 2018, carbon emissions growth consistently exceeded zero. Following 2019, growth rates turned negative, while economic growth rates for the same years consistently surpassed carbon emissions growth rates.

Table 10. Decoupling status of carbon emissions and GDP in the transportation industry in the Yangtze River Delta region from 2003 to 2022.

Year	$\Delta C/C^0$	$\Delta TG/TG^0$	Decoupling Index	Status
2003–2004	0.246	0.192	1.280	Expansionary negative decoupling
2004–2005	0.135	−0.111	−1.216	Strong decoupling
2005–2006	0.187	0.197	0.948	Expansive coupling
2006–2007	0.196	0.184	1.064	Expansive coupling
2007–2008	0.117	0.221	0.529	Weak decoupling
2008–2009	0.044	−0.043	−1.023	Strong decoupling
2009–2010	0.167	0.385	0.435	Weak decoupling
2010–2011	0.065	0.301	0.216	Weak decoupling
2011–2012	0.185	0.202	0.916	Expansive coupling
2012–2013	0.105	0.173	0.608	Weak decoupling

2013–2014	0.093	0.085	1.090	Expansive coupling
2014–2015	0.107	0.027	4.002	Expansionary negative decoupling
2015–2016	0.124	0.166	0.749	Weak decoupling
2016–2017	0.178	0.258	0.689	Weak decoupling
2017–2018	0.055	0.747	0.074	Weak decoupling
2018–2019	−0.027	0.209	−0.127	Strong decoupling
2019–2020	−0.133	−0.068	1.971	Recessive decoupling
2020–2021	0.038	0.672	0.056	Weak decoupling
2021–2022	−0.270	0.060	−4.530	Strong decoupling

To provide a clearer illustration of the decoupling index's dynamic trends, a decoupling trend chart has been produced as shown in Figure 5.

Between 2003 and 2022, the overall carbon decoupling index exhibited a W-shaped fluctuation pattern. Weak decoupling occurred eight times, representing the most frequent decoupling pattern over the 20-year period. This indicates that the growth rate of carbon emissions from the transport industry was lower than the growth rate of the sector's gross value added, while the sector's production value maintained positive growth over an extended period. Specifically, the changes in the decoupling index can be analyzed across three distinct phases.

Phase One: Between 2003 and 2009, with the exception of 2007–2008, the overall decoupling trend showed carbon emissions growth exceeding the growth rate of transport sector output value. Notably, 2004–2005 witnessed a strong negative decoupling between emissions and output value, representing the least favourable state. This indicates inefficiencies within the transport system. Regarding transport structure, long-distance bulk cargo transport remained predominantly reliant on road transport, a mode characterized by high non-clean energy consumption and consequently elevated carbon emissions. Concerning transport equipment efficiency, new energy technologies were not yet sufficiently mature at the time, presenting bottlenecks in long-distance haulage and heavy-load operations. Therefore, strengthening transport management, enhancing transport efficiency, optimizing transport structure, and promoting technological innovation became key priorities for the transport sector.

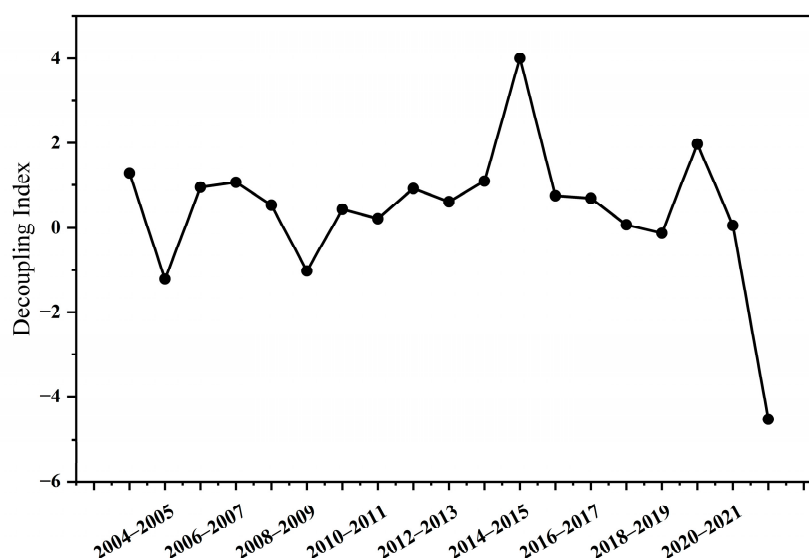


Figure 5. Decoupling trend of carbon emissions and GDP in the transportation industry in the Yangtze River Delta region from 2003 to 2022.

