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Original Research

Driving Factors and Early Warning System for Carbon Emissions in China's Export Trade

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Abstract

This paper systematically examines carbon emissions from China's export trade (2013-2022) amid the rising conflict between economic globalization and environmental protection. Using the Tapio decoupling and LMDI models, the spatiotemporal characteristics and key drivers of these emissions are identified, and a gray relational early warning system is introduced. Findings reveal that the primary contributor to carbon emissions is the expansion of export trade, with the industrial sector as the largest source. While occasional energy intensity and structure improvements have reduced emissions, the overall trend remains upward. Policy recommendations include optimizing energy structure, boosting efficiency, advancing industrial upgrades, and promoting green logistics to support China's "dual carbon" goals and foster sustainable economic-environmental development.

Keywords: export trade, carbon emissions, Tapio model, LMDI, early warning system

Introduction

In the context of economic globalization and environmental globalization, the conflict between trade liberalization and environmental protection has become increasingly prominent and tends to intensify [1]. The continuous rise in carbon dioxide emissions has drawn significant attention from the international community [2-4]. Balancing export trade with carbon reduction has become a crucial issue for the future world order, national development, and social security [5, 6]. Empirical analysis by Gavard et al. [7] and Khosla et al. [8] has reaffirmed the carbon leakage issues in developing countries initially highlighted by Wyckoff and Roop [9] and Grabowski et al. [10]. For a long time, developing countries have relied on an extensive trade growth model dominated by resource-, energy-, and pollution-intensive export products [11, 12], thereby increasing their carbon emission burdens and leading to the "carbon leakage" problem, which results in these countries becoming "carbon pollution havens".

China has become the world's largest exporter and carbon emitter [13, 14]. The carbon emission problems arising from the rapid development of China's export trade have garnered attention from both the government and scholars [15-17]. With the deepening of economic globalization, international cooperation has gradually shifted from inter-industry and intra-industry divisions to product divisions among various sectors. The total carbon emissions from China's export trade and the total import and export volume both show an upward trend. The continuous increase in export trade scale is the main reason for the growth of embodied carbon

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in China's trade. Simultaneously, the developed countries' unilateral implementation and strengthening of environmental regulations are significant factors contributing to the exacerbation of "carbon leakage" and other environmental pollution issues in developing countries, led by China [18, 19]. However, current literature fails to deeply explore the limitations inherent in these viewpoints. For instance, while some studies have acknowledged the issue of carbon leakage, few have provided robust solutions or alternative models to mitigate these effects. Additionally, the research on early warning systems for carbon emissions from export trade is still in its infancy, and the existing studies remain superficial. Most discussions of early warning systems, particularly in this field, offer only cursory analysis. In this study, for example, early warning system research is limited to a brief mention, spanning only a few sentences, which does not fully convey its importance or the necessity for a more sophisticated model. This gap highlights the need for a more comprehensive exploration of early warning mechanisms, especially in light of rapid global trade and environmental policy changes [20].

The academic community currently holds two distinct views on the environmental consequences of trade liberalization: one view posits that the environmental consequences of free trade are negative in both the short and long term, especially for developing countries; the other view suggests that although trade liberalization may lead to environmental deterioration in the short term, it will bring positive environmental impacts in the long term [21]. Export trade affects carbon emissions through various effects, and the sum of these effects represents the impact of export trade on carbon emissions.

The primary theories based on trade and the environment include the Pollution Haven Hypothesis and the Environmental Kuznets Curve (EKC) Hypothesis. The Pollution Haven Hypothesis suggests that pollution-intensive industries will transfer from developed countries with stringent environmental regulations to developing countries with more relaxed regulations, making the latter "pollution havens" for the former. Grossman [22], through empirical research on the relationship between environmental quality and per capita income, found an inverted U-shaped curve relationship between pollution and per capita income. Panayoyotou [23] termed this relationship the Environmental Kuznets Curve (EKC), suggesting that the relationship between trade and the environment also conforms to the EKC hypothesis, where trade liberalization initially has negative environmental effects but will positively impact the environment over time.

Despite these theoretical advancements, more recent international studies on trade and environmental impacts suggest a shift towards multifactorial approaches, considering the intersectionality of trade liberalization, environmental regulation, and technological innovation. For example, integrating green technology in export-driven economies has shown promising results in mitigating carbon leakage, a factor that earlier models did not adequately address. This shift underscores the importance of aligning national trade strategies with international sustainability goals, particularly in emerging economies like China. Most literature employs the input-output method to study the relationship between export trade and carbon emissions across different countries and industries. However, research on the early warning of carbon emissions from export trade is still in its infancy.

In recent years, studies on early warning systems have mainly focused on the fields of finance, investment, accounting, and financial management. Early warning systems remain underexplored in the context of carbon emissions from export trade, and the need for innovation in this area is critical. China's rapid economic growth has largely depended on the driving force of exports for a long time. Therefore, from the perspective of a low-carbon economy, it is essential to measure the relevant data on carbon emissions from China's export trade and establish an early warning system for these emissions. Further analysis and publication of the early warning levels and trends in carbon emissions from China's export trade will help China prepare contingency plans and take proactive measures. This will promote the sustainable development of China's ecological trade and provide references and insights for targeted regulatory measures.

Achieving the sustainable development goal of China's export trade based on carbon emissions involves using advanced development models and management methods to break the coupling state between export growth and carbon emissions, thus realizing the coordinated development of export growth and the environment. Our study aims to analyze the decoupling state and temporal characteristics of carbon emissions and export trade at the national level by constructing a Tapio decoupling model. Additionally, it intends to decompose the driving factors of carbon emissions in China's export trade based on the LMDI model and clarify the carbon sources of China's export trade. Using the gray relational analysis method to construct an early warning system for carbon emissions from China's export trade will help clarify the carbon reduction paths in China's export trade. This approach aims to provide recommendations for reducing carbon emissions from export trade and offer insights for achieving the "dual carbon" goals.

