

Article

Driving Factors and Decoupling Effects of Sea Port Carbon Emission with the “Dual Carbon” Goals: A Case Study of Shanghai Port

Lili Qu ^{1,*}, Yan Li ² and Shuangjie Yu ¹

¹ School of Maritime Economics and Management, Dalian Maritime University, Dalian 116026, China; yushuangjie@dlnu.edu.cn

² School of Medical Devices, Shenyang Pharmaceutical University, Shenyang 110016, China; liyanyan2533@163.com

* Correspondence: qulili@dlnu.edu.cn

Abstract

Sea ports play a crucial role in global trade and transportation, but their high energy consumption and associated carbon emissions challenge sustainable development. While carbon emissions have been widely studied in many sectors, research on port carbon emissions remains limited. The analysis covers 2008–2023, treats Shanghai Municipality as the principal economic hinterland of Shanghai Port, and draws primarily on SIPG’s annual and sustainability reports. This study quantifies carbon emissions at ports and analyzes their key drivers. Using the Logarithmic Mean Divisia Index (LMDI) method, a decomposition framework is developed to identify and assess the main factors contributing to port-related carbon emissions. By integrating the LMDI method with the Tapio decoupling model, the study further examines the decoupling process between carbon emissions and hinterland economic growth, as well as the mechanisms driving changes in decoupling. Shanghai Port, the world’s largest container port, is selected as a case study. The results show that: (1) hinterland economic development was the dominant positive driver (+90.69), whereas port throughput intensity exerted the strongest inhibitory effect (−63.24), followed by energy intensity (−47.42); (2) energy intensity and port throughput intensity promoted carbon reduction and decoupling, while hinterland economic growth constrained further decoupling, and energy structure optimization retained substantial mitigation potential.

Keywords: energy consumption; LMDI decomposition method; Tapio decoupling model; sea port carbon emission reduction



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1. Introduction

Global climate change has become one of the most pressing challenges facing the international community. In response, carbon emission reduction has increasingly been recognized as a common objective of global governance. China has proposed the strategic goals of reaching carbon peak by 2030 and achieving carbon neutrality by 2060. These targets impose considerable pressure on energy-intensive sectors to accelerate low-carbon transformation. As important nodes in the transportation system and major consumers of energy, ports are directly involved in this transition process. Ports not only serve as critical infrastructure supporting regional economic development and international trade, but also generate substantial carbon emissions due to cargo handling, storage, transportation,

and related logistics activities. Therefore, reducing port carbon emissions has become an essential component of the broader low-carbon transformation of the transportation sector.

Although carbon emissions in energy, manufacturing, and other industrial sectors have received extensive scholarly attention, research on port carbon emissions remains relatively insufficient. Existing studies have mainly focused on carbon emission accounting methods and technology-oriented emission reduction measures. However, limited attention has been paid to systematic emission reduction mechanisms, multi-stakeholder governance frameworks, and the interaction between port carbon emissions and hinterland economic development. This research gap is particularly significant because port activities are closely associated with the economic performance of their hinterlands. Hinterland economic growth affects international trade demand, cargo throughput, logistics intensity, and ultimately the level of carbon emissions generated by port operations.

To address the above gaps, this study takes Shanghai Port as the research object. Shanghai Port is the world's largest container port in terms of container throughput. It is also a representative case of both high carbon-emission pressure and green port development along China's coast. This study aims to identify the driving factors of carbon emissions at Shanghai Port and to examine the decoupling relationship between port carbon emissions and hinterland economic development. Specifically, the Logarithmic Mean Divisia Index method is combined with the Tapio decoupling model to construct an integrated analytical framework. This framework enables a systematic investigation of the mechanisms underlying carbon emission changes and the pathways through which port decarbonization can be promoted. The findings are expected to provide theoretical implications for port carbon emission research and practical policy references for the low-carbon transformation of the port sector.

The main contributions of this study are as follows:

1. Construct an integrated port-level analytical framework and enrich port carbon emissions research.

By combining the Tapio decoupling model with the LMDI decomposition method, this study shifts the analytical perspective from the macroeconomic or sectoral level to the individual port level. Taking Shanghai Port as a case study, it develops a targeted framework for examining carbon emission changes in port systems.

2. Reveal the dynamic decoupling relationship and identify the key drivers of port carbon emissions.

This study examines the evolving relationship between Shanghai Port's carbon emissions and hinterland economic development, showing an alternating pattern of weak and strong decoupling, with strong decoupling becoming increasingly dominant in recent years. The results indicate that energy intensity and port throughput intensity are the main factors influencing port carbon emissions, while energy structure optimization remains an important but insufficiently utilized pathway for future decarbonization.

3. Provide a transferable methodological reference and practical policy support for low-carbon port development.

The proposed framework can be applied to other ports for comparative analysis. It also provides empirical support for policymakers and port managers to identify key emission reduction factors, formulate targeted low-carbon strategies, and promote sustainable development in the port sector.

2. Literature Review

In the context of the "Dual Carbon" strategy, ports have become an important focus of carbon emission research because of their central role in international trade, transportation,

and energy consumption [1]. To establish a clear foundation for the present study, the literature is reviewed from four aspects: research on port carbon emissions, decomposition method and driving factors, decoupling analysis and the research gap addressed in this paper.

2.1. Research on Port Carbon Emissions

The estimation of carbon emissions in various sectors has progressed from simple accounting frameworks to more refined methodologies. The IPCC (2006) [2] laid the foundation for greenhouse gas inventories, providing standardized emission factors and calculation methods. On a macro scale, Andres et al. [3] and Schmalensee et al. [4] explored the long-term evolution of global carbon emissions from fossil fuel use, emphasizing the role of energy consumption patterns in emission trends. These early efforts set the stage for the development of more complex models for emission analysis.

Compared with the extensive literature on carbon emissions in other sectors, research on port carbon emissions remains relatively limited, although some recent studies have begun to address this topic. Existing port-related studies have mainly focused on emission accounting, scenario forecasting, and specific operational influences. For example, Shi et al. [5] applied a STIRPAT-Tapio-Monte Carlo framework to assess Shanghai Port's decarbonization pathways, while Li et al. [6] utilized the System Generalized Method of Moments (SYS-GMM) to show the significant role of geopolitical risks in increasing port emissions. Guo et al. [7] extended the analysis to hinterland-based intermodal transport networks, providing valuable insights into the relationship between port and hinterland emissions. In addition, Zhang et al. [1] systematically reviewed port carbon emissions estimation from the perspectives of accounting principles, practical applications, and machine-learning-based approaches. Yun et al. [8] developed a simulation model of container terminal operations to quantitatively assess the emission reduction effects of various green port strategies, and found that speed control and the use of shore power were the most effective mitigation measures. This study provided micro-level evidence for carbon emission management in port operations, but it did not further decompose the driving factors behind changes in carbon emissions.

Beyond decomposition and decoupling approaches, international research has increasingly examined port decarbonisation within the broader context of IMO climate targets and the transition toward net-zero maritime transport. Recent studies have investigated renewable energy integration and port energy systems through dynamic simulation and multi-objective optimization, while broader research has emphasized alternative-fuel infrastructure, shore power, renewable energy adoption, and green shipping corridors as key pathways for port decarbonisation [9,10].

Overall, existing studies have provided useful insights into port carbon emission estimation and operational mitigation strategies. However, comparatively few studies have systematically decomposed the driving factors of port carbon emissions within a unified analytical framework. More importantly, limited attention has been paid to the dynamic interaction between port carbon emissions and hinterland economic development. Therefore, further research is needed to integrate carbon emission accounting with decomposition analysis in the port context, so as to better identify the mechanisms underlying changes in port carbon emissions.

2.2. Decomposition Methods and Driving Factors

For carbon emission decomposition, the Kaya identity [11] was instrumental in identifying key drivers such as energy intensity, economic growth, and population size. The LMDI method, introduced by Ang [12], has become a cornerstone of emission decomposi-

tion due to its ability to separate the effects of various factors on emission changes without residual terms, allowing for clear interpretations.

The LMDI decomposition method has been widely used to disentangle the drivers of carbon emission changes across countries, regions, and sectors. Ming et al. [13] combined the LMDI framework with the LEAP platform to forecast carbon emission trajectories under multiple scenarios in Zhejiang Province. He et al. [14] applied LMDI to China's power sector and found that economic growth increased emissions, whereas power structure optimization and improvements in energy intensity reduced them. Shi et al. [15] used the LMDI method to decompose per capita urban carbon emissions and identified manufacturing as a key driver in major Chinese cities. Wang et al. [16] further combined weighting methods, LMDI decomposition, and an improved Grey Markov model to assess environmental effects in the Beijing–Tianjin–Hebei region. These studies confirm that LMDI is an effective tool for identifying the contribution of specific factors to carbon emission changes.