Phase Two: Between 2009 and 2015, decoupling trends showed marked improvement compared to the preceding period, with carbon emissions from transport exhibiting cyclical fluctuations relative to economic output growth. Specifically, from 2010 to 2013, carbon emission growth lagged behind economic output growth; conversely, from 2013 to 2015, the trend reversed, resulting in relatively weaker overall decoupling effects. This shift indicates that the Yangtze River Delta region is implementing policy measures to transform its development model, seeking to move away from resource-intensive and inefficient growth patterns. However, as this transition remains in its pilot phase, the changes have yet to stabilize. The region should continue advancing the low-carbon transformation of its transport sector, refining policy and market mechanisms to enhance transport efficiency.

Phase Three: From 2015 to 2022, weak decoupling predominated, with strong decoupling observed in 2018–2019—the most ideal scenario to emerge for the first time during this phase, reflecting that the cumulative effects of energy conservation and emissions reduction policies, energy structure transformation, and transportation structure adjustments had begun to take effect. In 2019–2020, both carbon emissions and GDP declined, indicating a recession-driven decoupling. Although strong decoupling reemerged in 2021–2022, it differed fundamentally from the strong decoupling observed in 2018–2019 in terms of driving mechanisms and must be discussed separately in light of external shock factors.

It should be noted that the decoupling observed from 2020 to 2022 was influenced by exogenous shocks from COVID-19 containment measures and should therefore be interpreted with caution. In 2020, both carbon emissions and GDP in the transportation sector declined, exhibiting a recession-driven decoupling. The decrease in carbon emissions occurred alongside a contraction in economic output, representing passive emission reductions rather than development decoupling. From 2021 to 2022, carbon emissions fell while GDP rose slightly. Although this is classified as a strong decoupling, the significant decline in carbon emissions was primarily due to shrunken demand from the suspension of transportation activities during lockdowns, rather than structural improvements from transportation structure optimization or enhanced energy efficiency. Compared to the strong decoupling observed between 2018 and 2019—when carbon emissions fell while GDP continued to grow—the two phases, though classified under the same decoupling category, exhibit fundamental differences in their driving mechanisms. When assessing the actual progress of low-carbon transformation in regional transportation, the decoupling data from 2020 to 2022 should be designated as a period of exogenous shocks to avoid extrapolating these trends to normal development phases.

4.2. Analysis of Decoupling Status Across Provinces and Municipalities

To explore the relationship between carbon emissions from the transport industry and economic growth across provinces and municipalities in the Yangtze River Delta region, this study calculated decoupling indices for Shanghai, Zhejiang, Jiangsu, and Anhui provinces from 2003 to 2022 based on Formula (8), as presented in Table 11 below.

Table 11. Decoupling index and status of carbon emissions in the transportation industry of various provinces and cities in the Yangtze River Delta region.

Year	Decoupling Index			
	Shanghai	Zhejiang	Jiangsu	Anhui
2003–2004	1.896	0.662	1.262	0.770
2004–2005	0.248	−0.406	−0.148	0.810
2005–2006	0.942	1.111	0.467	0.841
2006–2007	1.348	1.028	0.709	1.142

2007–2008	0.377	0.951	0.640	0.281
2008–2009	−0.039	0.719	0.718	−0.205
2009–2010	0.171	0.522	0.552	1.077
2010–2011	−0.368	0.820	0.223	1.096
2011–2012	0.280	0.785	0.647	4.300
2012–2013	−0.010	0.707	1.903	1.183
2013–2014	−5.342	−0.682	0.979	1.490
2014–2015	0.362	0.895	−0.408	3.776
2015–2016	0.761	0.018	0.590	0.332
2016–2017	0.503	0.506	0.499	1.541
2017–2018	−0.080	−0.440	0.595	0.136
2018–2019	0.946	−1.134	0.439	−1.808
2019–2020	0.829	13.120	6.802	0.023
2020–2021	0.071	0.242	−0.180	0.042
2021–2022	2.359	−0.490	6.733	−1.887