Materials and Methods

Data Sources

The data on China's export trade volume, total output value of various industries, and energy consumption across different industry classifications are sourced from the "China Energy Statistical Yearbook" and "China

Statistical Yearbook" published by the National Bureau of Statistics from 2014 to 2023. The classification of China's national economic sectors is based on the new national standard "Industrial Classification for National Economic Activities" (GB/T4754-2011), approved by the General Administration of Quality Supervision, Inspection and Quarantine and the Standardization Administration of China, which was implemented on November 1, 2011, after its third revision.

Research Methodology

Total Carbon Emissions Accounting

The Chinese government has not released direct monitoring data on carbon emissions. Consequently, most of the existing research on carbon emissions is based on estimates derived from energy consumption and carbon emission coefficients. According to the Fourth Assessment Report of the IPCC (2006), carbon emissions and the calculation methods for carbon emission intensity are provided. Using these methods, we estimate the carbon emissions generated by export trade based on the total primary energy consumption of various industries in China and the carbon emission coefficients of primary energy. The calculation formula is as follows:

$$C = \sum_{i=1}^{n} S_i T_i$$

In the formula, C represents the carbon emissions from export trade, S_i denotes the export volume of industry i, T_i represents the carbon emission intensity of industry i, and n is the number of industry classifications. According to the IPCC (2006), the calculation formula for carbon emission intensity T is as follows:

$$T_i = \frac{\sum_{j=1}^{n} E_j K_j}{\sum_{j=1}^{n} GDP_i}$$

In the formula, E_j represents the consumption of energy type j by industry i, K_j denotes the carbon emission coefficient of energy type j (as shown in Table 1), and GDP_i stands for the total output value of industry i.

Tapio Model

The "decoupling" theory originates from the concept of "decoupling" in the field of physics and was first proposed by the OECD [24, 25]. It aims to break the link between "environmental pollution" and "economic goods". The Tapio decoupling model uses an elasticity analysis method based on time span to derive the decoupling elasticity coefficient, which dynamically reflects the decoupling relationship between variables [26]. This makes the analysis results more accurate and objective. Based on Tapio's method for studying the relationship between economic development, transportation capacity, and carbon emissions in Europe, this study constructs a corresponding decoupling index model according to the variation relationship between carbon emissions and export trade volume:

$$\varepsilon_{C,X} = \frac{\Delta C / C}{\Delta X / X}$$

In the formula, $\varepsilon_{C,X}$ represents the decoupling index between the total export trade volume and the total carbon emissions, X denotes the total export trade volume, ΔC represents the difference in total carbon emissions between the current period and the base period, and ΔX denotes the difference in total export trade volume between the current period and the base period.

LMDI Model

In 1989, Professor Yoichi Kaya first proposed the Kaya identity at the IPCC workshop as a method for decomposing the influencing factors of carbon emissions [14, 27]. Our study appropriately modifies the Kaya identity to reflect the actual conditions of export trade activities and uses the Logarithmic Mean Divisia Index (LMDI) model for quantitative decomposition. The LMDI model has the advantages of factor reversibility and the ability to eliminate residuals, making the results more persuasive. The decomposition expression used in our study is as follows:

$$C = \frac{C}{E} \times \frac{E}{W} \times \frac{W}{X} \times \frac{X}{P} \times P$$

$$\alpha = \frac{C}{E}$$

$$\beta = \frac{E}{W}$$

$$\gamma = \frac{W}{X}$$

$$\delta = \frac{X}{P}$$

Table 1. Carbon emission coefficients of energy.

	Coal	Crude	Gasoline	Kerosene	Diesel	Fuel oil	Natural gas
Factor	0.7476	0.8363	0.8140	0.8442	0.8616	0.8823	0.5956

In the formula, C represents the total carbon emissions from export trade, E denotes the total energy consumption, W represents the total output value of the industry, X is the total export trade volume, and P represents the population size. The parameters α, β, γ, and δ, respectively, represent energy structure, energy intensity, export industry structure, and economic scale.

Using the LMDI model, after eliminating unexplainable residuals, the total contribution of export trade to carbon emissions is ΔC. The contributions of energy structure, energy intensity, export industry structure, economic scale, and population size to carbon emissions are Δα, Δβ, Δγ, Δδ, and ΔP, respectively. The expression is as follows:

$$\Delta \mathrm{C} = \Delta\alpha + \Delta\beta + \Delta\gamma + \Delta\delta + \Delta \mathrm{P} = C^t - C^0$$

$$\Delta\alpha = \sum \frac{C^t - C^0}{\ln C^t - \ln C^0} \ln \frac{\alpha^t}{\alpha^0}$$

$$\Delta\beta = \sum \frac{C^t - C^0}{\ln C^t - \ln C^0} \ln \frac{\beta^t}{\beta^0}$$

$$\Delta\gamma = \sum \frac{C^t - C^0}{\ln C^t - \ln C^0} \ln \frac{\gamma^t}{\gamma^0}$$

$$\Delta\delta = \sum \frac{C^t - C^0}{\ln C^t - \ln C^0} \ln \frac{\delta^t}{\delta^0}$$

$$\Delta \mathrm{P} = \sum \frac{C^t - C^0}{\ln C^t - \ln C^0} \ln \frac{\mathrm{P}^t}{\mathrm{P}^0}$$

In the formula, Δα represents the change in carbon emissions due to the energy structure factor from the base year to year t, assuming all other factors remain constant. Similarly, Δβ, Δγ, Δδ, and ΔP respectively represent the changes in carbon emissions due to energy intensity, export industry structure, economic scale, and population size from the base year to year t, assuming all other factors remain constant.

Carbon Emission Early Warning

Selection of Early Warning Indicators

The indicator system involved in export trade is vast and complex, making it challenging to consider all factors influencing carbon emissions from export trade. According to the principles of constructing an early warning indicator system, based on the monitoring data of carbon emissions from China's export trade, we have developed an early warning model for carbon emissions from export trade. This model ensures that the relationships between various factors are hierarchical and systematic, providing a feasible basis for the current monitoring and early warning of carbon emissions from export trade. Our study selects the following four main variables as early warning indicators to measure the impact on carbon emissions from export trade. The specific calculation methods for these indicators are as follows:

$$L_1 = \frac{X_t - X_{t-1}}{X_{t-1}}$$

$$L_2 = \frac{C_{t-1}}{C_t}$$

$$L_3 = \frac{E_{t-1}/E_t}{L_1}$$

$$L_4 = \frac{X_t}{GDP_t}$$

In the formulas, L_1 represents the export trade growth rate, L_2 represents the export trade carbon emission rate, L_3 represents the energy consumption elasticity coefficient, and L_4 represents the export trade dependency.