In addition to identifying emission drivers, the literature also explores whether carbon emissions can be decoupled from economic growth. Since the OECD introduced decoupling, it has become a key approach for evaluating whether economic growth can occur without a proportional increase in environmental pressure. The Tapio model is widely used as it offers a more detailed elasticity-based classification than the OECD framework [17,18]. This decoupling analysis is particularly relevant for port studies, as hinterland economic growth directly influences port throughput and emissions, yet research on port-hinterland decoupling remains limited.

2.3. Applications of the Integrated LMDI–Tapio Framework

To improve explanatory power, many studies have combined the Tapio decoupling model with the LMDI decomposition method. This integrated framework not only identifies the decoupling status between carbon emissions and economic development, but also reveals the contribution of individual driving factors to changes in the decoupling process. Wang et al. [19] and Engo [20] applied the integrated LMDI–Tapio framework to examine carbon emission drivers and decoupling effects in industrial sectors. Luo and Zhao [21] analyzed the decoupling relationship between economic growth and carbon emissions in RCEP member countries, while Sharma et al. [22] examined carbon emission dynamics across Indian states and manufacturing sub-sectors. Huang et al. [23] studied China's national carbon emissions, and Yue et al. [24] investigated the decoupling relationship and driving factors in the Beijing–Tianjin–Hebei region. Driha et al. [25] applied a similar framework to the EU tourism sector, showing that hotel numbers and tourism concentration increased emissions, whereas carbon intensity and tourist income promoted emission reduction. Gong and Guo [26] developed an expanded LMDI–Tapio model to analyze logistics emissions in Chongqing and identified an “expansive-weak-strong” decoupling trend. Li et al. [27] also extended this line of research to agricultural carbon emissions in Xinjiang.

Overall, the existing literature demonstrates that the integrated LMDI–Tapio framework is effective in explaining both the drivers of carbon emissions and the evolution of decoupling states across different sectors and spatial scales. However, most of these studies are conducted at the national, regional, or industry level, while port-specific applications remain scarce. In particular, limited research has systematically examined whether port carbon emissions can be decoupled from hinterland economic growth and how different driving factors shape this relationship over time. Therefore, it is necessary to further identify the specific gaps in the current literature and clarify the contribution of this study.

2.4. Research Gap

As shown in Table 1, the existing literature has enriched the understanding of carbon emissions from ports and related transport systems, but three limitations remain. First, most studies focus on emission accounting, scenario simulation, or isolated operational factors, while systematic decomposition of port emission drivers remains insufficient. Second, the majority of decomposition and decoupling studies are conducted at the national or regional scale, with limited evidence at the port level. Third, few studies explicitly examine whether port carbon emissions can be decoupled from hinterland economic growth and, if so, which factors shape this dynamic relationship. To address these gaps, this study develops a port-level analytical framework for Shanghai Port by integrating an extended Kaya identity, the LMDI decomposition method, and the Tapio decoupling model.

Table 1. Comparison of Previous Studies on Carbon Emission Drivers and Decoupling Effects.

Author/Year	Country	Study Scope	Time Period	Methodology
Hammond and Norman (2012) [28]	UK	national	1990–2007	LMDI
Wang et al. (2016) [19]	China	national	1994–2013	LMDI + Tapio
Wójtowicz et al. (2022) [29]	Poland	regional	2010–2019	LMDI
He et al. (2022) [14]	China	national	2005–2019	LMDI
Koilakou et al. (2023) [30]	USA and Germany	national	2000–2017	LMDI + Tapio
Gong and Guo (2024) [26]	China	logistics	1997–2021	LMDI + Tapio
Zhang and Sharifi (2024) [18]	China	regional	2011–2021	Tapio
Wang et al. (2024) [31]	EU and China	national	2004–2020	LMDI + Kaya + Tapio
Driha et al. (2025) [25]	EU-27	tourism	2008–2022	LMDI + Tapio
He et al. (2025) [32]	EU-28	national	2010–2020	LMDI + Tapio
Yue et al. (2025) [24]	China	regional	2000–2021	LMDI + Tapio
Luo and Zhao (2025) [21]	RCEP member countries	national	2005–2019	LMDI + Tapio
Li et al. (2025) [27]	China	agriculture	2001–2020	LMDI + Tapio
Zhao et al. (2026) [33]	Ireland	national	1995–2023	LMDI + Tapio
Sharma et al. (2026) [22]	India	national	2001–2022	LMDI + Tapio
this study	China	port	2008–2023	LMDI + Kaya + Tapio

3. Models and Data

Figure 1 illustrates the overall analytical framework and key findings. The upper section shows the five-factor decomposition of Shanghai Port’s carbon emissions, including energy structure, energy intensity, port throughput intensity, hinterland economic development, and hinterland population scale. Based on the LMDI decomposition framework, Tapio decoupling analysis is further applied to examine the dynamic relationship between port carbon emissions and economic development. The results indicate that the decoupling status of Shanghai Port is characterized by alternating weak and strong decoupling over the study period. In addition, energy intensity and port throughput intensity are identified as the main factors inhibiting carbon emissions, whereas hinterland economic development is found to be the primary factor driving emission growth.

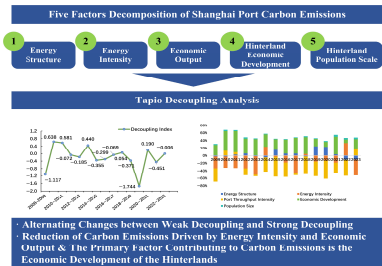


Figure 1. Research framework and key findings.

3.1. Port Carbon Emissions Quantification

Port carbon emissions can be estimated by aggregating annual energy consumption from fossil fuels, electricity, and other energy sources purchased by the port. The total energy consumption and associated carbon emissions are then calculated by multiplying the consumption of each energy type by its corresponding carbon emission factor.

$$C = C_E + C_F \quad (1)$$

1. Estimation of Carbon Emissions from Fossil Fuels

The fossil fuels consumed by the port include coal, diesel, gasoline, fuel oil, etc. Port carbon emissions of fossil fuels measurement equation can be built using the Guidelines for Greenhouse Gas Emissions Accounting and Reporting for Land Transportation Enterprises (Trial) as the guide [34].

$$C_F = \sum_i C_{iF} \quad (2)$$

where C_F is the total carbon emissions of fossil fuels in the port, and C_{iF} represents the carbon emissions from the i -th fossil energy source, such as coal, diesel, gasoline, fuel oil, etc.

In Equation (2), the carbon emissions C_{iF} from the i -th energy source are calculated as:

$$C_{iF} = AD_{iF} \times EF_{iF} \quad (3)$$

where AD_{iF} is the activity level of the i -th fossil fuel during the accounting period, and EF_{iF} is the carbon emission factor of the i -th energy source, which represents the CO₂ emissions per unit of calorific value of that energy source.

The carbon emission factor is determined based on the net calorific value, carbon content, and carbon oxidation rate of each fuel type, where

$$AD_{iF} = NCV_{iF} \times FC_{iF} \quad (4)$$

where NCV_{iF} denotes the average net calorific value of fossil fuel i during the accounting period, and FC_{iF} represents the consumption of fuel i during the same period.

The carbon emission factor EF_{iF} is calculated as:

$$EF_{iF} = CC_{iF} \times OF_{iF} \times \frac{44}{12} \quad (5)$$

where $44/12$ is the molecular weight ratio of CO₂ to carbon, OF_{iF} is the carbon oxidation rate of the i -th fossil fuel, and CC_{iF} is the carbon content per unit of calorific value of the i -th fuel.

Accordingly, the port carbon emissions accounting equation can be reformulated as follows:

$$C_F = \sum AD_{iF} \times EF_{iF} = \sum NCV_{iF} \times FC_{iF} \times CC_{iF} \times OF_{iF} \times \frac{44}{12} \quad (6)$$

Relevant carbon emission coefficients are derived with reference to the *Guidelines for Compiling Provincial Greenhouse Gas Inventories (Trial)*, China's 2005 Greenhouse Gas Inventory Study, and the 2006 IPCC Guidelines for National Greenhouse Gas Inventories.

2. Estimation of Carbon Emissions from Electricity Consumption

The equation for calculating CO₂ emissions from net purchased electricity consumed by the port is as follows:

$$C_E = \sum AD_{Ei} \times EF_{Ei} \quad (7)$$

where AD_{Ei} is the amount of electricity net purchased from the i -th regional power grid during the accounting period, EF_{Ei} is the average CO₂ emission factor of the electricity supply from the i -th regional grid, and i represents the regional power grid. To account for temporal changes in grid carbon intensity, time-varying regional grid CO₂ emission factors were applied throughout the 2008–2023 study period. As a representative example, the 2019 baseline emission factors published by the Ministry of Ecology and Environment are reported in Appendix A Table A1.

