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Green growth or pollution haven? Investigating the nexus between carbon emissions, FDI, and trade openness based on artificial neural network

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Abstract

This paper employs a neural network algorithm to analyze the effects of trade openness and foreign direct investment (FDI) on carbon emissions. The neural network technique effectively captures nonlinear interactions among variables, as seen by the model's high prediction accuracy (MSE = 0.004 and $R^2 = 0.93$). The analysis reveals a strong positive relationship between carbon emissions, trade openness, and foreign direct investment (FDI). Significant results show that FDI (0.518573) has a greater impact on carbon emissions than trade openness (0.44). Foreign investment, particularly in industrial and energy-intensive sectors, can significantly increase carbon dioxide emissions through increased energy consumption. Similarly, increased trade openness increases emissions through increased production and transportation, as well as countries' acceleration of production to meet global demand for their products. The study shows that both FDI and trade openness contribute to higher carbon emissions, but FDI is the more significant factor. Although these economic factors promote growth and globalization, they also pose significant environmental risks if they are not regulated and internationally controlled. The findings underscore the importance of cooperation among countries to establish a regulatory framework and controls that govern foreign direct investment (FDI) and trade activities. To achieve a balance between economic growth and reducing carbon emissions, policymakers should encourage foreign investment in environmentally friendly activities, use energy-efficient technologies, and establish trade regulations that support environmental sustainability.

Keywords: CO_2 emissions, Foreign direct investment, Neural network, Trade openness.

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1. Introduction

The rapid growth of globalization has fostered a complex relationship among economic expansion, foreign direct investment (FDI), trade openness, and environmental sustainability. As nations increasingly integrate into the global market, concerns regarding carbon emissions (CO_2) have intensified. This has prompted researchers and policymakers to evaluate whether globalization promotes green growth or exacerbates environmental harm. By encouraging innovation and knowledge transfer, the essay suggests that trade openness and foreign direct investment (FDI) can support sustainable economic growth [1]. However, some studies indicate that these factors can reinforce the "pollution haven" theory, which postulates that highly polluting companies might relocate to countries with laxer environmental laws [2]. Given the urgent need to address climate change and the effects of economic globalization on environmental outcomes, it is crucial to explore the intricate connections between CO_2 emissions, FDI, and trade openness. This study employs a neural network algorithm to offer a new analytical perspective on these relationships, clarifying whether globalization fosters sustainable economic development or deteriorates environmental quality.

The debate over the impact of foreign direct investment (FDI) and trade openness on environmental sustainability is hotly debated in academia. The "pollution halo" theory posits that FDI can improve environmental quality by fostering cleaner production technologies and increasing corporate ecological responsibility [3]. However, "pollution havens" indicate that multinational companies often relocate their polluting operations to nations with laxer environmental regulations, increasing $CO2$ emissions [4]. In a similar vein, trade openness introduces two main challenges. On the one hand, it can promote resource-heavy industries and elevate industrial emissions. However, it provides access to revolutionary environmental technologies that can help reduce carbon emissions [5]. These divergent perspectives highlight the need for advanced analytical techniques, such as artificial intelligence (AI) models, to represent complex nonlinear dynamics properly.

Econometric models, including panel regressions and cointegration methods, are frequently used to analyze the interactions between CO_2 emissions, foreign direct investment (FDI), and trade openness. The findings present a mixed perspective. Some research suggests that FDI adversely affects environmental quality [6] while other studies propose that trade liberalization may result in higher $CO2$ emissions [7]. Conventional methods often depend on linear relationships, which can oversimplify the complex links between economic factors and environmental outcomes. In contrast, neural network algorithms, a form of AI, offer significant methodological benefits by effectively identifying nonlinear interactions and patterns, free from restrictions of specific functional forms. This research utilizes a neural network approach to enhance prediction accuracy and offer a more detailed insight into the environmental impacts of economic globalization.

This study contributes to the expanding domains of sustainable development and computational economics by integrating AI into environmental economics analysis. The results have important policy implications, illuminating the interplay between international economic policies and ecological sustainability. These findings could help governments and international organizations formulate regulations that capitalize on the benefits of globalization while tackling environmental issues.

Policymakers must grasp the link between FDI, trade openness, and CO_2 emissions to harmonize economic advancement with environmental sustainability. Governments can promote green growth by supporting trade openness and attracting foreign direct investment (FDI). This involves creating trade agreements that benefit low-carbon industries and implementing measures to draw sustainable overseas investments. Conversely, enhancing international cooperation and enforcing stricter environmental laws will be crucial to reducing the negative ecological impacts of globalization if the pollution haven theory holds. Policymakers can utilize AI-powered forecasting models to formulate adaptive strategies that diminish carbon emissions while preserving economic competitiveness.