Based on the analysis of the data presented in the table above, decoupling performance in Shanghai between 2009 and 2018 was generally favourable, characterized by alternating periods of strong and weak decoupling. This indicates that carbon emissions growth consistently remained below economic growth levels during this phase. However, post-2018, the decoupling pattern exhibited volatility, reflecting short-term instability in the economic growth of the transport industry. Zhejiang Province experienced fluctuations between weak decoupling, strong negative decoupling, and renewed weak decoupling during 2003–2009, indicating uncertainty in the relationship between carbon emissions and economic growth. From 2009 to 2020, Zhejiang predominantly maintained a state of weak decoupling or expansive coupling, suggesting low dependence of carbon emissions on economic growth. Between 2021 and 2022, Zhejiang Province achieved a state of strong decoupling, representing the most favourable outcome. Jiangsu Province exhibited expansionary negative decoupling in the early period from 2003 to 2007, subsequently transitioning to weak decoupling, reflecting a gradual improvement in the relationship between economic growth and carbon emissions. From 2007 to 2022, Jiangsu Province predominantly exhibited weak decoupling, though periods of expansionary coupling and expansionary negative decoupling occurred in 2011–2012 and 2019–2020, indicating synchronous growth in economic expansion and carbon emissions during certain phases. Anhui Province experienced multiple states between 2003 and 2014, including weak decoupling, expansion linkage, and strong negative decoupling, indicating a complex and fluctuating relationship between economic growth and carbon emissions. Between 2014 and 2022, it frequently exhibited expansionary negative decoupling and strong decoupling, notably achieving strong decoupling during 2018–2019. This indicates that the relationship between economic growth and carbon emissions significantly improved during certain periods, yet synchronized growth occurred during others.

To visualize spatial decoupling dynamics, Figure 6 illustrates the decoupling trajectory between carbon emissions from the transport sector and economic output at the provincial level across the Yangtze River Delta. Shanghai exhibited seven distinct decoupling states during the 2003–2022 study period, with a higher frequency of state transitions than the other three provinces. From 2007 to 2018, a predominantly weak decoupling pattern emerged, reflecting that while the scale of the transport economy expanded alongside rising carbon emissions, the differential growth rates exhibited economic elasticity characteristics, aligning with phased optimization objectives for low-carbon transition. Post-2018, the decoupling state showed pronounced fluctuations, with

recessionary decoupling observed in 2022. Analysis traced this to Shanghai's citywide lockdown during the second quarter of 2022, which caused systemic disruptions in logistics and manufacturing supply chains, delivering a significant negative shock to economic activity. Although marginal improvements emerged after the third quarter, the economic inertia from the pandemic substantially delayed the recovery process. Jiangsu, forming a deep industrial synergy network with Shanghai, saw manufacturing hubs like Suzhou and Wuxi heavily reliant on Shanghai Port's logistics hub functions. The logistical bottlenecks triggered by pandemic control policies led to a recession decoupling phenomenon in Jiangsu during 2022. Historical data analysis reveals that within the 2003–2022 cycle, Jiangsu exhibited cumulative weak decoupling over a ten-year period, specifically manifesting in two sustained phases: 2005–2011 and 2015–2019. Historically accumulated industrial resilience underpins the regional economic system's disturbance resistance.

Zhejiang and Anhui provinces exhibit divergent trajectories, demonstrating synchronized transformation during the 2020–2022 observation period, shifting from a state of weak decoupling to one of strong decoupling. Zhejiang exhibited a predominantly weak decoupling pattern from 2015 onwards, achieving a transition to strong decoupling by 2022. Data released by the Zhejiang Provincial Department of Commerce indicates that the province's live-streaming e-commerce transaction volume exceeded 2.8 trillion yuan in 2022, while express delivery and logistics volume increased to 22.96 billion parcels, representing a year-on-year growth of 5.1%. This reflects the high level of activity maintained by Zhejiang's tertiary industry (including e-commerce logistics, digital services, etc.) during this period. However, the specific causal mechanisms between the digital economy and transportation carbon emissions require further empirical testing, and this paper only provides a correlational description. Anhui exhibited characteristics of expansive coupling and negative decoupling prior to 2016, achieving sustained positive decoupling from 2017 onwards. Exponential growth in new energy vehicle manufacturing and photovoltaic industrial clusters provided core momentum. In 2022, Anhui's new energy vehicle production capacity exceeded 675,000 units. The synergistic expansion of the new energy sector and logistics node upgrades triggered non-linear growth in logistics demand for supporting industries such as power batteries. The implementation of a key enterprise directory system during exceptional periods ensured the stability of new energy and emergency supply chains, underpinning Anhui's maintenance of strong decoupling system stability throughout 2022.