3.2. LMDI Model

Building on the methodological foundations discussed in the literature review, this study applies the LMDI decomposition method to identify the driving factors of Shanghai Port's carbon emissions. By extending the Kaya identity and incorporating port cargo throughput, a port-specific decomposition framework is constructed.

The Kaya identity expresses the relationship between factors such as economy, policy, and population and carbon dioxide emissions through a concise mathematical Equation (8):

$$C = \frac{C}{PE} \times \frac{PE}{GDP} \times \frac{GDP}{POP} \times POP \quad (8)$$

C stands for carbon emissions, PE for port energy consumption, GDP for gross domestic product, and POP for population size in Equation (8). C/PE is CO₂ emissions per unit of energy consumption, which reflects the energy structure; PE/GDP is energy consumption per unit of GDP, which indicates energy intensity; GDP/POP is GDP per capita, which indicates the degree of economic development; POP is population scale.

According to existing literature regarding the drivers of carbon emissions and the features of port carbon emissions, port cargo throughput is presented as a significant port factor, and the previous equation is expanded as follows:

$$C = \frac{C}{PE} \times \frac{PE}{T} \times \frac{T}{GDP} \times \frac{GDP}{POP} \times POP \quad (9)$$

where T denotes port cargo throughput. Let $s = C/PE$, representing the port energy structure; $e = PE/T$, representing the port energy intensity; $f = T/GDP$, representing port throughput intensity; $g = GDP/POP$, representing hinterland economic development; and $p = POP$, representing the hinterland population size.

Specifically, port throughput intensity captures the evolving relationship between hinterland economic growth and port throughput growth. A decline in f indicates that hinterland GDP is growing faster than port throughput, suggesting a gradual decoupling of economic activity from freight demand. Conversely, an increase in f indicates that port throughput is growing faster than GDP, reflecting a stronger dependence of economic activity on freight demand.

Thus, the LMDI decomposition model for port carbon emissions is obtained as shown in Equation (10):

$$C = s \times e \times f \times g \times p \quad (10)$$

As illustrated above, the LMDI method decomposes the change in port carbon emissions into a combination of changes in various contributing factors. The LMDI decomposition method includes both additive and multiplicative modes, which can be interconverted for validation purposes. In the additive mode, the decomposition results show the contribution of each factor to the change in carbon emissions, with a larger absolute value indicating a more significant impact on emission increase or reduction. In the multiplicative mode, the results represent the relative contribution rate of each factor to carbon emission changes, focusing on the deviation degree of each factor's effect from 1. A larger deviation indicates

a more significant influence in either promoting or mitigating emissions. Although the calculation results of both decomposition modes are very similar, the additive mode is simpler and more intuitive, and thus, this study adopts the additive decomposition method for calculation.

Therefore, the LMDI decomposition model for changes in port carbon emissions is expressed as follows:

$$\Delta C = C^t - C^0 = \Delta C_s + \Delta C_e + \Delta C_f + \Delta C_g + \Delta C_p \quad (11)$$

The port carbon emissions for period t and the base period are represented by C^t and C^0 , respectively in Equation (11). The energy structure effect, energy intensity effect, port throughput intensity effect, hinterland economic development effect, and hinterland population effect are represented by ΔC_s , ΔC_e , ΔC_f , ΔC_g and ΔC_p respectively.

Based on the additive LMDI decomposition model, the following can be derived:

$$\text{Energy structure effect : } \Delta C_s = \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{s_i^t}{s_i^0} \quad (12)$$

$$\text{Energy intensity effect : } \Delta C_e = \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{e_i^t}{e_i^0} \quad (13)$$

$$\text{Port throughput intensity effect : } \Delta C_f = \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{f_i^t}{f_i^0} \quad (14)$$

$$\text{Hinterland economic development effect : } \Delta C_g = \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{g_i^t}{g_i^0} \quad (15)$$

$$\text{Hinterland Population Scale Effect : } \Delta C_p = \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{p_i^t}{p_i^0} \quad (16)$$

3.3. Tapio Decoupling Model

3.3.1. Decoupling Relationship

Port operations and management are closely linked to the macroeconomic development of the hinterland. Changes in hinterland economic growth directly affect trade demand, cargo generation, and cargo flow organization, and therefore have a significant influence on port throughput and related carbon emissions. To examine whether Shanghai Port's carbon emissions have been decoupled from hinterland economic growth, this study employs the Tapio decoupling model. The decoupling elasticity between port carbon emissions and hinterland economic growth is expressed as follows:

$$I_i = \frac{\Delta C / C_0}{\Delta GDP / GDP_0} = \frac{C_{tot} \%}{GDP_{tot} \%} \quad (17)$$

where I_i represents the decoupling elasticity coefficient between hinterland economic growth and port carbon emissions in the i -th year; ΔC represents the change in port carbon emissions; C_0 represents base year carbon emissions; $C_{tot} \%$ represents the change rate for carbon emissions; ΔGDP represents the change in regional gross domestic product; GDP_0 represents base year GDP; and $GDP_{tot} \%$ represents the change rate for GDP. Table 2 illustrates the eight states into which the degree of decoupling between economic growth and carbon emissions can be separated [35].

Table 2. Decoupling state division of the Tapio decoupling model.

Decoupling State [36]		$C_{tot}\%$	$GDP_{tot}\%$	I_i	Description [37]
Decoupling	Strong Decoupling	<0	>0	$(-\infty, 0]$	Carbon emissions are decreasing and GDP is growing.
	Weak Decoupling	>0	>0	$(0, 0.8)$	Carbon emissions and GDP are growing but the pace of growth of CO ₂ is lower than that of GDP.
	Recessive Decoupling	<0	<0	$(1.2, +\infty)$	Carbon emissions and GDP are decreasing but the pace of decrease in CO ₂ is higher than that of GDP.
Coupling	Expansive Coupling	>0	>0	$[0.8, 1.2]$	Carbon emissions and GDP are growing with a similar pace.
	Recessive Coupling	<0	<0	$[0.8, 1.2]$	Carbon emissions and GDP are declining with a similar pace.
Negative decoupling	Strong Negative Decoupling	>0	<0	$(-\infty, 0]$	Carbon emissions increase while GDP decrease.
	Weak Negative Decoupling	<0	<0	$(0, 0.8)$	Carbon emissions and GDP are decreasing but the pace of decrease in GDP is higher than that of CO ₂ .
	Expansive Negative Decoupling	>0	>0	$(1.2, +\infty)$	Carbon emissions increase with a higher pace with respect to GDP.

3.3.2. Port Carbon Emissions Decoupling Model

Integrating the Tapio decoupling model with the LMDI decomposition method enables a clearer and more comprehensive assessment of how each driving factor is decoupled from port carbon emissions. This makes it possible to develop an extended model of the factors driving port carbon emissions, as shown in Equation (18).

$$\begin{aligned}
 I_i &= \frac{\Delta C/C_0}{\Delta GDP/GDP_0} \\
 &= \frac{(\Delta C_s + \Delta C_e + \Delta C_f + \Delta C_g + \Delta C_p)/C_0}{\Delta GDP/GDP_0} \\
 &= \Delta C_s \times \left(\frac{GDP_0}{\Delta GDP \times C_0} \right) + \Delta C_e \times \left(\frac{GDP_0}{\Delta GDP \times C_0} \right) + \Delta C_f \times \left(\frac{GDP_0}{\Delta GDP \times C_0} \right) \\
 &\quad + \Delta C_g \times \left(\frac{GDP_0}{\Delta GDP \times C_0} \right) + \Delta C_p \times \left(\frac{GDP_0}{\Delta GDP \times C_0} \right) \\
 &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{s_i^t}{s_i^0} \times \left(\frac{GDP_0}{\Delta GDP \times C_0} \right) + \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{e_i^t}{e_i^0} \times \left(\frac{GDP_0}{\Delta GDP \times C_0} \right) \\
 &\quad + \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{f_i^t}{f_i^0} \times \left(\frac{GDP_0}{\Delta GDP \times C_0} \right) + \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{g_i^t}{g_i^0} \times \left(\frac{GDP_0}{\Delta GDP \times C_0} \right) \\
 &\quad + \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{p_i^t}{p_i^0} \times \left(\frac{GDP_0}{\Delta GDP \times C_0} \right) \\
 &= I_s + I_e + I_f + I_g + I_p
 \end{aligned} \tag{18}$$

Energy structure, energy intensity, port throughput intensity, economic development, and population size are the five driving forces, and their corresponding decoupling elasticity coefficients are represented by I_s , I_e , I_f , I_g , I_p in Equation (18).