Gray Relational Dynamic Analysis

The relational analysis method is used for dynamic comparative analysis of variable development trends and has quantitative characteristics [28, 29]. It aligns with the dynamic principles of early warning and can be used for early warning analysis of carbon emissions from China's export trade. Gray relational analysis (GRA) is particularly suited for analyzing complex systems where relationships between variables are uncertain or not fully understood, which is common in environmental and economic studies. The GRA method is based on gray system theory, which allows for exploring dynamic systems with incomplete or limited data, providing a quantitative measure of the strength of relationships between multiple variables. This is particularly important in this study, where various interdependent economic and environmental variables may influence the driving factors of carbon emissions. Since the selected early warning indicators are primarily inverse indicators and moderate indicators, a mean normalization method is uniformly applied to process the data for each early warning indicator. This results in dimensionless early warning indicator data. This normalization ensures that all variables are on a comparable scale, which is crucial for accurately assessing their relative influence on carbon emissions. By using GRA, we aim to quantify not only the correlations between indicators but also to infer potential causal relationships. Variables with high gray relational coefficients will likely significantly impact carbon emissions, indicating possible causality. The further established covariance matrix can reflect the variation degree of each early warning indicator in the original data and contain information on the degree of mutual influence among the early warning indicators. The calculation formula is as follows:

$$L = L_i / \overline{L_i}$$

$$\overline{L_i} = \frac{\sum_{t=1}^{N} L_i(t)}{N}$$

In the formula, L_i represents the value of the i-th early warning indicator. Next, we calculate the gray relational coefficients by first computing the difference sequence. The absolute differences between L_i and the reference sequence L_0 at each time point are as follows, with the calculation formula given below:

$$\Delta i = |L_i - L_0|$$

Thus, we derive the difference sequence for the dimensionless early warning indicators. Then, we take the minimum and maximum values of the two levels to calculate the numerator of the gray relational coefficient. In this study, we use 0.5 as the distinguishing coefficient to prevent distortion of the gray relational coefficient caused by excessively large maximum values, thereby enhancing the significant differences between the gray relational coefficients. The data are then substituted into the gray relational coefficient calculation formula:

$$\Psi_i(t) = \frac{min_i[\Delta_i(min)] + 0.5max_i[\Delta_i(max)]}{|L_0(t) - L_1(t)| + 0.5max_i[\Delta_i(max)]}$$

In the formula, $\Psi_i(t)$ is the relative difference between the comparison curve L_i and the reference curve L_0 at time t. This becomes the gray relational coefficient of L_i relative to L_0 at time t. The gray relational coefficient quantifies the degree of similarity between the development trends of different indicators, providing insight into the strength of their relationships with carbon emissions. While GRA primarily reflects correlation, high gray relational degrees can suggest underlying causal relationships, making it a useful tool in identifying key drivers of carbon emissions. To centrally process the information of related indicators, the average value r of the gray relational coefficients at each time point is calculated using the following formula:

$$r = \frac{\sum_{t=1}^{N} \Psi_i(t)}{N}$$

In the formula, the comparison sequence is L_i, and the reference sequence is L_0. The gray relational degree between L_i and L_0 is r. The closer the r value is to 1, the higher the correlation between the indicators. In this study, gray relational analysis not only helps determine the strength of the relationship between driving factors and carbon emissions but also aids in exploring potential causal pathways, offering insights into how different factors may contribute to or mitigate carbon emissions over time.

Early Warning Interval Setting

To quantitatively use the statistical early warning system, we first conduct a correlation test on the early warning indicator variables. Based on the analysis of the gray relational coefficient r values of the early warning indicators, we then select the appropriate indicators. Subsequently, we perform interval analysis according to the correlation coefficients and make a comprehensive judgment of the warning levels by combining the importance of the indicator variables. This process identifies early warning signals categorized as green warning, yellow warning, and red warning. Finally, based on the relationship between warning signals and various socio-economic impact factors, we provide early warnings on the severity of carbon emission monitoring in export trade, further determining the levels of mild, moderate, and severe warnings, as shown in Table 2.

Results

Carbon Emissions

As shown in Fig. 1, the total carbon emissions generated by China's export trade have generally exhibited an upward trend. In 2013, the total carbon emissions from China's export trade amounted to $198{,}192.82 \times 10^4$ tons, which increased to $258{,}094.39 \times 10^4$ tons by 2022, marking a growth rate of 30.22%. In 2016, demand weakened due to significant economic slowdowns in emerging market countries. However, from 2017 to 2022, the trend remained positive. Despite the outbreak of the COVID-19 pandemic in China in 2020, it did not appear to impact the total carbon emissions from export trade significantly. In both 2020 and 2021, the total carbon emissions from China's export trade remained well above 2.00×10^9 tons. This can be attributed to China's relatively effective pandemic control measures.

Table 2. Classification of early warning levels.

Warning level	r value range	Meaning	Significance	Early warning signal
Mild	[0,0.35]	Weak Correlation	Good	Green
Moderate	[0.35,0.65]	Moderate Correlation	Fair	Yellow
Severe	[0.65,1]	Strong Correlation	Poor	Red

Regarding the total carbon emissions generated by export trade across different industries, the industrial sector contributed the highest emissions among all sectors. From 2013 to 2022, the industrial sector's export trade generated approximately 1.98×10^{10} tons of carbon emissions, accounting for 97.74% of China's total cumulative carbon emissions over the same period. Although the other four major sectors also produced significant carbon emissions, their contributions were negligible compared to the industrial export trade.