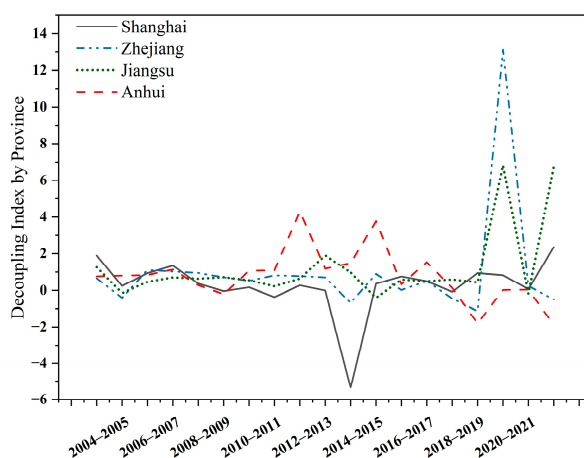


Figure 6. Decoupling trend of carbon emissions and GDP in the transportation industry of various provinces and cities in the Yangtze River Delta region from 2003 to 2022.

Overall, all four regions experienced multiple decoupling states during the observation period, indicating the complex and dynamic relationship between transportation GDP and carbon emissions. However, this state remains influenced by multiple factors, including policy adjustments and shifts in economic development models. To achieve more sustainable economic growth, all regions must continue strengthening environmental protection policies, promoting green development, and exploring more efficient and eco-friendly economic growth models.

4.3. Analysis of Carbon Emission Drivers

To further investigate the factors influencing decoupling of carbon emissions in the transport industry of the Yangtze River Delta region, Equations (10)–(16) were employed to decompose these factors. The contribution values of each factor to decoupling carbon emissions in the region's transport industry are presented in Table 12. Among these, the decoupling contribution values for per capita GDP (T_G), year-end resident population (T_P), and energy intensity (T_{EI}) are all positive, which indicate that these three factors hindered the decoupling of carbon emissions from economic growth in the region's transport sector between 2003 and 2022. The decoupling contribution value for transport intensity (T_{TI}) turned negative after 2009, suggesting it can promote the decoupling of carbon emissions from economic growth.

Table 12. Decoupling contribution values of carbon emission driving factors in the transportation industry of various provinces and cities in the Yangtze River Delta region.

Year	T_G	T_P	T_{TS}	T_{EI}	T_{TI}	T_{IS}
2003–2004	0.545	0.072	−0.291	0.137	0.153	−0.016
2004–2005	1.631	0.201	−0.945	1.179	0.648	0.019
2005–2006	1.292	0.171	−0.621	0.611	0.204	0.034
2006–2007	1.342	0.181	−0.504	0.454	0.133	0.071
2007–2008	1.222	0.165	0.572	0.376	0.010	0.080
2008–2009	1.442	0.205	0.773	0.515	0.178	0.165
2009–2010	1.196	0.163	0.499	0.279	−0.056	0.108
2010–2011	1.094	0.145	0.229	0.333	−0.129	0.098
2011–2012	1.074	0.139	0.270	0.316	−0.106	0.114
2012–2013	1.070	0.137	0.231	0.261	−0.127	0.134
2013–2014	1.110	0.138	0.226	0.296	−0.109	0.152
2014–2015	1.180	0.140	0.266	0.213	−0.098	0.189
2015–2016	1.185	0.140	0.300	0.123	−0.112	0.211
2016–2017	1.167	0.134	0.227	0.159	−0.124	0.204
2017–2018	0.952	0.104	0.161	0.059	−0.194	0.180
2018–2019	0.916	0.101	0.134	0.058	−0.210	0.182
2019–2020	0.932	0.098	0.218	0.105	−0.209	0.187
2020–2021	0.831	0.083	0.242	0.032	−0.252	0.151
2021–2022	0.739	0.076	0.176	0.027	−0.275	0.138

As shown in Table 12, the decoupling index contribution value highest among the driving factors is that of per capita GDP (T_G). Its maximum contribution value occurred between 2004 and 2005 at 1.631, with an annual average contribution value of 1.101, exhibiting a strong inhibitory effect on the decoupling state. The decoupling contribution value for transport intensity (T_{TI}) is the smallest, with a minimum value of −0.275 occurring between 2021 and 2022 and an annual average contribution value of −0.036. It significantly promotes the decoupling state.