3.4. Data Sources

Given the difficulty in obtaining energy consumption data for port enterprises, the relevant data for Shanghai Port and Shanghai City in this paper are primarily sourced from publicly available information, including the *Shanghai International Port (Group) Co., Ltd.* (Shanghai, China), *Annual Financial Reports*, *Shanghai International Port (Group) Co., Ltd. Sustainability Reports*, *Port Statistical Yearbooks*, *Shanghai Statistical Yearbooks*, and the website of the Ministry of Transport. To ensure temporal comparability, changes in reporting scope and statistical classifications across years were carefully checked, and the data were standardized to a consistent analytical boundary and measurement unit. Data such as the

coal equivalent conversion coefficients, average lower heating values, carbon content per unit calorific value, and carbon oxidation rates for various energy types are derived from the *General Rules for Calculation of Comprehensive Energy Consumption* (GB/T 2589-2020) and the *Provincial Greenhouse Gas Inventory Compilation Guideline (Trial)*. The carbon dioxide emission coefficients are referenced from the *IPCC Guidelines for National Greenhouse Gas Inventories* and *2005 Study on China's Greenhouse Gas Inventory*. The People's Republic of China's Ministry of Ecology and Environment's official website provides the baseline emission parameters for regional power grids in that country.

4. Results and Discussion

4.1. Carbon Emissions Accounting Results

The *Shanghai International Port (Group) Co., Ltd. Sustainability Report 2008–2023's* energy consumption statistics and the applicable carbon emissions accounting formulas are used to calculate Shanghai Port's carbon emissions from 2008 to 2023. As the primary energy sources consumed by Shanghai Port Group are diesel, fuel oil, and electricity, only these three main energy types were considered in the statistical analysis. Figure 2 shows the changes in Shanghai Port's throughput and carbon emissions from 2008 to 2023.

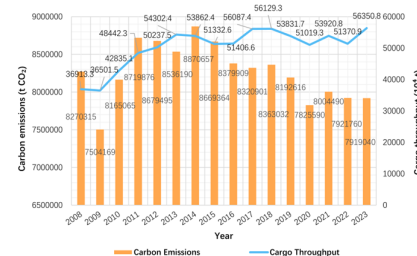


Figure 2. Trends in cargo throughput and carbon emissions of Shanghai Port from 2008 to 2023.

4.2. LMDI Decomposition Analysis Results

The results of the LMDI decomposition of carbon emissions for Shanghai Port from 2008 to 2023 are presented in Table 3 and Figure 3.

Table 3. Carbon emissions LMDI decomposition results of Shanghai Port from 2008 to 2023.

Time (Year)	Energy Structure Effect ΔC_s	Energy Intensity Effect ΔC_e	Port Throughput Intensity Effect ΔC_f	Hinterland Economic Development Effect ΔC_g	Hinterland Population Scale Effect ΔC_p
2008–2009	−0.4845	−6.2928	−7.1628	5.7332	0.5454
2009–2010	−0.4577	−5.4617	2.4039	9.4775	0.6469
2010–2011	0.4282	−5.2619	1.0515	8.9107	0.4196
2011–2012	0.7274	−4.2968	−2.2936	4.9965	0.4628
2012–2013	−0.2805	−7.8499	−0.6501	7.0217	0.3257
2013–2014	−1.0218	5.0744	−8.1295	7.0365	0.3849
2014–2015	2.8560	−0.6501	−9.6588	5.1795	0.2605
2015–2016	1.2822	−4.2995	−8.8938	8.6023	0.4143
2016–2017	1.0333	−8.9003	−0.8070	7.7890	0.2949
2017–2018	−0.3410	0.7000	−7.4133	7.0610	0.4146
2018–2019	5.0544	−3.2989	−7.8809	4.0305	0.3908
2019–2020	3.0221	−1.6438	−6.3569	1.6944	0.3458
2020–2021	0.6141	−3.2861	−4.6592	8.1460	0.9302
2021–2022	−1.4613	4.4915	−5.7083	1.2334	0.5847
2022–2023	−1.5927	−6.4483	2.9149	3.7822	0.6615
Total	9.3781	−47.4241	−63.2437	90.6944	7.0827

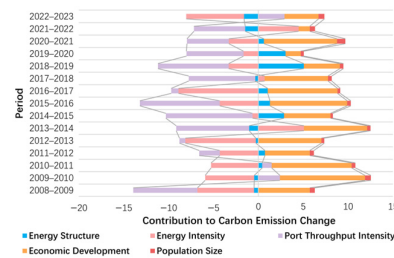


Figure 3. Annual contributions of the five driving factors to changes in Shanghai Port's carbon emissions, 2008–2023.

The results in Table 3 indicate that Shanghai Port's carbon emissions are restrained by the energy intensity effect and the port throughput intensity effect. In contrast, the energy structure effect, economic development effect, and hinterland population scale effect contribute positively to carbon emission growth. Among these factors, hinterland economic development is the strongest driver of increased port emissions, whereas port throughput intensity produces the most significant inhibitory effect. The influence of population scale is relatively limited. These findings suggest that further optimization of Shanghai Port's energy structure remains essential for reducing carbon emissions and promoting low-carbon port development.

1. Energy Structure Effect

According to Table 3 and Figure 3, the contribution value of the energy structure effect to Shanghai Port's carbon emissions is 9.38, indicating that changes in the energy mix still produced a net positive effect on carbon emission growth during the study period. However, this result should be distinguished from the direction of energy structure adjustment. From 2008 to 2023, the proportion of fuel oil and diesel consumption gradually declined, while the share of electricity consumption increased, indicating that the port's energy structure was moving toward greater electrification and a relatively lower-carbon direction.

Nevertheless, this favorable structural change has not yet translated into a significant net emission reduction effect. The main reason is that China's electricity generation still relies substantially on fossil fuels, particularly coal, resulting in a relatively high carbon emission coefficient for electricity. Therefore, although replacing direct fossil fuel consumption with electricity represents a positive long-term transition, the reduction in direct fossil fuel emissions during the study period was not sufficient to offset the indirect emissions associated with electricity consumption. This explains why the energy structure effect remained positive despite the favorable direction of structural adjustment.

In addition, due to data availability constraints, this study only considers three types of energy: electricity, fuel oil, and diesel. This limitation may affect the accuracy and completeness of the results. Therefore, to achieve deeper carbon reduction through energy structure optimization, Shanghai Port should not only reduce the share of fossil fuels, but also increase the use of cleaner energy sources, such as natural gas. Meanwhile, the proportion of renewable electricity generated from wind, solar, and tidal power should be further expanded.

2. Energy Intensity Effect

Energy intensity, measured as energy consumption per unit of throughput, reflects the relationship between energy input and port production output. This indicator is closely associated with the level of technological innovation. A decline in energy intensity generally indicates an improvement in energy efficiency, which is often driven by technological progress and operational upgrading. As shown in Figure 2, Shanghai Port's energy consumption per unit of throughput has shown a continuous downward trend, suggesting that energy efficiency improvements have exerted a strong inhibitory effect on carbon emissions.

The decomposition results further indicate that the contribution value of the energy intensity effect is -47.42 , making it the second most important factor restraining the growth of Shanghai Port's carbon emissions. Over the study period, Shanghai Port has maintained a leading position in technological development among Chinese ports. To support its goal of becoming a world-class shipping hub, the port has actively promoted green, low-carbon, and intelligent development. By participating in major national and local research projects, Shanghai Port has achieved continuous improvement in key port operation technologies. In particular, technological innovation over the past decade has helped the port maintain a relatively high level of energy efficiency. This confirms the important role of technological progress in reducing port carbon emissions.

3. Port Throughput Intensity Effect

Port throughput intensity is measured by port throughput per unit of GDP, reflecting the linkage between hinterland economic growth and port development. The decomposition results show that the contribution value of port throughput intensity to Shanghai Port's carbon emissions is -63.24 , indicating the strongest inhibitory effect among all driving factors. As shown in Figure 4, the decline in port throughput intensity indicates that hinterland GDP grew faster than port throughput, reflecting a gradual decoupling of economic activity from freight demand. This trend is closely associated with industrial structure adjustment. With the increasing share of the tertiary sector, economic growth became less freight-intensive, resulting in slower growth in freight demand relative to GDP and a gradual weakening of the dependence of economic expansion on port throughput growth.