Correlation Analysis

Agriculture shows a significant negative correlation with industry, construction, storage, and total carbon emissions, whereas industry has a significant positive correlation with agriculture, construction, storage, wholesale, and total carbon emissions (Fig. 2). Construction is significantly negatively correlated with agriculture, storage, and wholesale but significantly positively correlated with industry and total carbon emissions. Storage shows a significant negative correlation with agriculture, construction, and total carbon emissions, as well as a significant positive correlation with industry and wholesale. Wholesale is significantly negatively correlated with agriculture and total carbon emissions and significantly positively correlated with industry, construction, and storage. Overall, total carbon emissions are negatively correlated with agriculture but positively correlated with industry, construction, and storage, all with significant correlations. This indicates that industry is the primary driver of carbon emissions, while agriculture negatively correlates with other industries (especially industry, construction, and storage), suggesting that as carbon emissions in these industries increase, agricultural emissions decrease, and vice versa. Construction and storage also significantly impact total carbon emissions but show a negative correlation with agriculture and wholesale. Although the wholesale sector has some impact on total carbon emissions, it is not as significant as industry and construction.

Decoupling Relationship Analysis

As shown in Table 3, the decoupling relationship between China's export trade volume and total carbon emissions has exhibited significant variations over different years. From 2014 to 2017, carbon emissions decreased while export trade volume increased, indicating weak decoupling and recession decoupling phenomena. From 2017 to 2019, although both carbon emissions and export trade volume increased, the decoupling index remained low, still reflecting weak decoupling. From 2019 to 2021, the increase in carbon emissions outpaced the growth in export trade volume,

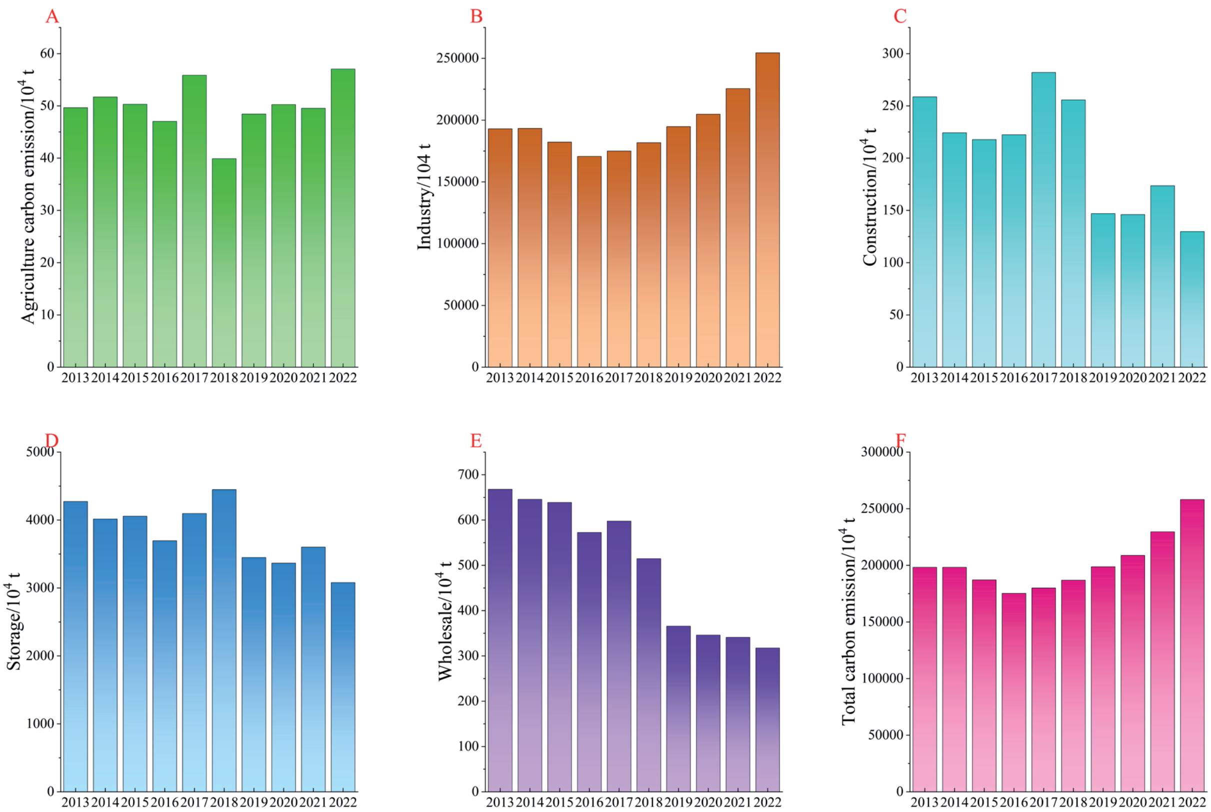

Fig. 1. Total Carbon Emissions from China's Export Trade (2013-2022).
Note: Agriculture includes farming, forestry, animal husbandry, and fishery. Storage includes transportation, storage, and postal services. Wholesale includes wholesale and retail trade.

