International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(6), 281-286.

Industrial Exports and Global Carbon Emissions: Assessing the Impact of the U.S. and China Using a Decision Tree Algorithm

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Received: 20 April 2025 **Accepted:** 04 September 2025 **DOI:** https://doi.org/10.32479/ijeep.20146

ABSTRACT

This research employs a decision tree approach to investigate the impact of industrial exports from China and the United States on global carbon emissions in the industrial sector. Drawing on panel data from 1992 to 2023 provided by the World Bank, the results reveal a substantial positive relationship between China's manufacturing exports- accounting for 81% of the feature importance- and global industrial CO_2 emissions (Pearson coefficient: 0.837). The feature importance of U.S. exports, on the other hand, is lower at 19%, suggesting a negative association (Pearson coefficient: −0.901). With an R-squared value of 0.96 and a mean squared error (MSE) of 0.002, the decision tree model outperformed the other two models, random forests and support vector machines, among the five machine learning models evaluated. These findings demonstrate the disparate environmental effects of export-driven industrialization, with a focus on China's significant emissions from energy-intensive manufacturing, and the urgent need for focused measures, like carbon pricing, the incorporation of green technologies, and sustainable trade agreements, to bring industrial growth into line with climate goals, especially the Sustainable Development Goals (SDGs 9 and 13) of the United Nations. This study advances the application of machine learning in environmental economics, providing valuable insights for balancing economic and ecological priorities in international trade systems.

Keywords: China Industrial Exports, U.S. Industrial Exports, Decision Tree Algorithm, Industrial CO2 Emissions, Machine Learning
JEL Classifications: Q15, C63, C80, C81, C87

1. INTRODUCTION

The global economy relies more on industrial exports, with manufacturing as the key force behind economic growth and international trade. The United States and China are pivotal in these exports, markedly impacting the worldwide supply of manufactured goods. However, the rise of industrial exports has raised concerns about its environmental impact, particularly concerning carbon emissions from the industrial sector. As nations pursue economic development, they must thoughtfully assess the environmental costs of industrialization and export-driven economies.

Carbon emissions from industry account for a substantial share of global greenhouse gas emissions, driving climate change and damaging the environment. Key factors include manufacturing processes that depend on fossil fuels, energy-intensive production methods, and extended supply chains. Many studies have examined how industrialization affects the environment. Yet, the influence of industrial exports—precisely their proportion of total merchandise exports—on global carbon emissions remains a vital issue that warrants more profound analysis. Grasping this relationship is crucial for policymakers, environmental regulators, and trade economists who aim to harmonize economic expansion with ecological stewardship.

The United States and China display unique yet interlinked industrial and trade dynamics. China stands out as the top exporter of manufactured goods globally, propelled by its vast industrial framework, inexpensive labor, and tactical trade approaches. Conversely, the U.S. features a technologically sophisticated manufacturing sector focusing on high-value exports like aerospace, pharmaceuticals, and electronics. Despite differences in production structures and energy efficiencies, both countries play a significant role in global industrial emissions.

China's rapid industrial growth has led to a significant rise in coal consumption, making it the top emitter of carbon dioxide (CO_2) worldwide. Conversely, even though industrial development in the U.S. is slower, it remains one of the leading emitters. This is primarily due to its dependence on energy-heavy manufacturing and transportation. The connection between industrial exports and carbon emissions in these economies is intricate, shaped by factors like production efficiency, energy sources, and environmental policies. This study analyzes how industrial exports influence carbon footprints by assessing their impact on global industrial emissions. The share of industrial exports in total commodity exports has evolved in both countries under study, and each country differs from the other. For example, the share of industrial exports in total exports during the study period was constantly increasing, starting with a contribution rate of 78.6% in 1992 and reaching 91.88% in 2023. In contrast, the United States went in the opposite direction to China, starting with a contribution rate of 76.3% in 1992 and declining during the period to reach 56.45% of total commodity exports.