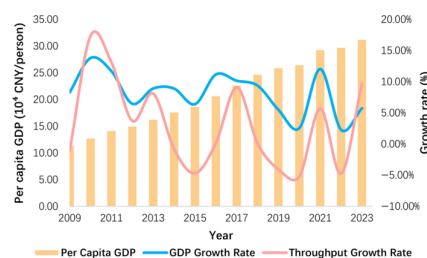


Figure 4. Comparison of Shanghai GDP and Shanghai Port Throughput Growth Rate and Per Capita GDP from 2008 to 2023.

4. Economic development effect

The economic development effect is measured by per capita GDP. As shown in Figure 4, Shanghai's per capita GDP maintained a steady upward trend during the study period. This indicator not only reflects the level of economic development in the port hinterland, but also represents the living standards of local residents. The decomposition results show that the contribution value of the hinterland economic development effect reaches 90.69, making it the most important factor driving the increase in Shanghai Port's carbon emissions. This suggests that sustained economic growth has placed considerable pressure on port carbon reduction. However, carbon mitigation should not be achieved by slowing economic development. Instead, the core issue is to balance economic growth with emission reduction and to identify effective pathways for achieving low-carbon development under continued economic expansion.

5. Hinterland population scale effect

The hinterland population scale effect represents the impact of population size in the port hinterland on carbon emissions. The decomposition results indicate that this factor had a relatively limited driving effect on Shanghai Port's carbon emissions. This may be attributed to the port's location in an economically developed region, where the resident

population has continued to grow steadily and has therefore contributed to increased carbon emissions. However, with the slowdown of population growth in recent years, the positive driving effect of population scale has gradually declined.

4.3. Decoupling Analysis

Using Equation (17), the decoupling elasticity coefficient between Shanghai Port's carbon emissions and the economic growth of Shanghai, its principal hinterland, is calculated. The decoupling status of Shanghai Port is presented in Table 4 and Figure 5.

Table 4. Dynamic changes in the decoupling state between carbon emissions in Shanghai Port and economic growth in its hinterland from 2008 to 2023.

Time (Year)	$C_{tot}\%$	$GDP_{tot}\%$	Decoupling Index	Decoupling State
2008–2009	−0.093	0.083	−1.117	Strong Decoupling
2009–2010	0.088	0.138	0.638	Weak Decoupling
2010–2011	0.068	0.117	0.581	Weak Decoupling
2011–2012	−0.005	0.065	−0.072	Strong Decoupling
2012–2013	−0.017	0.089	−0.185	Strong Decoupling
2013–2014	0.039	0.089	0.440	Weak Decoupling
2014–2015	−0.023	0.064	−0.355	Strong Decoupling
2015–2016	−0.033	0.112	−0.299	Strong Decoupling
2016–2017	−0.007	0.102	−0.069	Strong Decoupling
2017–2018	0.005	0.094	0.054	Weak Decoupling
2018–2019	−0.020	0.055	−0.371	Strong Decoupling
2019–2020	−0.045	0.026	−1.744	Strong Decoupling
2020–2021	0.023	0.120	0.190	Weak Decoupling
2021–2022	−0.010	0.023	−0.451	Strong Decoupling
2022–2023	−0.0003	0.057	−0.006	Strong Decoupling

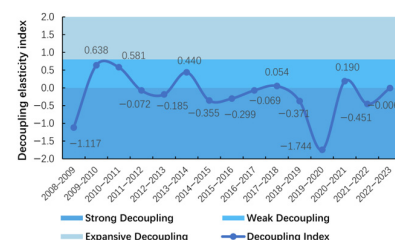


Figure 5. Decoupling status of carbon emissions growth and economic growth at various stages in Shanghai Port.

Between 2008 and 2023, the relationship between Shanghai Port's carbon emissions and hinterland economic growth generally showed a pattern of alternating weak decoupling and strong decoupling. In the most recent decade, strong decoupling became increasingly dominant. However, the decoupling index for 2022–2023 was close to zero (−0.006), indicating that Shanghai Port's carbon emissions remained relatively stable while hinterland economic activity continued to expand. This result may be associated with the combined effects of the post-COVID recovery of port activity, changes in cargo composition, and temporary fluctuations in energy intensity. Therefore, the near-zero elasticity may reflect a short-term transitional adjustment rather than a stable long-term decoupling pattern.

As shown in Figure 4, Shanghai, as one of China's major economic centers, maintained steady GDP growth during the study period. Both its total economic scale and growth rate remained at a relatively high level. Meanwhile, Shanghai Port continued to expand its operational capacity. In 2024, its container throughput reached 51.5063 million TEUs, making it the world's largest container port and the first port globally to exceed 50 million

TEUs in annual throughput. It also retained its position as the world's leading container port for fifteen consecutive years.

Shanghai is the principal economic hinterland of Shanghai Port. Against the background of sustained GDP growth and continuously increasing port throughput, Shanghai Port has still maintained a predominantly strong decoupling relationship between carbon emissions and economic growth. This outcome is closely associated with the continuous implementation of energy-saving and emission-reduction measures by Shanghai International Port (Group) Co., Ltd. These measures have helped reduce the carbon intensity of port operations while supporting the continued growth of port activity.

As a leading port in China, Shanghai Port has taken energy conservation, emission reduction, and ecological protection as key foundations for building a green port development system. It has consistently promoted the transformation of port operations toward intelligent, green, high-tech, and efficient development. To support this transition, Shanghai Port has issued several policy and management documents, including the *Special Plan for Building a Green, Circular, Low-Carbon Port with Energy Saving and Emission Reduction* and the *Shanghai Port Group Carbon Emissions Management Regulations (Trial)*. In addition, the Shanghai municipal government and SIPG have introduced action plans such as the *Shanghai Green Port Three-Year Action Plan* and the *Shanghai Clean Air Action Plan*. These policies provide institutional support and a clear implementation pathway for Shanghai Port's green and low-carbon development.

4.4. Mechanism Analysis of Decoupling Index Variation

Based on the analysis above, the carbon emission decoupling index of Shanghai Port is broken down using Equation (18) in order to explore the underlying mechanisms driving the changes in the decoupling state between port carbon emissions and hinterland economic growth. Table 5 and Figure 6 show the total contributions of each driving factor to Shanghai Port's decoupling process, as well as the trends in their annual dynamic variation from 2008 to 2023.

Table 5. Contribution of various driving factors to the decoupling effect of carbon emissions in Shanghai Port from 2008 to 2023.

Time (Year)	Energy Structure I_s	Energy Intensity I_e	Port Throughput Intensity I_f	Economic Development I_g	Population Size I_p
2008–2009	−0.0706	−0.9175	−1.0444	0.8360	0.0795
2009–2010	−0.0442	−0.5273	0.2321	0.9150	0.0625
2010–2011	0.0449	−0.5513	0.1102	0.9336	0.0440
2011–2012	0.1288	−0.7609	−0.4061	0.8848	0.0819
2012–2013	−0.0363	−1.0150	−0.0841	0.9079	0.0421
2013–2014	−0.1345	0.6678	−1.0698	0.9260	0.0507
2014–2015	0.5031	−0.1145	−1.7014	0.9124	0.0459
2015–2016	0.1325	−0.4445	−0.9194	0.8893	0.0428
2016–2017	0.1213	−1.0449	−0.0947	0.9144	0.0346
2017–2018	−0.0437	0.0897	−0.9503	0.9051	0.0531
2018–2019	1.1016	−0.7190	−1.7176	0.8784	0.0852
2019–2020	1.4362	−0.7812	−3.0210	0.8052	0.1644
2020–2021	0.0646	−0.3456	−0.4901	0.8568	0.0978
2021–2022	−0.7904	2.4296	−3.0878	0.6672	0.3163
2022–2023	−0.3470	−1.4049	0.6351	0.8240	0.1441

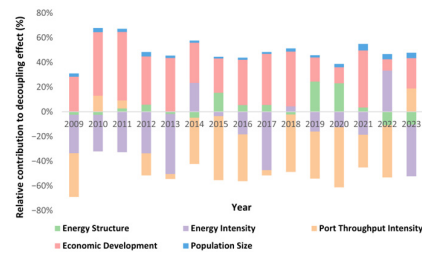


Figure 6. Changes in the impact of various factors on the decoupling status of carbon emissions in Shanghai Port from 2008 to 2023.