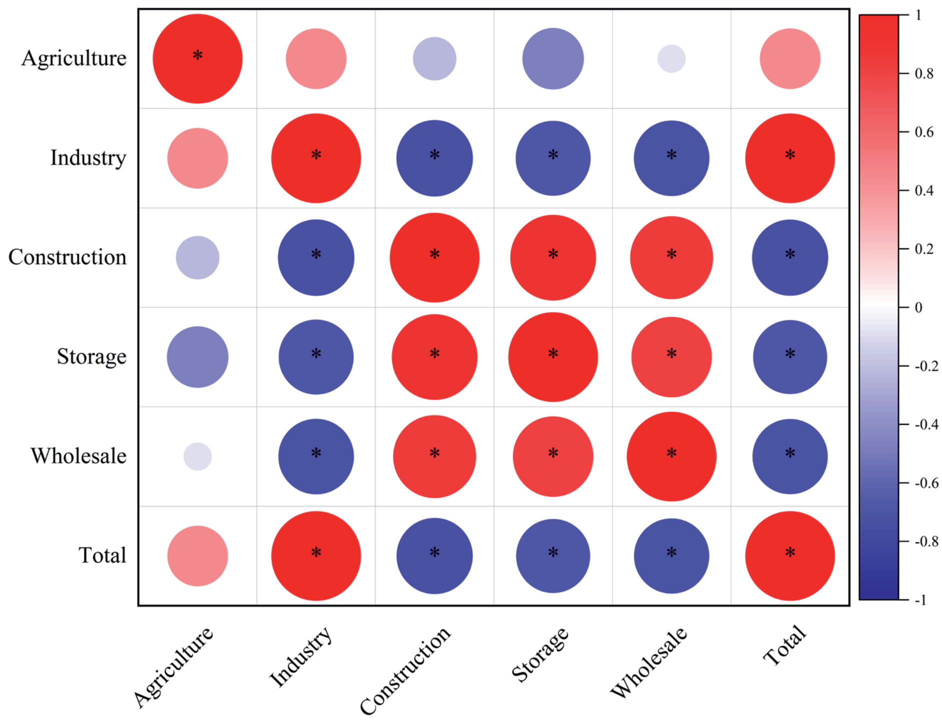

Fig. 2. Correlation analysis of carbon emissions from China's export trade.
Note: * presents a significant difference $P<0.05$.

leading to expansive negative decoupling and expansive coupling phenomena. In 2021, the decoupling index reached its highest level, indicating a significant increase in both carbon emissions and export trade volume, characterized by expansive coupling.

In the long term, from 2013 to 2022, although both carbon emissions and export trade volume increased substantially, the overall state was one of weak decoupling. Overall, China exhibited weak decoupling in most years, but recent years have shown signs of expansive negative decoupling and expansive coupling. This highlights the need to further strengthen environmental policies and technological innovations to achieve true decoupling.

Driving Factors

As shown in Table 4, from 2014 to 2022, the changes in carbon emissions from China's export trade were influenced by multiple factors. The energy structure significantly reduced carbon emissions from 2014 to 2016, with a reduction of $15{,}001.64\times10^4$ tons in 2016. However, starting in 2018, it gradually increased, reaching $21{,}557.90\times10^4$ tons in 2022. Energy intensity

Table 3. Analysis of the decoupling relationship between China's export trade volume and total carbon emissions.

Year	$\Delta C/C$	$\Delta X/X$	Decoupling Index	Decoupling Type
2014-2013	0.0003	0.0575	0.0063	Weak Decoupling
2015-2014	-0.0593	-0.0291	2.0346	Recession Decoupling
2016-2015	-0.0681	-0.0125	5.4465	Recession Decoupling
2017-2016	0.0268	0.1149	0.2333	Weak Decoupling
2018-2017	0.0368	0.0784	0.4705	Weak Decoupling
2019-2018	0.0594	0.0389	1.5270	Expansive Negative Decoupling
2020-2019	0.0477	0.0284	1.6747	Expansive Negative Decoupling
2021-2020	0.0912	0.1821	0.5007	Weak Decoupling
2022-2021	0.1101	0.1209	0.9110	Expansive Coupling
2022-2013	0.3022	0.8597	0.3515	Weak Decoupling

contributed to reducing carbon emissions in most years, notably in 2017 and 2021, with reductions of 12,370.43×10^4 tons and 20,459.99×10^4 tons, respectively. However, in 2020, energy intensity increased by 2,291.33×10^4 tons, negatively impacting carbon emissions. The export industry structure positively impacted carbon emissions in the early years, increasing by 1,575.77×10^4 tons in 2014, but fluctuated in recent years. In 2017, the export industry structure reduced carbon emissions by 3,647.64×10^4 tons, while in 2022, it reduced them by 19,259.25×10^4 tons, demonstrating the significant impact of industry structure adjustments on carbon emissions.

Economic scale was the primary driving factor for the increase in carbon emissions, with positive values in all years. Particularly in 2017 and 2021, it contributed the most to carbon emissions, increasing by 22,231.91×10^4 tons and 45,069.33×10^4 tons, respectively. This indicates that the expansion of economic scale was the main driving force behind the growth in carbon emissions. The impact of population size was relatively small and stable, with changes ranging from -1,535.06×10^4 tons to 967.02×10^4 tons in most years. It only slightly increased in 2014 and 2015, while the impact remained stable in other years.

Early Warning of Carbon Emissions from China's Export Trade

Fig. 3 illustrates the relationships between export trade growth rate, export trade carbon emission rate, energy consumption elasticity coefficient, export trade dependency, and export trade carbon emissions. The gray relational coefficients not only indicate the strength of the relationships but also suggest potential causal links between these factors and carbon emissions. Regarding the export trade growth rate, as China's total exports have steadily increased, the growth rate of China's export trade expanded from 4.14% in 2014 to 13.16% in 2022. Its gray relational coefficient with export trade carbon emissions has consistently remained above 0.88, reaching 0.9845 in 2022. This strong correlation suggests that the rapid increase in export trade directly contributes to higher carbon emissions, primarily through increased industrial production and energy consumption.

In terms of the export trade carbon emission rate, the proportion of carbon emissions generated by export trade in total industry carbon emissions has generally remained between 18.93% and 25.30%. Its gray relational coefficient with export trade carbon emissions has consistently stayed above 0.98, reaching 0.9915 in 2022. This indicates a near-linear relationship, where any increase in export trade is closely followed by a proportional increase in carbon emissions, likely driven by energy-intensive industries. Such a strong relational degree points to a direct causal pathway where the scale and structure of export activities dictate carbon output. Regarding the energy consumption elasticity coefficient, a significant downward trend has been observed since 2019, decreasing from 0.81 in 2019 to 0.21 in 2022. Its gray relational coefficient with export trade carbon emissions has shown a clear upward trend since 2019, reaching 0.9877 in 2022. This shift reflects improvements in energy efficiency within China's export sector; however, despite these improvements, the strong gray relational coefficient suggests that energy consumption remains a key determinant of carbon emissions. The causal link here lies in the continued reliance on non-renewable energy sources, which means that even small increases in energy use can lead to disproportionately large increases in emissions. Export trade dependency has consistently remained around 30%, with a dependency rate of 33.16% in 2022. Its gray relational coefficient with export trade carbon emissions has remained above 0.96, reaching 0.9672 in 2022. The close relationship between export trade dependency and carbon emissions highlights the systemic nature

Table 4. LMDI decomposition results of carbon emissions from China's export trade (×10^4 t).