This research employs a decision tree algorithm, a widely recognized machine learning technique for classification and regression, to examine this relationship. Decision tree models are particularly adept at managing complex, non-linear interactions among variables, which makes them especially effective in assessing the impact of industrial exports on carbon emissions. The decision tree method thoroughly assesses key factors by integrating trade statistics, carbon emission data, and economic indicators, revealing trends that traditional econometric models may overlook.

This research investigates critical issues: How do industrial exports from the U.S. and China affect global carbon emissions in the industrial sector? What key factors influence the variations in emissions, and how do these differ between the two economies? Can decision tree models offer predictive insights into the link between trade and the environment, aiding policymakers in crafting sustainable trade policies? This study will enhance the ongoing dialogue about sustainable trade practices by addressing these issues and offering empirical insights that can inform global climate policies.

This study's conclusions are crucial for the United Nations' Sustainable Development Goals (SDGs), especially Goals 9 (Industry, Innovation, and Infrastructure) and 13 (Climate Action). Industrial exports significantly contribute to economic growth, complicating the achievement of long-term environmental goals. To address this, policymakers must encourage the shift to low-carbon technologies, improve energy efficiency, and ensure industrial growth aligns with sustainable manufacturing practices. Accordingly, reducing the environmental impact of industrial exports requires the creation of international trade agreements, the implementation of carbon pricing mechanisms, and the support of corporate sustainability initiatives. By understanding the trade-offs between industrial development and climate strategies, decision-makers can formulate trade policies that reconcile economic and environmental concerns.

2. LITERATURE REVIEW

Academic literature has thoroughly examined the connection between industrial exports and global carbon emissions, especially in major industrial nations like China and the United States. This section presents key studies that investigate (1) how industrial exports influence carbon emissions, (2) the displacement of carbon associated with trade, and (3) the policy implications for promoting sustainable trade.

Many studies have examined how carbon emissions relate to industrial exports. Lin (2013) studied the impact of China's industrial exports and found that energy-intensive production significantly elevates emissions. Zhang (2015) expanded on this research by evaluating CO_2 emissions in 18 Chinese export sectors, showing that increased export volumes correlate with higher carbon emissions.

Building on these conclusions, Hong-Guang et al. (2011) explored the connection between foreign trade and CO_2 emissions in China, showing that an inappropriate export structure played a significant role in the rise of CO_2 emissions. The study indicated that after China joined the WTO, net exports accounted for a quarter of the country's total CO_2 emissions. Wang and Li (2021) further developed this analysis by employing a panel threshold regression on data from 282 Chinese cities, uncovering a positive link between imports and carbon emissions, while exports were found to have a negative association with carbon emissions (Wei et al., 2011).

Emissions research has become more interested in carbon's role in international trade. According to Liu et al. (2014) analysis of carbon emissions associated with China's foreign trade, the country exports carbon emissions on a net basis, especially between 2004 and 2007, when it began to transition to high-end manufacturing. In a similar vein, Zhang (2009) estimated that about 30-35% of China's total emissions were attributed to exported goods, while Wei et al. (2009) stated that emissions from Chinese exports ranged from 288.22 to 330.49 MtC, with domestic production accounting for 23.45% of this total.

Baumert (2017) assessed the global influence of international trade on emissions displacement, finding that Anglophone nations, especially the United States, act as net importers of carbon emissions. Meanwhile, China is the predominant global net exporter of emissions. Similarly, Fan et al. (2017) evaluated CO_2 trade positions among 14 leading economies and identified China as the top exporter of CO_2, with the U.S. being the principal importer. This disparity in emissions obligations prompts a reevaluation of trade policies' roles in addressing carbon leakage (Ding, et al., 2017).

Many studies have explored how industrial strategies influence carbon emissions. Song and Zhou (2021) examined the link between emissions in the manufacturing sector and China's industrial policies. Their research reveals that government support for specific companies resulted in a 10.3% rise in emissions, highlighting variations based on region and industry. Liu et al. (2024) analyzed international industrial transfers, revealing that their effects on emissions and public health in China surpass those of direct export trade, thereby emphasizing the environmental hazards associated with globalization (Zhao et al., 2023).