4.4.1. Driving Factors Under the LMDI-Tapio Framework

By integrating the LMDI decomposition method with the Tapio decoupling model, this study quantifies the effects of five major driving factors on the decoupling of Shanghai Port's carbon emissions. A positive contribution value indicates that the corresponding factor restrains the decoupling process, whereas a negative value suggests that the factor promotes decoupling. As shown in Table 5, energy structure, economic development, and population scale inhibit the decoupling of carbon emissions at Shanghai Port. In contrast, energy intensity and port throughput intensity promote the decoupling process. However, port carbon emissions are influenced by multiple interacting factors across different dimensions. These drivers are not independent but are closely interrelated. Therefore, although the decomposition results identify the main influencing factors, further analysis is required to explain their specific mechanisms and relative importance.

4.4.2. Energy Structure Effect on Carbon Decoupling

The energy structure effect captures the extent to which changes in the consumption proportions of different energy sources influence CO₂ emissions at Shanghai Port. Since different energy types are associated with different carbon emission coefficients, adjustments in the energy mix can directly affect the level of port carbon emissions, even when total energy consumption remains unchanged. This effect is closely associated with the port's energy use preferences, energy management practices, and the share of clean and non-fossil energy sources, particularly electricity generated from renewable sources.

As presented in Table 5 and Figure 6, the influence of the energy structure factor on the decoupling of Shanghai Port's carbon emissions varies across the study period. Its effect shows clear fluctuations, alternating between promoting and restricting decoupling. From the perspective of energy consumption trends, Shanghai Port has continuously improved its energy structure by reducing dependence on fossil fuels and increasing the use of cleaner energy, especially electricity. Nevertheless, changes in port operational organization and industrial structure have increased the difficulty of achieving further reductions in energy consumption. At the same time, the marginal benefits of existing energy-saving measures have gradually weakened. Although the cumulative contribution of the energy structure effect is positive over the entire study period, its overall magnitude remains relatively limited. This suggests that further optimization of the port energy structure still represents an important pathway for reducing carbon emissions and strengthening the decoupling between port development and economic growth.

4.4.3. Energy Intensity Effect on Carbon Decoupling

The energy intensity effect directly influences Shanghai Port's carbon emissions, as it reflects the port's overall level of energy efficiency. This factor is mainly determined by technological capability. Greater investment in technological innovation can improve energy utilization efficiency, reduce the energy consumption of port machinery and equipment, enhance operational productivity, and ultimately lower energy intensity. In addition,

energy intensity is also associated with port management practices. The expectation of achieving low-carbon operations encourages port authorities to invest in energy-saving and emission-reduction technologies, thereby further improving energy efficiency.

As shown in Table 5, the energy intensity factor promotes the decoupling of Shanghai Port's carbon emissions, indicating that technological progress has played an important role in reducing energy consumption. In recent years, Shanghai International Port Group has strengthened its emphasis on technological innovation, research and development, and intelligent transformation. Relevant measures include upgrading traditional terminals, promoting the electrification of non-road mobile machinery, and replacing or retrofitting high-emission diesel engines. The results show that, except for a few individual years, the energy intensity effect has consistently promoted the decoupling process. This demonstrates that technological innovation has significantly supported Shanghai Port's transition toward a green, low-carbon, and intelligent development model.

4.4.4. Port Throughput Intensity Effect on Carbon Decoupling

The port throughput intensity effect reflects the relationship among hinterland economic development, port growth, industrial structure, and port throughput. Different industries generate different levels of freight demand for each unit of port throughput intensity. Among the primary, secondary, and tertiary sectors, the growth of port cargo throughput is mainly driven by the secondary industry, followed by the primary industry. In contrast, the tertiary industry is largely service-oriented and usually creates relatively limited demand for physical freight transportation. Therefore, its freight generation coefficient is generally the lowest among the three sectors.

An increase in the output ratio of the secondary industry to the tertiary industry tends to increase port throughput intensity, as industrial production usually requires greater cargo movement and logistics support. However, when the regional economy enters a stage of high-quality development, the share of the tertiary sector gradually increases. At the same time, the ratio of secondary to tertiary industry output tends to decline as the hinterland industrial structure is continuously optimized. Although this structural transformation supports economic growth and improves the quality of development, it also reduces the dependence of economic expansion on freight transportation. As a result, port throughput grows more slowly relative to GDP. With the continuous expansion of value added in the tertiary sector, the decline in the port's port throughput intensity effect may restrain throughput growth, thereby reducing energy consumption and carbon emissions generated by port operations.

As shown in Table 5 and Figure 6, the port throughput intensity factor is the most important contributor to the decoupling of carbon emissions at Shanghai Port. Table 6 further indicates that Shanghai's industrial structure is currently dominated by the tertiary sector, whose share has shown a stable upward trend. Meanwhile, the ratio of secondary to tertiary industries has continued to decrease. Although the secondary sector still accounts for a larger share than the primary sector, Shanghai is promoting new-type industrialization by encouraging manufacturing industries to move toward high-technology and high-value-added activities. The primary sector accounts for only a very small proportion of the overall economy, while finance, modern services, and advanced manufacturing have become Shanghai's major competitive industries. This diversified industrial structure, led by modern services and supported by advanced manufacturing, provides a strong basis for sustained economic growth. At the same time, it moderates the expansion of port throughput, reduces carbon emission pressure, and plays a positive role in promoting the decoupling of Shanghai Port's carbon emissions from economic growth.

Table 6. Value added and proportion of three industries in Shanghai from 2008 to 2023.

Time (Year)	Primary Industry Value-Added (Billion Yuan)	Proportion of Primary Industry (%)	Secondary Industry Value-Added (Billion Yuan)	Proportion of Secondary Industry (%)	Tertiary Industry Value-Added (Billion Yuan)	Proportion of Tertiary Industry (%)
2008	109.4	0.75%	6215.5	42.76%	8212.1	56.49%
2009	112.4	0.71%	6184.8	39.29%	9445.3	60.00%
2010	114.5	0.64%	7434.9	41.50%	10,366.1	57.86%
2011	126.4	0.63%	8169.3	40.83%	11,713.9	58.54%
2012	129.3	0.61%	8174.1	38.37%	13,002.1	61.03%
2013	131.6	0.57%	8286.5	35.71%	14,786.0	63.72%
2014	132.0	0.52%	8633.3	34.16%	16,504.5	65.31%
2015	125.5	0.47%	8408.7	31.27%	18,352.8	68.26%
2016	114.3	0.38%	8570.2	28.68%	21,202.4	70.94%
2017	110.8	0.34%	9525.9	28.93%	23,288.3	70.73%
2018	104.8	0.29%	10,360.8	28.77%	25,546.3	70.94%
2019	107.1	0.28%	10,193.6	26.83%	27,686.9	72.88%
2020	107.7	0.28%	10,258.6	26.33%	28,597.1	73.39%
2021	96.1	0.22%	11,366.7	26.04%	32,190.4	73.74%
2022	99.9	0.22%	11,407.2	25.46%	33,302.0	74.32%
2023	96.1	0.20%	11,613.0	24.60%	35,509.6	75.20%

4.4.5. Economic Development and Population Effects on Carbon Decoupling

GDP per capita is used to represent the economic development effect, while the hinterland population is employed to capture the population scale effect. Hinterland economic development is shaped by multiple interacting factors, which makes its influence on port activities and carbon emissions relatively complex. Among these factors, GDP and population size are two important determinants. GDP is closely associated with consumption, investment, foreign trade, and other macroeconomic variables. Population size, by contrast, is affected by social, demographic, and policy-related factors, and may also exhibit a certain degree of regulatory flexibility.

The influence of the economic development effect and the population scale effect on port carbon emissions can be explained from two perspectives. First, these two indicators reflect the level of economic activity and the size of the labor force in the hinterland. A higher level of economic development usually corresponds to more active foreign trade, stronger cargo demand, and more frequent logistics activities. Meanwhile, a larger labor force may support technological innovation and industrial upgrading. The expansion of foreign trade and the improvement of production efficiency can further stimulate port throughput, increase freight demand, and promote the expansion of port operating capacity. As a result, port energy consumption may rise, leading to an increase in carbon emissions.

Second, GDP per capita also reflects the living standards of residents. As income levels improve, residents' demand gradually shifts from basic material consumption to higher-quality and healthier lifestyles. At the same time, public awareness of environmental protection tends to increase. This change in social preference can strengthen the demand for green and low-carbon development. It may also encourage local governments and port authorities to pay greater attention to sustainability issues. Consequently, more financial and managerial resources may be allocated to energy conservation, emission reduction, and green port construction.

According to Table 5 and Figure 6, the economic development factor consistently inhibits the decoupling between hinterland economic growth and Shanghai Port's carbon emissions. It is also the most significant restraining factor throughout the study period. This indicates that the expansion of hinterland economic activity still places considerable pres-

sure on port carbon reduction. In comparison, the population scale factor also constrains the decoupling process, but its inhibitory effect is relatively limited and less obvious.