Year	$\Delta\alpha$	$\Delta\beta$	$\Delta\gamma$	$\Delta\delta$	ΔP	ΔC
2014	-5285.42	-7959.25	1575.77	10768.24	972.51	71.85
2015	-13688.63	-3518.45	11638.85	-6505.49	967.02	-11106.71
2016	-15001.64	-7275.01	12581.40	-414.87	-1838.78	-11948.89
2017	-844.99	-12370.43	-3647.64	22231.91	-538.48	4830.36
2018	529.51	-9788.79	1174.75	15886.70	-905.15	6897.03
2019	5564.78	-4163.52	2760.85	6845.68	812.05	11819.83
2020	5482.90	2291.33	-3703.74	7421.56	-1535.06	9956.99
2021	9146.08	-20459.99	-11779.54	45069.33	-1030.57	20945.31
2022	21557.90	-5262.61	-19259.25	35051.80	-3652.01	28435.81
Total	7460.47	-68506.74	-8658.55	136354.86	-6748.47	59901.58

of the trade-emissions link in China's economy. As China's economic growth relies heavily on exports, any fluctuations in trade dependency are likely to result in immediate changes in carbon emissions. This suggests a deep-rooted causal chain where economic dependency on trade reinforces carbon-intensive production processes.

As shown in Table 5, by performing carbon emission early warnings for various indicators, it can be seen that the export trade growth rate, export trade carbon emission rate, energy consumption elasticity coefficient, and export trade dependency have all reached severe early warning levels, with the energy consumption elasticity coefficient having the lowest r value of 0.6928. These severe warning levels highlight the urgent need for interventions to decouple economic growth from carbon emissions. The high gray relational coefficients across all these indicators suggest a network of interlinked causal chains, where export trade is the central driving force, amplifying both energy consumption and carbon emissions. The export trade growth rate has the highest correlation with export trade carbon emissions, indicating that the export trade growth rate is the primary driving factor for the increase in carbon emissions from China's export trade. This suggests that policies aimed at reducing carbon emissions must address the scale of export trade and the energy efficiency of production processes, as these are the key factors driving the upward trend in emissions.

Discussion

In recent years, China's foreign trade openness has increased steadily, with rapid export growth to emerging economies [30, 31]. The "Belt and Road" initiative and establishing the China-ASEAN Free Trade Area have created both opportunities and challenges for China's

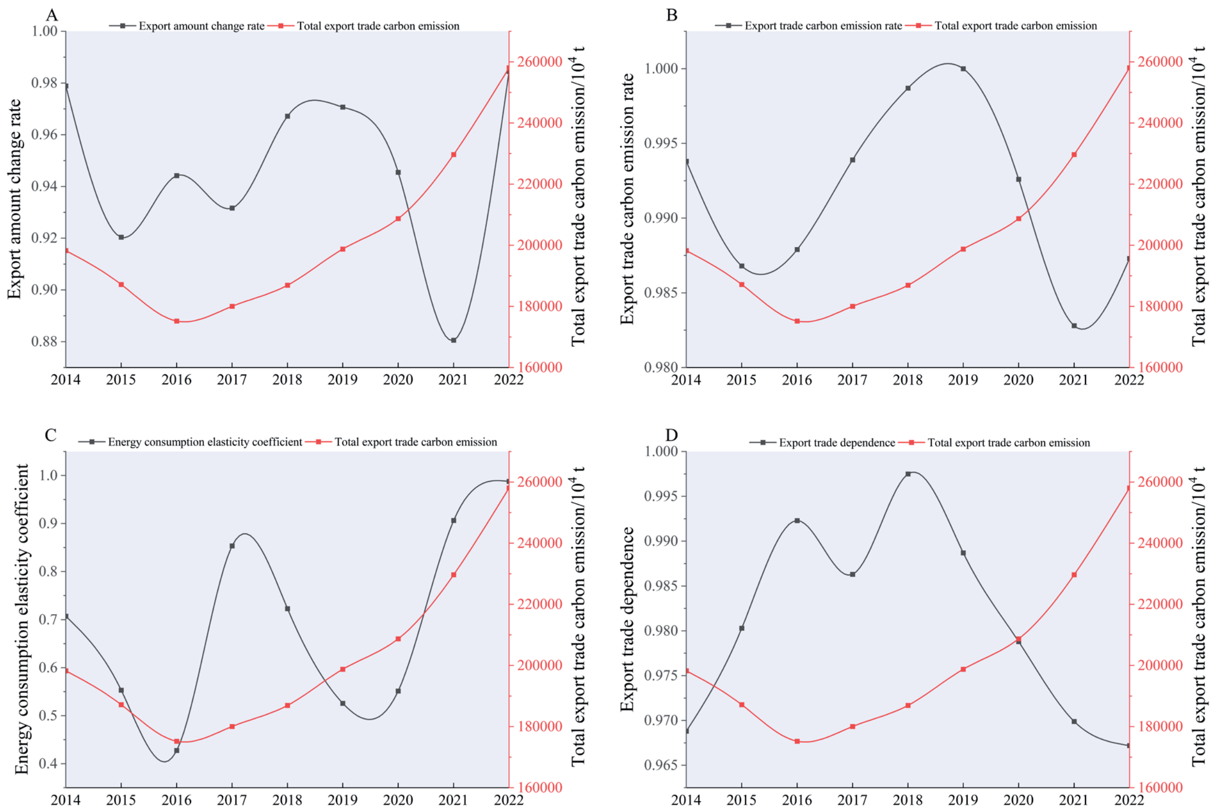

Fig. 3. gray relational coefficients of various indicators with total carbon emissions from export trade.

Table 5. Early warning levels of various indicators.

	r-value	Meaning	Significance	Warning level	Early warning signal
L1	0.9471	Strong Correlation	Poor	Severe	Red
L2	0.9915	Strong Correlation	Poor	Severe	Red
L3	0.6928	Strong Correlation	Poor	Severe	Red
L4	0.9811	Strong Correlation	Poor	Severe	Red

trade development [32, 33]. Export trade is a "double-edged sword"; while it drives China's economic growth, it also directly leads to a continuous increase in domestic carbon emissions, exacerbating China's environmental pollution problems [34]. Predicting and assessing carbon emissions from China's export trade in a low-carbon era is crucial for meeting global climate regulations [35, 36].