Recent progress in machine learning improves environmental decision-making and fosters sustainable economic growth. This study showcases how neural network algorithms facilitate AI-driven analytics to tackle intricate ecological problems. Machine learning enhances climate policy frameworks by delivering accurate forecasts, optimizing resource allocation, and revealing patterns that traditional econometric models may overlook. Utilizing AI in environmental research can inspire innovative solutions that promote sustainable development as society embraces the digital revolution.

2. Related Works

This section comprehensively analyzes various studies examining the relationship between FDI, trade openness, and carbon emissions. The studies reviewed cover a variety of geographical contexts, methodologies, and theoretical perspectives, providing detailed insights into these complex relationships.

Numerous studies support the Pollution Haven Hypothesis (PHH), suggesting that weak environmental regulations entice foreign direct investment (FDI), which results in higher carbon emissions. Khan and Ozturk [8] illustrate that incoming FDI notably raises CO_2 emissions in Asia, indicating a two-way relationship. In a similar vein, Murshed [9] uncovers an inverted U-shaped link between FDI and carbon intensity in BRICS countries, pointing out that initially, FDI boosts emissions but leads to a decline at elevated economic stages. Zhang, et al. [10] further support this in China, indicating that while FDI promotes growth, it also intensifies industrial pollution. Conversely, Rahma, et al. [11] question the PHH in ASEAN Plus Six countries, suggesting that FDI lowers emissions while trade openness worsens them. Achuo and Ojong [12] also identify a quantile-dependent dynamic in Africa: FDI decreases emissions in high-income brackets but increases them in low-income brackets, highlighting the situation's complexity.

The temporal aspect of foreign direct investment (FDI) and trade effects is crucial. According to Ekesiobi, et al. [13] and Ekesiobi, et al. [14]. FDI and trade initially reduce emissions in Nigeria but lead to an increase over the long term. Additionally, Bagadeem, et al. [15] use threshold regression to show that the effect of FDI on emissions varies, while trade openness affects different sectors in various ways. In China, Liu, et al. [16] demonstrate that FDI and trade increase industrial emissions in the long run, influenced by technological innovations. Furthermore, Shahbaz, et al. [17] highlight a global feedback loop between trade openness and emissions, resulting in adverse environmental impacts across different income groups.

Renewable energy and technological advancements are essential in addressing climate change. Murshed [9] and Zeng, et al. [18] highlight the importance of renewable energy in lowering carbon intensity among BRICS nations. Ho, et al. [19] emphasize the immediate emission reductions resulting from technological innovation in Malaysia, while Ke, et al. [20] discuss the positive impacts of ICT on developing countries. The quality of the institution is essential. Leitão [21] connects human development and renewable energy to reduced emissions in G7 countries, while Huay, et al. [22] associate corruption with increasing polluting FDI inflows in developing nations. Khan, et al. [23] emphasize how human capital moderates the impact of foreign direct investment (FDI) emissions in educated regions.

Many studies conducted in Nigeria (e.g., Ekesiobi, et al. [13] and Ekesiobi, et al. [14] support the Pollution Haven Hypothesis (PHH), suggesting that foreign direct investment (FDI) and trade contribute to a rise in long-term emissions. In China, research by Liu, et al. [16] and Zhang, et al. [10] supports the "pollution shelter" hypothesis, while He, et al. [24] reveal that tariff policies influence emissions asymmetrically. Tachie, et al. [25] found that trade openness raises emissions across 18 EU countries. Farooq, et al. [26] connect FDI with rising emissions in OECD nations, where urbanization and renewable energy present mitigating factors. In ASEAN and Asia, Hossain, et al. [27] affirm the Environmental Kuznets Curve (EKC), indicating that FDI can lower emissions via green technology, contrasting with Effendi, et al. [28] who argue that FDI and trade exacerbate emissions in Indonesia.

Numerous studies utilize sophisticated econometric methods. Bagadeem, et al. [15] employ threshold regression to identify sectoral variations, whereas Achuo and Ojong [12] use quantile regression to examine income-related disparities. Dou, et al. [29] investigation of nonlinear and mediation effects reveals a U-shaped relationship between trade openness and carbon productivity. Using dynamic panel data, Gök, et al. [30] differentiate between the impact of strict and lax regulations, demonstrating the influence of green havens under strict rules and PHH effects under loose regulations.