Judging by the signs of the contribution values for each factor, the decoupling contribution values for GDP per capita (T_G), year-end resident population (T_P), and energy intensity (T_{EI}) were all positive throughout the study period, indicating that these three factors had a suppressing effect on the decoupling of carbon emissions from economic growth. Among them, the average annual contribution value of GDP per capita was 1.101, making it the primary factor suppressing decoupling. In contrast, the contribution value of transport intensity (T_{TI}) turned negative starting in 2009, and its absolute value showed a trend of generally increasing amid fluctuations, indicating that the decline in transport intensity has become a key factor promoting decoupling.

Figure 7 provides a more intuitive observation of the contribution values of decoupling indices across various influencing factors in different years. From 2008 to 2009, the total decoupling contribution value of driving factors reached its peak at 3.278, indicating the strongest suppression effect on both economic growth and carbon emissions. During the period from 2003 to 2005, the total decoupling contribution value stood at 2.733. It is discernible that during 2011–2022, the decoupling state exhibited a fluctuating downward trend, with the promoting effect on decoupling becoming increasingly pronounced. This indicates that economic growth is progressively reducing its dependence on the transport industry. Concurrently, the contribution of policy factors to decoupling within the transport industry demonstrated a marked upward trajectory from 2003 to 2022. Particularly during the Twelfth and Thirteenth Five-Year Plan periods, the government implemented a series of energy-saving, emission-reduction, and green transport policy measures. These policies substantially enhanced the decoupling effect within the transport industry, providing robust support for the industry's sustainable development.

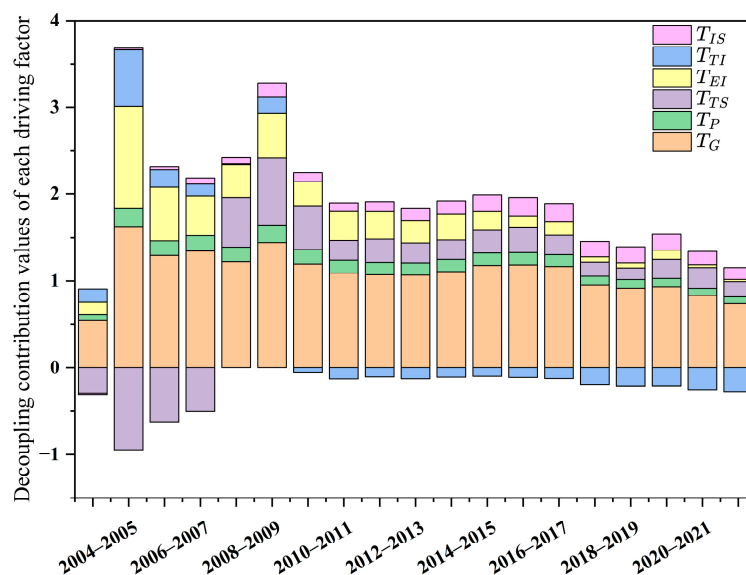


Figure 7. Decoupling contributions of various influencing factors in the transportation industry in the Yangtze River Delta region from 2003 to 2022.

5. Discussion

5.1. Identification of Influencing Factors and Comparison of Results

This study found that the year-end permanent resident population is the factor most strongly associated with carbon emissions from transportation in the Yangtze River Delta (regression coefficient: 3.773), followed by industrial structure (0.436), with transport intensity (0.273) and per capita GDP (0.235) coming next.

Regarding demographic and economic factors, the conclusions of this study are highly consistent with existing literature. A ridge regression analysis on transportation carbon emissions in Henan Province has indicated that population size, per capita GDP, and the economic share of transportation are all positively associated with carbon emissions [29]. An STIRPAT-Ridge model applied to a case study of Shandong Province similarly found that population size and per capita GDP are positively associated with carbon emissions [30]. An analysis based on the LMDI decomposition method further indicated that per capita GDP is the primary contributor to carbon emissions growth in China's transportation sector, with population also exerting a positive influence [31].