Liu (2016) further explored carbon emissions in China, revealing that 90% stem from fossil fuel combustion, with the manufacturing and power sectors accounting for 85% of total emissions. In 2024, Zhao et al. studied the carbon lock-in effect within China's industrial sector. Their findings indicate that the electric generation, metal smelting, and oil processing industries play a significant role in persistent emissions. According to Levinson's (2007; 2009) analysis of U.S. industrial emissions patterns, pollution from U.S. industry has reduced by 60% over the past three decades despite increased production. The research attributed this reduction to technological advances rather than trade changes, emphasizing innovation's crucial role in reducing emissions. Likewise, a multi-region study by Abbood et al.(2022) identified agriculture and electricity as the leading sources of the nation's carbon footprint.

In addressing the climate trade challenge, Liu et al. (2016) identified opportunities to reduce emissions through targeted improvements in specific provinces and sectors. At the same time, Chen et al. (2022) explored the integration of global value chains (GVC), indicating that forward embedding contributes to emission reductions. Conversely, backward embedding increases emissions, underscoring the need for supply chain optimization.

Islam et al. (2016) observed that greater trade openness leads to increased embodied emissions, underscoring the necessity for strict environmental regulations in international trade. Concurrently, Işık et al. (2024) presented the domestic exports/re-exports ratio as a new variable influencing pollution levels in the U.S. Their research revealed that an increase in re-exports significantly reduces CO_2 CO_2 emissions, suggesting that varied trade strategies can act as an effective mitigation mechanism (Marland and Pepin, 1990).

The analyzed studies underscore the crucial impact of industrial exports on global carbon emissions. As the largest exporter, China remains a net carbon emitter, whereas developed nations such as the United States are net carbon importers. Additionally, research shows that industrial policies, trade frameworks, and technological progress affect emission levels.

Despite existing research, there are still notable gaps. Underutilization of machine learning techniques: While numerous studies have analyzed the link between trade and emissions through econometric models, few have utilized decision tree algorithms to investigate the non-linear relationships between these factors. Additionally, comparative research between the U.S. and China is scarce. Most studies examine each country in isolation, missing the opportunity for a combined analysis of how their industrial exports impact global emissions. Furthermore, there is a need for predictive modeling; existing research primarily provides descriptive insights that concentrate on historical trends instead of utilizing data-driven methods to forecast future interactions between trade and emissions.

This study applies a decision tree algorithm to investigate the influence of U.S. and China industrial exports on global carbon emissions. Utilizing sophisticated data analytics, it offers predictive insights into the relationship between trade policies and emissions. The research comprehensively evaluates how exports from both nations affect emissions while delivering data-driven recommendations to policymakers navigating the trade expansion and environmental sustainability balance.

3. DATA

This research utilizes a panel dataset from 1992 to 2023, obtained from World Bank (2025) databases, which ensures the inclusion of credible and globally recognized macroeconomic and environmental metrics. It investigates carbon emissions from the global industrial sector as the dependent variable, vital for evaluating the environmental repercussions of industrial activities worldwide. The independent variables consist of exports from China and the United States, represented as a percentage of their total commodity exports. These variables were selected to emphasize the export performance of each country in the global commodity market and its possible impact on industrial carbon emissions.

A natural logarithm transformation was applied to all data series to bolster the robustness and clarity of regression outcomes. This transformation stabilizes variance, linearizes exponential trends, and improves the overall fit of the econometric models. The altered variables allow for more precise comparisons of growth rates and elasticity, ultimately providing more trustworthy insights into the interplay between export performance and carbon emissions in the industrial sector; Table 1 shows the data statistics description:

4. DECISION TREE ALGORITHM METHODOLOGY

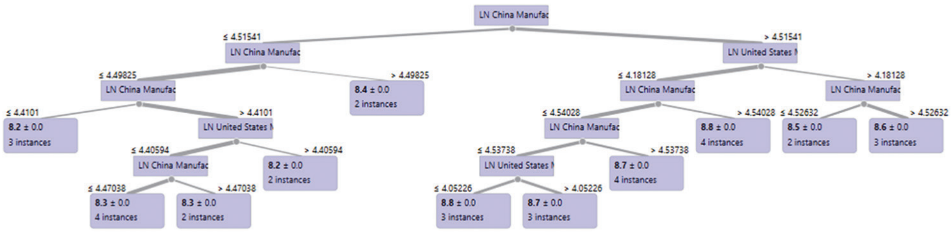
Decision tree algorithms are parameter-free supervised learning methods ideal for regression and classification tasks. They partition

Table 1: Data statistics and descriptions

Variables	Source of data	Mean	Mode	Median	Dispersion	Minimum	Maximum
World Carbon dioxide (CO_2) emissions from Industrial Combustion (Mt CO2e)	World bank	5153.4	3697.1	5493.03	0.21	3697.1	6427.7
China Manufactures exports (% of merchandise exports)	World bank	90.36	78.65	92.53	0.047	78.65	94.3
United States manufacturing exports (% of merchandise exports)	World bank	70.17	53.46	73.15	0.13	53.46	82.81

Source: Made by the author (using Python language)

Figure 1: Decision tree viewer



Source: Made by author

the feature space into regions for regression and calculate the average data points within each area to establish the target variable. This technique is advantageous for capturing complex, nonlinear relationships between input and response variables (Breiman, 2001).

4.1. Building Trees

To construct a decision tree, the dataset is systematically divided based on the values of the input variables. The goal is to classify the data into clearly defined subgroups related to the target variable, as illustrated in Figure 1.

- Splitting Criterion: Regression tasks typically use the splitting criterion to minimize mean squared error (MSE). The system calculates the MSE for the resulting child nodes at each node to evaluate potential splits.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y})^2$$

In this context, y_i represents the actual values at the node, ($\bar{y}$) denotes the average target value for the node, and N signifies the number of observations. The split that yields the most significant reduction in MSE is selected.

- Recursive Partitioning: The chosen split divides the data into two child nodes, and this splitting is recursively applied to each child node until a stopping condition is reached. Standard stopping criteria involve a minimum observation count per node or a maximum tree depth.

4.2. Forecasting Formula

This approach starts at the base of the tree and moves up to the leaf node that corresponds to the new observation, x, for regression predictions. The predicted value, ŷ, is calculated by averaging the values of the independent variables from the training observations located within that leaf node.

$$\hat{y} = \frac{1}{N_{leaf}}\sum_{i \in leaf} y_i$$

This method takes advantage of the consistency of the targeted variable in each segment produced by the tree's splits.

5. EMPIRICAL RESULTS

5.1. Assessment of the Model

Several metrics are commonly used to evaluate the performance of the Decision Tree regression model:

Table 2: Machine learning algorithms accuracy metrics

Models	MSE	RMSE	MAE	R^2
DT	0.002	0.045	0.034	0.96
RF	0.002	0.049	0.033	0.952
KNN	0.003	0.058	0.034	0.933
GB	0.005	0.071	0.036	0.898
SVM	0.007	0.082	0.077	0.864

Source: Made by author

- The Mean Squared Error (MSE) measures the average squared difference between the observed and predicted results.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

- The Root Mean Squared Error (RMSE) translates the error values back to the target variable's original units by computing the square root of the mean squared error.

$$RMSE = \sqrt{MSE}$$

- The Mean Absolute Error (MAE) indicates the average absolute difference between the actual and expected values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

- R-squared (R^2) shows the proportion of variance in the dependent variable that the independent variables can explain.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

Evaluate the accuracy of the algorithms (decision tree (DT), random forest (RF), k-nearest neighbor (KNN), gradient boosting (GB), and support vector machine (SVM)) as measured by the metrics listed in Table 2:

From Table 2, all algorithms used in the analysis are highly accurate for Global CO_2 emissions from the Industrial sector, depending on the independent variables. However, the decision tree is more accurate than other algorithms, with a higher R^2 value and lowest MSE value. So, the paper relies on it for analysis.