The literature emphasizes the necessity of customized policies. Zeng, et al. [18] support investing in renewable energy within BRICS, whereas Khan and Ozturk [8] emphasize the importance of aligning FDI with sustainability efforts in Asia. Liu, et al. [16] advocate for incentives to promote green innovation in China, and Huay, et al. [22] suggest implementing anti-corruption measures to limit polluted FDI. Leitão [21] and Farooq, et al. [26] point out that urbanization and renewable energy are key factors in reducing emissions in developed economies.

Although considerable research has been conducted on the relationship between FDI, trade, and emissions, significant gaps remain, especially regarding methodology and context. Most studies primarily rely on traditional econometric methods, such as panel data analysis and threshold regression. However, none of the examined papers use neural network algorithms to analyze the nonlinear, dynamic interactions among carbon emissions, foreign direct investment (FDI), and trade openness. This methodological shortcoming is vital, as neural networks can capture intricate, high-dimensional relationships and temporal dependencies more effectively, particularly in diverse settings like sectoral or regional variations [15, 19].

Second, while many studies recognize the asymmetric and threshold-dependent impacts of FDI and trade (e.g., [12, 29]), limited research exists on how these dynamics change with different policy regimes or levels of technological adoption. For instance, predictive machine-learning algorithms have not thoroughly analyzed the impact of green financing on the transition to renewable energy, as explored by Liu, et al. [16] and Tariq, et al. [31].

Third, it is common to oversimplify sectoral and regional differences. Gök, et al. [30] distinguish between lax and stringent regulatory settings, yet no study combines spatial or institutional data with neural networks to forecast emission trends across varied policy contexts. Likewise, sector-focused assessments (like those by Liu, et al. [16]) fail to detail the interaction between foreign direct investment in high-pollution sectors and trade openness over time.

In conclusion, frameworks for policy integration are largely missing. While many studies suggest separate initiatives, such as anti-corruption measures [22] and renewable energy incentives [18] none effectively model the combined effects of

green growth strategies through algorithmic methods. This highlights the necessity for AI-based models to explore multiple policy avenues that can reconcile economic advancement with emission reductions.
Utilizing neural network applications to bridge these gaps can improve predictive accuracy, guide targeted policies, and provide data-driven insights that reconcile the "green growth versus pollution haven" debate.

3. Data

This research employs an extensive World Bank [32] dataset spanning from 1979 to 2023. It encompasses essential economic and environmental indicators from various countries, facilitating a thorough examination of the connections among CO_2 emissions, foreign direct investment (FDI), and trade openness.

3.1. Variables Used

- The dependent variable in this study, carbon emissions (CO_2), is measured in metric tons. These are the primary variables.
- Foreign direct investment (FDI) refers to the inflow of foreign capital as a percentage of GDP.
- Trade openness reflects economic integration with the global market. It is computed as the sum of imports and exports divided by GDP.

To ensure accuracy and consistency, missing values are addressed as necessary using mean imputation or interpolation. The data is normalized by applying log transformations to variables with skewed distributions, like CO2 emissions, foreign direct investment, and trade openness; Table 1 shows the feature statistics.

Table 1.
Feature Statistics.

Variables	Source Of Data	Mean	Mode	Median	Dispersion	Minimum	Maximum
CO2 emissions	World Bank	28162.9	19165	26031.2	0.23	19165	39023.9
Trade openness (% GDP)	World Bank	47.29	33.8	45.8	0.19	33.8	61.25
FDI (%GDP)	World Bank	1.95	0.36	1.79	0.63	0.36	542

4. Research Methodology

4.1. Artificial Neural Networks

This study simulates human-like learning processes using artificial neural networks (ANNs) to assess complex correlations between variables. The network architecture consists of an input layer, several hidden layers, and an output layer interconnected by weighted connections and nonlinear activation functions. Input moves successively through these layers, allowing the model to identify complex patterns in the dataset [33].

4.2. Layer Computations

- Input Layer:

The features of the input are shown as $X = \{x_1, x_2, \dots, x_n\}$, where n indicates the number of input variables.