With regard to energy intensity, the regression coefficient in this study is positive (0.221), which differs from the conclusions of some studies using the LMDI decomposition method. LMDI studies have found that energy intensity acts as a constraining factor [32], while STIRPAT-Ridge-based provincial-level studies [29,30,33] have also found energy intensity to be a facilitating factor, consistent with the findings of this study. This discrepancy primarily stems from the fundamental differences between the LMDI and STIRPAT-Ridge methods: the former analyzes the direction of contribution of changes in various factors to changes in carbon emissions, while the latter estimates the strength of partial correlation between the levels of these factors and carbon emission levels. Additionally, differences in the study regions and industry boundaries may also have contributed to this discrepancy.

At the methodological level, the STIRPAT-Ridge model was used in both this study and the aforementioned literature to address multicollinearity among variables through ridge regression. The R^2 value of the model used in this study is 0.981, which is comparable to that of similar studies, validating the model's applicability in analyzing the drivers of regional transportation carbon emissions. A distinctive feature of this study is the integration of the STIRPAT-Ridge model with the Tapio decoupling model within a single analytical framework, achieving synergy between "factor decomposition" and "relationship diagnosis"—an approach that remains uncommon in existing research on transportation carbon emissions in the Yangtze River Delta.

5.2. Phased Evolutionary Characteristics of Decoupling Trends

Regarding decoupling effects, this study's analysis of the 2003–2022 period identified eight instances of weak decoupling, making it the most frequent type of decoupling observed over the 20-year period. A provincial-level decoupling analysis of China's transportation carbon emissions using the Tapio decoupling model for the period 2012–2021 has indicated that 40% of provinces achieved absolute decoupling and 53% achieved relative decoupling [32]. The generalized Divisia index method was employed to analyze 30 Chinese provinces from 2005 to 2022, and it was further found that national decoupling improved from weak to strong [34]. The decoupling conclusions of this study are consistent with the overall trends in the aforementioned literature. Building on this, this study further reveals a three-stage evolutionary pattern: the period from 2003 to 2009 was dominated by expansive negative decoupling; the period from 2009 to 2015 was characterized by cyclical fluctuations; and since 2015, weak decoupling has predominated, with strong decoupling achieved in 2018–2019. This detailed phased analysis provides a valuable supplement to the existing literature.

6. Conclusions and Recommendations

6.1. Conclusions

This study constructs a multidimensional analytical framework for examining the evolution of carbon emissions from transport within the Yangtze River Delta urban cluster,

focusing on deconstructing the dynamic coupling relationship between driving factors and economic development quality. The research framework comprises two major modules: firstly, relying on the STIRPAT-Ridge extended model to conduct quantitative analysis of carbon emission drivers; secondly, based on the Tapio decoupling model, systematically deconstructing the decoupling state between carbon emissions and economic growth, along with its evolutionary characteristics.

In the carbon emission driver analysis, a three-dimensional screening system integrating policy orientation, technological evolution, and literature review ultimately identified six key variables: per capita GDP, year-end resident population, transport structure, energy intensity, transport intensity, and industrial structure. A quantitative association model linking carbon emissions to these drivers was constructed using the STIRPAT-Ridge extended model. Empirical findings reveal that between 2003 and 2022, the contribution ranking of drivers to carbon emissions was: year-end resident population > industrial structure > transport intensity > per capita GDP > energy intensity > transport structure. This sequence indicates that population expansion is the dominant factor driving carbon emissions growth in the transport industry of the Yangtze River Delta region.

In the decoupling effect analysis, the Tapio elasticity framework was employed to dynamically deconstruct the carbon-economic relationship within the Yangtze River Delta urban cluster over the past two decades (2003–2022). Empirical findings reveal six distinct evolutionary modes within the regional transport system during the observation period: expansive negative decoupling, growth coupling, reinforced negative decoupling, weak decoupling, absolute decoupling, and pandemic-induced decoupling. Furthermore, significant variations in decoupling states were observed across provinces and municipalities within the region. Shanghai and Jiangsu exhibited pronounced decoupling trends in certain years, whereas Zhejiang and Anhui demonstrated relatively weaker decoupling effects. Analysis of driving factors' contributions to decoupling indicates that per capita GDP exerted the strongest influence, acting as a suppressor of carbon emissions decoupling, while transport intensity contributed the least, yet facilitated decoupling between carbon emissions and economic growth.