Overall, the energy intensity effect and the energy structure effect directly influence port carbon emissions and their decoupling from economic growth. In contrast, the port throughput intensity effect, hinterland economic development effect, and hinterland population scale effect operate through broader socioeconomic mechanisms. These mechanisms include hinterland GDP growth, foreign trade expansion, population changes, industrial structure adjustment, and public awareness of low-carbon consumption. By affecting port production, operational activities, and energy demand, these factors further shape both the level of port carbon emissions and the decoupling relationship between emissions and economic growth. The decomposition results show that different driving factors contribute unevenly to the decoupling process, indicating that their underlying determinants vary substantially in terms of influence and policy relevance.

5. Conclusions and Recommendations

5.1. Conclusions

This study examines the determinants of carbon emission changes at Shanghai Port using the energy consumption data of Shanghai International Port Group from 2008 to 2023. The LMDI decomposition method is adopted to decompose changes in port carbon emissions into five factors: energy structure, energy intensity, port throughput intensity, economic development, and population scale. On this basis, the study systematically identifies the major forces influencing the evolution of carbon emissions during the research period.

In addition, the Tapio decoupling model is employed to investigate the dynamic relationship between Shanghai Port's carbon emissions and the economic growth of its hinterland. By combining the Tapio model with the LMDI decomposition method, this study further constructs a decoupling index decomposition framework. This framework helps explain the interaction mechanism between hinterland economic development and port carbon emission growth. It also enables a detailed assessment of the contribution of different factors to the decoupling process. By focusing on Shanghai Port, this study provides empirical evidence for port-level carbon emission research and offers practical implications for the sustainable development of comparable port regions.

The main findings are as follows.

1. Shanghai Port's carbon emissions are measured using the emission factor method, and their driving factors are analyzed through the LMDI decomposition approach. The results indicate that energy intensity and port throughput intensity have inhibitory effects on carbon emissions. Among them, the port throughput intensity effect plays the most significant role, followed by the energy intensity effect. In contrast, hinterland economic development, population scale, and energy structure contribute positively to carbon emission growth. Hinterland economic development is the dominant factor driving the increase in port carbon emissions, while the effects of population scale and energy structure are relatively limited. The positive contribution of the energy structure effect also indicates that Shanghai Port still has considerable room to optimize its energy consumption structure.
2. From 2008 to 2023, the relationship between Shanghai Port's carbon emissions and hinterland economic growth alternated between weak decoupling and strong decoupling. Overall, the decoupling trend remained relatively stable and showed favorable prospects for further improvement. The decomposition results show that economic development and population scale continuously restrain the decoupling process. By contrast, energy intensity and port throughput intensity promote decoupling, with port throughput intensity serving as the most important facilitating factor. The ef-

fect of energy structure varies across different periods and remains relatively small overall. Although the cumulative energy structure effect restrained the decoupling process during the study period, the ongoing shift toward electrification indicates substantial future mitigation potential. As the carbon intensity of the power supply declines and renewable electricity use expands, the emission-reduction benefits of terminal electrification are expected to become more pronounced. Therefore, energy structure optimization remains an important pathway for reducing port carbon emissions and strengthening the decoupling between port development and hinterland economic growth.

5.2. Recommendations

Based on the above findings, energy intensity and port throughput intensity are the main factors influencing the decoupling relationship between Shanghai Port's carbon emissions and hinterland economic development. They are also key determinants of port emission reduction. Although the current impact of energy structure remains relatively weak, it still has considerable potential for further improvement. Therefore, the following policy recommendations are proposed.

First, the empirical results show that the energy structure effect still contributes positively to carbon emission growth, despite the declining share of fossil fuels and increasing electrification. Therefore, Shanghai Port should shift its focus from simply increasing electricity use to coordinating terminal electrification with cleaner electricity supply. The port should further expand shore power and electric equipment, improve their utilization efficiency, and increase the share of renewable electricity through green power procurement and distributed renewable energy generation. For operations that are difficult to electrify, low-carbon alternative fuels should be gradually introduced to achieve deeper emission reductions.

Second, the results in Sections 4.2 and 4.4 show that declining energy intensity contributes to both emission reduction and decoupling. Therefore, Shanghai Port should further improve energy efficiency through technological innovation, equipment upgrading, and refined energy management. Advanced digital technologies can support this process by strengthening real-time monitoring, operational optimization, and intelligent scheduling, thereby reducing energy consumption per unit of port activity and reinforcing the emission reduction effect of declining energy intensity [38].

Third, the findings in Sections 4.3 and 4.4 show that hinterland economic development still constrains the decoupling process despite the increasing dominance of strong decoupling. Therefore, Shanghai Port should strengthen low-carbon coordination with its hinterland by optimizing industrial and cargo structures, developing advanced manufacturing and high-tech industries, increasing the added value of containerized goods, and improving multimodal transport connections. These measures can reduce the carbon pressure associated with throughput growth and promote coordinated port decarbonization and hinterland economic development.

5.3. Limitations and Future Research

First, due to data availability constraints, this study covers only three major energy categories—electricity, fuel oil, and diesel—and focuses exclusively on CO₂ emissions. The estimated energy structure effect should therefore be interpreted as reflecting substitution among these observed energy categories rather than the port's complete energy-transition pathway. This limitation may reduce the comprehensiveness and generalizability of the results. Future research should incorporate a broader range of energy sources and greenhouse gases, supported by more detailed activity data and emission factors.

Second, the future energy structure effect may differ from its historical pattern as the power sector continues to decarbonize. During 2008–2023, increased electrification did not produce a net emission-reduction effect because indirect emissions from electricity consumption remained substantial. However, declining grid carbon intensity and greater use of renewable electricity may strengthen the mitigation benefits of terminal electrification. Therefore, the positive historical energy structure effect should not be directly extrapolated into the future. Future studies should distinguish energy substitution effects from changes in electricity carbon intensity and further examine how power-sector decarbonization reshapes port emission trajectories.

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Appendix A

Table A1 presents the regional grid baseline emission factors published by the Ministry of Ecology and Environment of China. These factors characterize the carbon intensity of electricity generation across different regional power grids and provide the official basis for selecting the grid emission parameters used to estimate indirect CO₂ emissions associated with purchased electricity. As Shanghai is located within the East China Power Grid, the corresponding regional parameters were matched to the electricity consumption data of Shanghai Port.

Table A1. Baseline emission factors for China’s regional power grids, 2019.

Regional Power Grid	EF _{grid,OM Simple,y} (t CO ₂ /MWh)	EF _{grid,BM,y} (t CO ₂ /MWh)
Central China Power Grid	0.8587	0.2854
East China Power Grid	0.7921	0.3870
Northwest China Power Grid	0.8922	0.4407
Northeast China Power Grid	1.0826	0.2399
North China Power Grid	0.9419	0.4819
Southern China Power Grid	0.8042	0.2135

References

1. Zhang, Z.; Rong, W.; Liu, Y.; Yang, Y. Port Carbon Emission Estimation: Principles, Practices, and Machine Learning Applications. *Transp. Res. Part E Logist. Transp. Rev.* **2025**, *199*, 104159. [\[CrossRef\]](#)
2. Eggleston, H.S.; Buendia, L.; Miwa, K.; Ngara, T.; Tanabe, K. 2006 *IPCC Guidelines for National Greenhouse Gas Inventories*; Intergovernmental Panel on Climate Change IPCC: Kanagawa, Japan, 2006.
3. Andres, R.J.; Fielding, D.J.; Marland, G.; Boden, T.A.; Kumar, N.; Kearney, A.T. Carbon Dioxide Emissions from Fossil-Fuel Use, 1751–1950. *Tellus B* **1999**, *51*, 759–765. [\[CrossRef\]](#)
4. Schmalensee, R.; Stoker, T.M.; Judson, R.A. World Carbon Dioxide Emissions: 1950–2050. *Rev. Econ. Stat.* **1998**, *80*, 15–27. [\[CrossRef\]](#)