- First Hidden Layer:

The weighted sum of inputs plus a bias term is determined for every neuron j in the hidden layer as follows:

$$a_j = \sum_{i=1}^{n} v_{ij} \cdot x_i + c_j$$

Where:

- *Vij* : Weight connecting input *xi* to hidden neuron *j*.
- *cj*: Term for bias in neurons *j*.
- *aj*: Pre-activation value.

aj is subjected to a nonlinear activation function. Typical tasks consist of:

Sigmoid:

$$h_j = \frac{1}{1 + e^{-a_j}}$$

ReLU:

$$h_j = max(0, a_j)$$

Output Layer:
The weights from the hidden layer are used to calculate the final output, which is o.

$$o = \sum_{j=1}^{m} u_j \cdot h_j + d$$

Where:

- *uj* Hidden neuron weight connecting *j* to the output.
- *d*: bias in the output layer.

No activation is used for regression problems. A softmax function is applied to multi-class outputs for classification:

$$\hat{y}_k = \frac{e^{o_k}}{\sum_{l=1}^{C} e^{o_l}}$$

4.3. Error Minimization

The error function is used to assess the model's performance. Mean Squared Error (MSE) is used for regression:

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

We use Cross-Entropy Loss for classification:

$$\mathcal{L} = -\sum_{k=1}^{C} y_k \log(\hat{y}_k)$$

4.4. Optimization via Backpropagation

To reduce $\mathcal{L}$, the network uses gradient descent to modify weights iteratively. The following is the most recent weights rule:

$$v_{ij} \leftarrow v_{ij} - \eta \frac{\partial \mathcal{L}}{\partial v_{ij}}$$

Where the learning rate is denoted by η. Gradients are calculated by backpropagation by:
1. Forward Pass: Distribute inputs to calculate forecasts.
2. Backward Pass: Beginning with the output layer, derive gradients using the chain rule.

5. Model Evaluation

To determine the model evaluation, the prediction performance shown in Table 2 and Figure 1 must be determined, as must the accuracy performance shown in Table 3.

5.1. Prediction Performance

Table 2.
CO2 emissions actual values vs. prediction values.

year	CO2 emissions actual values (Mt)	Neural Network prediction (Mt)
1979	20031.87432	19646.4119
1980	19782.4409	19708.0015
1981	19411.67562	20312.46468
1982	19164.98126	20027.06725
1983	19310.22447	19778.68259
1984	19942.53167	19844.2585
1985	20206.5078	20304.95045
1986	20565.49602	20362.9021
1987	21224.68139	21615.80416
1988	21984.21555	21923.62278
1989	22370.53567	22622.494
1990	22681.38901	23825.22089
1991	22808.7611	21911.12987
1992	22708.62302	21446.35543
1993	22801.9195	22234.49076
1994	23033.38582	22836.14804
1995	23680.32941	23673.22638
1996	24146.62747	23815.69271
1997	24597.49777	24267.66294
1998	24755.42659	24644.27744
1999	24939.29622	24966.74454
2000	25724.52253	25614.14457
2001	26029.8699	26095.02599
2002	26433.83243	26236.32028
2003	27656.05582	27526.37734
2004	28949.26228	31697.71895
2005	30043.45162	33266.29496
2006	31063.84867	33533.49268
2007	32231.51566	30980.08941

2008	32431.97183	32640.20207
2009	32019.48811	31997.08232
2010	34002.8628	36420.97049
2011	35059.43349	34348.03188
2012	35521.73352	35893.08724
2013	36221.20501	35867.97087
2014	36428.25541	36856.96908
2015	36300.97938	34971.89437
2016	36424.61277	32532.66694
2017	37049.12449	36073.00209
2018	37975.63314	38859.19472
2019	38066.88412	36849.59842
2020	36156.06548	34721.00103
2021	38120.21508	36809.08615
2022	38246.21959	38204.17187
2023	39022.74655	38657.65137