For decades, China's economic growth has relied on an export-oriented model [37]. At present, China faces multiple pressures, including resource and environmental constraints, CO_2 emission reductions, and sustainable economic growth [38, 39]. Optimizing the import-export structure, enhancing trade quality, and shifting focus from exports to domestic consumption could help China align its economy with long-term plans to "adjust structure and expand demand". This would also address the embodied carbon in exported goods, promoting both economic and environmental benefits [40, 41].

Our study calculated total carbon emissions from China's export trade from 2013 to 2022, showing an output of around 2.02×10^{10} tons of carbon emissions. The industrial sector is the largest contributor, responsible for over 97% of total emissions, driven by the high energy needs of industries like steel, cement, and chemicals. This strong link between industrial growth and emissions reflects how increased production leads to higher fossil fuel use, thus boosting carbon emissions. According to the China Energy Statistical Yearbook (Table 6), China's industrial sector continues to heavily consume coal and crude oil, which supports economic growth but increases environmental pressure. China has recognized this issue and has been investing significantly in renewable energy to reduce reliance on fossil fuels [42, 43].

An analysis of energy consumption elasticity further demonstrates the link between energy use and export trade. Although energy efficiency has improved in recent years, our gray relational analysis reveals that even small increases in energy use can significantly impact carbon emissions due to China's heavy reliance on coal and other fossil fuels. This suggests that changes in energy efficiency, especially in the industrial sector, directly affect carbon emissions.

Carbon emission intensity is another key indicator in calculating emissions [44]. Using 2022 data (Fig. 4), the carbon emissions per billion yuan of export output in agriculture, industry, construction, transportation, and retail were 0.03, 1.12, 0.24, 0.47, and 0.02 million tons, respectively. The industrial sector had the highest emission intensity, making up 1.88×10^4 tons per billion yuan in 2022. From 2013 to 2022, the carbon emission intensity of China's export trade decreased by approximately 33.10%, reflecting a partial decoupling of economic growth from environmental impact. However, our analysis shows that while emission intensity is decreasing, total emissions continue to rise due to export growth, highlighting a causal chain where export-driven growth still leads to higher emissions despite gains in efficiency [45, 46].

After decomposing the factors influencing carbon emissions from China's export trade, it is clear that from 2014 to 2022, economic scale and export industry structure were the main drivers of carbon emission changes, with energy structure and energy intensity also playing significant roles. Although emissions were reduced in some years, the overall trend remained upward. The key factors identified – economic scale, energy intensity, and industry structure – show a complex link between economic growth and environmental impact. For instance, while energy structure adjustments can temporarily reduce emissions, continued growth in energy-intensive industries directly impacts carbon emissions.

The early warning system proposed has theoretical value but faces challenges in practical application. Monitoring and updating data for key indicators like energy consumption elasticity and export growth

Table 6. Energy consumption in China's industrial sector (2013-2022).

	Coal	Crude	Gasoline	Kerosene	Diesel	Fuel oil	Natural gas
2013	403157.01	48503.42	523.38	27.41	1675.88	2421.05	1129.06
2014	390497.43	51502.10	489.04	17.36	1595.28	2835.74	1221.33
2015	378190.00	54752.43	477.08	21.16	1516.37	3133.03	1234.48
2016	367435.00	57103.59	436.32	19.96	1412.91	3035.41	1338.59
2017	371160.00	59393.50	382.10	14.55	1459.94	3043.74	1575.25
2018	380696.00	62995.51	296.51	24.94	1259.47	2688.17	1940.07
2019	387268.00	67259.08	262.00	10.97	1290.60	2612.54	2092.05
2020	390891.00	69476.54	183.97	9.39	1026.12	3262.33	2304.02
2021	417585.00	72298.29	194.28	8.98	1192.49	3130.65	2678.25
2022	437175.00	70022.29	307.01	7.95	1645.00	3264.03	2675.79

Note: The unit of measurement for natural gas is 100 million cubic meters, while other energy sources are measured in 10,000 tons.

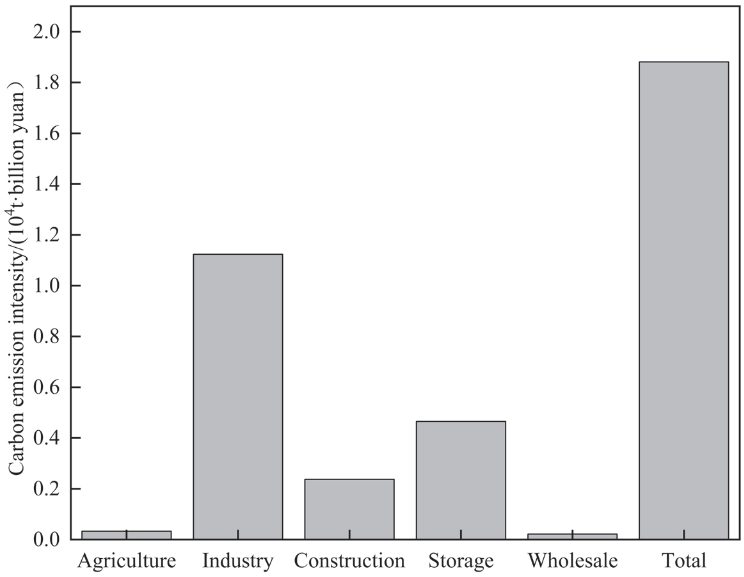

Fig. 4. Carbon emission intensity of China's export trade in 2022.

requires ongoing coordination among government agencies and industries. To keep the system effective, data collection must be integrated into the regulatory framework and be supported by policies that enforce carbon reduction, especially in key sectors like steel and cement.

Aligning the early warning system with international climate commitments may also be challenging. As China's export trade is deeply embedded in global supply chains, any policy change must consider impacts on trade and competitiveness. International cooperation, such as aligning the system with global carbon standards, will be essential for its success, requiring integration into both domestic and international frameworks.