5.2. The Relationship between Variables at Present and in the Future

The relationship between variables must be determined based on the Pearson correlation coefficient. The shape of the relationship can also be determined in the future based on the regression

Table 3: Pearson correlation coefficient

Independent variables	Dependent variable	Pearson correlation
China Manufactures exports (% of merchandise exports)	global CO_2 emissions from Industrial ($Mt\ CO_2e$)	0.837
United States manufacturing exports (% of merchandise exports)	global CO_2 emissions from Industrial ($Mt\ CO_2e$)	−0.901

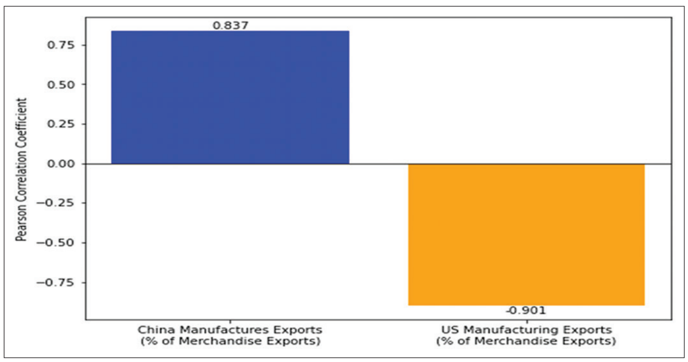
Source: Made by author

Table 4: Decision tree feature importance

Independent variables	Feature importance
China Manufacturing exports (% of merchandise exports)	0.810203
United States manufacturing exports (% of merchandise exports)	0.189797

Source: Made by author

Figure 2: Pearson correlation coefficient



Source: Made by author

coefficients of the decision tree algorithm. This relationship is illustrated in Tables 3 and 4.

From Table 3, the current relationship between global CO_2 emissions from industrial sources and China's manufacturing exports is positive, while the relationship between U.S. manufacturing exports and global industrial CO_2 emissions is negative. Figure 2 shows that clearly. Table 4 shows China Manufacturing sector more influence on CO_2 emission by 81% compare to United States manufacturing sector by 19%. Therefore, China must adopt policies to reduce emissions from its manufacturing sector.

6. CONCLUSION

This study has comprehensively analyzed the relationship between industrial exports from China and the United States and global carbon emissions from the industrial sector by employing a decision tree algorithm. Our empirical findings reveal that China's manufacturing exports are positively associated with increased CO_2 emissions, whereas U.S. Manufacturing exports show an inverse relationship with global industrial emissions. The effectiveness of the decision tree model is confirmed by its strong R^2 and low MSE values, which surpass those of other machine learning approaches. These findings underscore the significant impact of industrial trade on environmental outcomes, illustrating how the export profiles of both countries distinctly influence global carbon emissions. These efforts could help align economic advancement with environmental sustainability, thus advancing global climate policy goals.

The study provides valuable insights into how industrial exports affect carbon emissions and identifies several potential research paths. Future studies should examine how sensitive these relationships are to changes in model assumptions and incorporate more variables that could reflect additional aspects of environmental impact. Expanding the investigation to include multiple nations could provide a more thorough understanding of the relationship between trade and emissions across various economic conditions. The decision tree algorithm's findings indicate that employing advanced ensemble methods or hybrid models may lead to even deeper insights.

It is crucial to recognize the limitations of this study. Although effective, the decision tree model may encounter over-fitting and parameter-setting sensitivity issues. Future research should employ strong cross-validation methods and explore hybrid models integrating decision trees with machine learning to improve predictive accuracy and generalizability. Furthermore, additional studies may gain from including temporal dynamics and external economic factors, such as regulatory changes and market fluctuations, to enhance our understanding of the relationship between industrial exports and carbon emissions over time. These enhancements will contribute to academic knowledge and provide valuable insights for policymakers focused on promoting sustainable industrial practices.

7. FUNDING

This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (grant number IMSIU-DDRSP2503(

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