In summary, carbon emissions from the transport sector in the Yangtze River Delta region are influenced by multiple factors, with year-end resident population and industrial structure serving as primary drivers. Concurrently, the decoupling between carbon emissions and economic growth exhibits fluctuating characteristics, though recent years have witnessed a gradually more pronounced decoupling trend driven by government policies and market mechanisms. Moving forward, the Yangtze River Delta region should continue strengthening the implementation of energy conservation and emission reduction policies, promoting energy structure transformation and the green transition of transport, to achieve sustainable socio-economic development.

6.2. Recommendations

Analysis based on the STIRPAT-Ridge model and the Tapio decoupling model found that growth in the year-end resident population and changes in industrial structure are the primary factors influencing carbon emissions from transportation in the Yangtze River Delta, while the decoupling of carbon emissions from economic growth shows a fluctuating but positive trend. Empirical results show that the conditional correlation strengths between various influencing factors and carbon emissions are ranked as follows: year-end resident population (3.773) > industrial structure (0.436) > transport intensity (0.273) > per capita GDP (0.235) > energy intensity (0.221) > transport structure (0.080). Based on this, the following differentiated emission reduction pathways are proposed:

(1) Strategies for Low-Carbon Transformation of Urban Transportation Amid Population Growth

The conditional correlation coefficient for year-end resident population ranks first, indicating that travel and logistics demand driven by population growth is the primary factor associated with carbon emissions. It is recommended that the Yangtze River Delta region densify the rail transit networks within its urban clusters, increase the public transit mode share, and reduce reliance on private vehicles. The TOD (Transit-Oriented Development) model should be integrated into urban planning to guide the formation of low-carbon commuting corridors between population centers and employment hubs, thereby reducing high-carbon travel demand at its source.

(2) Coordinated Regulation of Industrial Layout and Transportation Carbon Emissions Against the Background of Industrial Structure Upgrading

The rising share of the tertiary sector, accompanied by increased logistics demand, is positively correlated with carbon emissions. It is recommended to incorporate transportation impact assessment mechanisms into regional industrial planning to guide the clustering of high-value-added industries around low-carbon transportation hubs—such as railways and ports—thereby reducing reliance on long-distance road freight. For cities with concentrated e-commerce and express delivery demand, efforts should be made to promote the electrification of last-mile delivery vehicles and centralized shared delivery models to reduce the incremental carbon emissions resulting from industrial expansion.

(3) Optimizing Pathways for Reducing Energy Intensity and Promoting Clean Energy Substitution

Although the energy intensity coefficient ranks lower on the list, it remains an effective regulatory approach for reducing carbon emissions. It is recommended to strictly enforce fuel consumption limits for transportation vehicles and promote lightweight and intelligent energy-saving technologies; establish a roadmap for the promotion of clean-energy vehicles, prioritizing the electrification or hydrogen-powered conversion of operational vehicles in settings such as ports, airports, and logistics parks. Based on the trend identified in decoupling analysis—where “weak decoupling” has dominated since 2015—strengthening policy enforcement can further shift “weak decoupling” toward a normalized state of “strong decoupling”.

At the same time, the policy orientation of “shifting freight from road to rail and waterways” should be strictly implemented. Through a combination of policies—such as differentiated right-of-way allocation and tax and fee incentives—the share of rail and waterway freight should be increased, the development of multimodal transport hubs should be strengthened, and energy consumption and emissions per unit of freight turnover should be systematically reduced.

6.3. Limitations and Future Directions

This study has the following limitations: First, due to the statistical scope of the China Energy Statistical Yearbook, aggregated data for “Transportation, Warehousing, and Postal Services” were used to approximate energy consumption in the transportation sector. Although it has been demonstrated that this does not affect the core conclusions, the inclusion of energy consumption from fixed facilities in the warehousing and postal sectors may still lead to a limited overestimation of total carbon emissions. Second, the study period ends in 2022, so it does not track carbon emission trends after 2023, which could be further extended once statistical classifications are harmonized. Third, the 2020–2022 data used in the decoupling analysis were subject to exogenous shocks from COVID-

19 prevention and control measures; the long-term structural impact of the pandemic on carbon emissions in the transportation sector remains to be observed.

Future research could zoom in to the prefecture-level city scale to reveal the spatial heterogeneity of transportation-related carbon emissions within the Yangtze River Delta urban agglomeration and, by incorporating the latest energy statistical standards, explore continuous refinements in carbon emission estimation methods.

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