To reduce export-related carbon emissions, several policies are recommended. First, since the industrial sector is the largest source, reducing reliance on coal through renewable energy development is critical. Energy efficiency improvements are also vital. The study highlights a strong link between energy consumption elasticity and emissions, with a decrease from 0.81 in 2019 to 0.21 in 2022. Better energy efficiency management and stricter standards will help decouple growth from emissions, encouraging firms to adopt advanced processes and technology [47]. Optimizing export product structures by promoting high-value, low-energy industries will further reduce carbon intensity and support trade sustainability. Carbon markets and carbon taxes can also drive emission reductions by providing economic incentives for low-carbon practices.

Logistics and supply chains significantly contribute to emissions. Promoting clean energy vehicles, optimizing transport routes, and adopting green packaging are essential steps to lowering the logistics sector's footprint.

International cooperation is key for China, the world's largest exporter and emitter. Aligning policies with global standards and participating in climate governance can enhance China's global influence, while integrating the early warning system with international frameworks will strengthen cross-border coordination.

Finally, promoting green consumption and raising public environmental awareness is crucial for long-term change. Encouraging low-carbon products and sustainable consumption behaviors can drive broader environmental goals, with green campaigns supporting both corporate and consumer shifts toward a low-carbon economy.

These measures, supported by empirical data and theoretical analysis, can help China control export trade emissions, align economic growth with environmental goals, and achieve its "dual carbon" objectives.

Limitations

In this study, we selected the Tapio decoupling model and the Logarithmic Mean Divisia Index (LMDI) model to analyze the relationship between carbon emissions and export trade. While these models provide a robust framework for analyzing the driving factors of carbon emissions, their selection is based on specific advantages over other existing models and certain limitations that should be acknowledged. The Tapio decoupling model was chosen for its ability to quantify the decoupling relationship between economic growth and environmental degradation through elasticity analysis. Unlike earlier decoupling models that focused primarily on static snapshots of economic-environment relationships, the Tapio model offers a dynamic approach, allowing for the assessment of changes over time. However, one limitation of the Tapio model is that it primarily focuses on the direct relationship between variables such as trade volume and carbon emissions without considering the potential impact of other macroeconomic factors, such as policy shifts or technological advancements, which may influence the decoupling results. This limitation is partially addressed by including the LMDI model, which allows for a decomposition of the factors driving carbon emissions.

The LMDI model is widely recognized for its ability to decompose changes in carbon emissions into various contributing factors, such as energy intensity, economic structure, and population size. This method ensures that all factors are accounted for without leaving any unexplained residuals, which is a common issue in other decomposition methods like the Shapley-Sun method. However, the LMDI model is not without limitations. One significant limitation is its reliance on historical data, which may not fully capture the future impact of emerging technologies or unanticipated shifts in global trade policies. Additionally, while the LMDI model provides a thorough breakdown of influencing factors, it assumes that they are independent, which may not always reflect the complexities of real-world interactions. Other models, such as the Environmental Kuznets Curve (EKC) hypothesis, while useful in explaining the relationship between economic growth and environmental degradation, tend to oversimplify the dynamics between trade and carbon emissions. The EKC hypothesis suggests that environmental degradation first increases and then decreases with economic growth, but it fails to account for the role of international trade and its embodied carbon emissions, which are central to this study.

Similarly, input-output analysis (IOA) has been used in many studies to estimate the carbon footprint of trade activities by tracing the flow of goods and services across different industries. However, IOA models are limited by their static nature. They often assume fixed production technologies and consumption patterns, which do not accurately reflect the dynamic nature of modern global trade. Furthermore, IOA models often rely on highly aggregated data, which may obscure sector-specific trends in carbon emissions.

In comparison, combining the Tapio and LMDI models allows for a more comprehensive and dynamic analysis of the decoupling relationship between carbon emissions and export trade. By integrating these two models, we aim to provide a more nuanced understanding of the factors driving carbon emissions in China's export trade and how these factors change over time.

Despite the strengths of these models, future research could benefit from integrating other methodologies, such as agent-based modeling or system dynamics models. These could offer more detailed insights into the interactions between various economic, environmental, and policy variables. These approaches could help address some of the limitations mentioned and provide a more holistic view of the factors influencing carbon emissions in global trade.

Conclusions

Several key findings can be highlighted based on the calculation and analysis of carbon emissions from China's export trade between 2013 and 2022. First, the total carbon emissions from export trade have significantly increased over the past decade, rising from 1,981.92 million tons in 2013 to 2,580.94 million tons in 2022, representing a 30.22% growth. The industrial sector remains the dominant contributor, accounting for over 97% of the total emissions. Although improvements in energy structure and intensity in certain years have led to limited reductions in emissions, the overall upward trend persists, reflecting the ongoing challenges in reducing carbon emissions within a rapidly growing trade sector.

Developing a gray relational early warning system for carbon emissions from export trade has shown potential in providing dynamic forecasting based on early warning metrics. This system offers a valuable tool for monitoring and predicting carbon emissions, facilitating timely intervention and policy adjustments to mitigate environmental impacts.

While the analysis provides important insights, several unresolved issues warrant further research. One critical area is the long-term effectiveness of policy measures aimed at decoupling export growth from carbon emissions. Future research should explore the impact of emerging technologies, such as renewable energy integration and smart manufacturing, on reducing emissions in the export sector. Additionally, further investigation into the role of international supply chains in contributing to China's carbon emissions is needed, particularly in the context of global trade dynamics.

Moreover, there is a need for more detailed sector-specific analysis to understand the varying impacts of different industries on overall emissions. This can inform more targeted policy interventions. Finally, expanding the scope of the early warning system to incorporate international cooperation and cross-border carbon accounting mechanisms could enhance its effectiveness in addressing the global nature of carbon emissions.

In conclusion, while this study highlights the increasing carbon emissions from China's export trade and offers initial policy recommendations, the path forward will require continued research and innovation to achieve meaningful decoupling of trade from environmental degradation.

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Conflict of Interest

The authors declare no conflict of interest.

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