5. Shi, R.; Chen, Y.; Yang, S.; Guo, X.; Wang, X. Decarbonization Pathways and Key Emission Drivers in Ports: A Scenario-Based Study of Shanghai Port. *Sustain. Cities Soc.* **2025**, *133*, 106877. [[CrossRef](#)]
6. Li, C.; Cariou, P.; Yang, D. Geopolitical Risks and Port-Related Carbon Emissions: Evidence and Policy Implications. *Transp. Policy* **2025**, *173*, 103809. [[CrossRef](#)]
7. Guo, X.; He, J.; Lan, M.; Yu, H.; Yan, W. Modeling Carbon Emission Estimation for Hinterland-Based Container Intermodal Network. *J. Clean. Prod.* **2022**, *378*, 134593. [[CrossRef](#)]
8. Peng, Y.; Li, X.; Wang, W.; Liu, K.; Li, C. A Simulation-Based Research on Carbon Emission Mitigation Strategies for Green Container Terminals. *Ocean Eng.* **2018**, *163*, 288–298. [[CrossRef](#)]
9. Buonomano, A.; Del Papa, G.; Giuzio, G.F.; Palombo, A.; Russo, G. Future Pathways for Decarbonization and Energy Efficiency of Ports: Modelling and Optimization as Sustainable Energy Hubs. *J. Clean. Prod.* **2023**, *420*, 138389. [[CrossRef](#)]
10. Halpe, P.; Adams, M.; Walker, T.R. Challenges and Opportunities for Ports in Achieving Net-Zero Emissions in Maritime Transport. *Transp. Res. Interdiscip. Perspect.* **2025**, *30*, 101379. [[CrossRef](#)]
11. Kaya, Y. *Impact of Carbon Dioxide Emission Control on GNP Growth: Interpretation of Proposed Scenarios*; IPCC Energy and Industry Subgroup, Response Strategies Working Group: Paris, France, 1989.
12. Ang, B.W. The LMDI Approach to Decomposition Analysis: A Practical Guide. *Energy Policy* **2005**, *33*, 867–871. [[CrossRef](#)]
13. Ming, X.; Wang, Q.; Luo, K.; Zhang, X.; Fan, J. Multi-Scenario Carbon Emission Forecasting through Boosting-Assisted Logarithmic Mean Divisia Index and Low Emission Analysis Platform in Zhejiang, China. *J. Clean. Prod.* **2025**, *537*, 147202. [[CrossRef](#)]
14. He, Y.; Xing, Y.; Zeng, X.; Ji, Y.; Hou, H.; Zhang, Y.; Zhu, Z. Factors Influencing Carbon Emissions from China's Electricity Industry: Analysis Using the Combination of LMDI and K-Means Clustering. *Environ. Impact Assess. Rev.* **2022**, *93*, 106724. [[CrossRef](#)]
15. Shi, L.; Sun, J.; Lin, J.; Zhao, Y. Factor Decomposition of Carbon Emissions in Chinese Megacities. *J. Environ. Sci.* **2019**, *75*, 209–215. [[CrossRef](#)] [[PubMed](#)]
16. Wang, X.; Lu, C.; Cao, Y.; Chen, L.; Abedin, M.Z. Decomposition, Decoupling, and Future Trends of Environmental Effects in the Beijing-Tianjin-Hebei Region: A Regional Heterogeneity-Based Analysis. *J. Environ. Manag.* **2023**, *331*, 117124. [[CrossRef](#)] [[PubMed](#)]
17. Chen, J.; Wang, P.; Cui, L.; Huang, S.; Song, M. Decomposition and Decoupling Analysis of CO₂ Emissions in OECD. *Appl. Energy* **2018**, *231*, 937–950. [[CrossRef](#)]
18. Zhang, Z.; Sharifi, A. Analysis of Decoupling between CO₂ Emissions and Economic Growth in China's Provincial Capital Cities: A Tapio Model Approach. *Urban Clim.* **2024**, *55*, 101885. [[CrossRef](#)]
19. Wang, Q.; Li, R.; Jiang, R. Decoupling and Decomposition Analysis of Carbon Emissions from Industry: A Case Study from China. *Sustainability* **2016**, *8*, 1059. [[CrossRef](#)]
20. Engo, J. Driving Forces and Decoupling Indicators for Carbon Emissions from the Industrial Sector in Egypt, Morocco, Algeria, and Tunisia. *Environ. Sci. Pollut. Res.* **2021**, *28*, 14329–14342. [[CrossRef](#)] [[PubMed](#)]
21. Luo, X.; Zhao, H. Evolution Analysis of the Decoupling State and Drivers between Economic Growth and CO₂ Emissions in RCEP Member Countries. *Energy Strategy Rev.* **2025**, *59*, 101709. [[CrossRef](#)]
22. Sharma, H.; Padhi, B.; Rath, B.N. Decoupling and Decomposition Analysis of Carbon Emission in Case of Indian Manufacturing Sector. *Energy Sustain. Dev.* **2026**, *91*, 101903. [[CrossRef](#)]
23. Huang, W.; Ye, H.; Khabarov, N.; Chen, J.; Yu, Y. Decoupling Carbon Emissions, Economic Growth, and Health Costs toward Carbon Neutrality in China's Regions. *Energy Sustain. Dev.* **2025**, *88*, 101789. [[CrossRef](#)]
24. Yue, H.; Gao, D.; Gao, J.; Wei, C.; Duan, J.; Mei, S. Decoupling and Driving Forces in Economic Growth, Energy Consumption, and Carbon Emissions: Evidence from China's BTH Region. *Energy Eng.* **2025**, *122*, 5091. [[CrossRef](#)]
25. Driha, O.M.; Cascetta, F.; Nardini, S.; Bianco, V. Decomposition and Decoupling Analysis of Carbon Emissions of the EU Tourism Sector. *Sci. Total Environ.* **2025**, *994*, 180075. [[CrossRef](#)] [[PubMed](#)]
26. Gong, Q.; Guo, G. Decoupling Relationship between Logistics Growth and Carbon Emissions and Driving Factors in Chongqing: A Novel Decomposition Framework. *J. Environ. Manag.* **2024**, *370*, 122931. [[CrossRef](#)] [[PubMed](#)]
27. Li, X.; Chen, B.; Liu, H.; Xu, M.; Yang, H. Characteristics of Agricultural Carbon Emissions in Arid Zones, Drivers and Decoupling Effects: Evidence from Xinjiang, China. *Energy* **2025**, *328*, 136373. [[CrossRef](#)]
28. Hammond, G.P.; Norman, J.B. Decomposition Analysis of Energy-Related Carbon Emissions from UK Manufacturing. *Energy* **2012**, *41*, 220–227. [[CrossRef](#)]
29. Wójtowicz, K.A.; Szołno-Koguc, J.M.; Braun, J. The Role of Public Spending in CO₂ Emissions Reduction in Polish Regions: An LMDI Decomposition Approach. *Energies* **2022**, *15*, 103. [[CrossRef](#)]
30. Koilakou, E.; Hatzigeorgiou, E.; Bithas, K. Carbon and Energy Intensity of the USA and Germany. A LMDI Decomposition Approach and Decoupling Analysis. *Environ. Sci. Pollut. Res.* **2023**, *30*, 12412–12427. [[CrossRef](#)] [[PubMed](#)]
31. Wang, Z.; Hu, T.; Liu, J. Decoupling Economic Growth from Construction Waste Generation: Comparative Analysis between the EU and China. *J. Environ. Manag.* **2024**, *353*, 120144. [[CrossRef](#)] [[PubMed](#)]

32. He, H.; Jiang, W.; Gao, Z.; Liu, T. Influencing Factors of Carbon Emissions from Final Consumption Based on LMDI Decomposition and Tapio Index: The EU 28 as an Example. *Energy Rep.* **2025**, *13*, 4884–4899. [[CrossRef](#)]
33. Zhao, T.; Andreoni, V.; Daly, H.; Eakins, J. Ireland's Carbon Emission Trends and Degrowth Opportunities: Based on Modified Tapio—LMDI Model. *Energy Policy* **2026**, *209*, 114943. [[CrossRef](#)]
34. National Development and Reform Commission of the People's Republic of China. Available online: <https://www.ndrc.gov.cn/> (accessed on 14 May 2026).
35. Tapio, P. Towards a Theory of Decoupling: Degrees of Decoupling in the EU and the Case of Road Traffic in Finland between 1970 and 2001. *Transp. Policy* **2005**, *12*, 137–151. [[CrossRef](#)]
36. Li, R.; Jiang, R. Investigating Effect of R&D Investment on Decoupling Environmental Pressure from Economic Growth in the Global Top Six Carbon Dioxide Emitters. *Sci. Total Environ.* **2020**, *740*, 140053. [[CrossRef](#)] [[PubMed](#)]
37. Pan, X.; Guo, S.; Xu, H.; Tian, M.; Pan, X.; Chu, J. China's Carbon Intensity Factor Decomposition and Carbon Emission Decoupling Analysis. *Energy* **2022**, *239*, 122175. [[CrossRef](#)]
38. Eslamipoor, R. Digital Technology's Role in Circular Waste Management: A Systematic Review. *Bus. Strategy Environ.* **2026**, 1–40. [[CrossRef](#)]

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