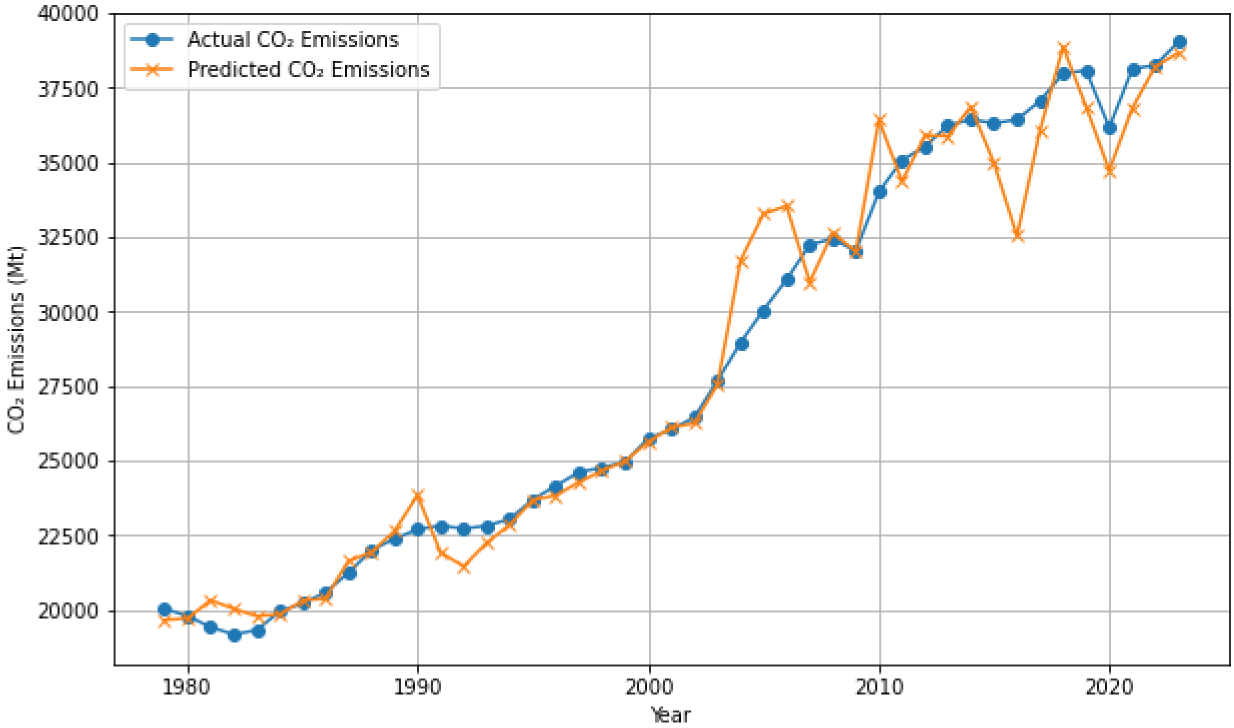

Figure 1.
CO2 emissions actual vs. predicted values.

Table 2 and Figure 1 show the great degree of the neural network's prediction dependence on independent variables; actual values often match predicted values.

5.2. Accuracy Performance

The efficacy of neural network regression is assessed using a variety of error measurements:

- Mean Squared Error (MSE):

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

- Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{MSE}$$

- Mean Absolute Error (MAE):

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

- R-squared (R^2):

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

Table 3.
Neural Networks Accuracy.

Algorithms	MSE	RMSE	MAE	R^2
NNs	0.004	0.63	0.045	0.93

Table 3 shows a great degree of neural network accuracy, with the MSE value very low near zero and R2 very high near one. These results led to high prediction performance and relationship determination.

5.3. Neural Network Feature Importance

Feature importance of algorithms determines the degree of effect every independent variable has on the dependent variable; Table 5 determines the impact degree.

Table 4.
Neural network feature importance.

Feature	Score
Trade Openness	0.445498
Foreign direct investment	0.518573

Table 4 shows the significance scores, demonstrating the impact of Trade Openness and foreign direct investment (FDI) on CO_2 emissions forecasts generated by a Neural Network model.

Foreign Direct Investment: (0.518573) Foreign Direct Investment (FDI) affects CO_2 emissions. An increase in foreign investment, particularly in industrial and energy-intensive sectors, could significantly elevate emissions. This surge in investment typically leads to increased energy use, enhanced infrastructure, and industrial growth, all of which elevate CO_2 emissions. Trade Openness: (0.44) While trade openness is essential, foreign direct investment (FDI) is more significant. Increased trade activities, including exports and imports, can increase energy consumption during production and transportation, thus impacting CO_2 emissions. The strength of the relationship between variables can be determined using the Pearson correlation coefficient, as shown in Table 5.

The Pearson correlation coefficient shows the degree to which two variables are linearly connected. Weak linear relationships are represented by values around 0, strong negative relationships are represented by values near -1 and strong positive correlations are represented by values near 1.

Table 5.
Pearson correlations.

Independent variables	Dependent variable	Correlation coefficient
Trade openness (%GDP)	CO2 emissions	0.94
FDI (% GDP)	CO2 emissions	0.70

Table 5 shows a strong positive relationship between CO2 emissions and both variables, trade openness and FDI.

6. Conclusion

Using a neural network regression model, This study has comprehensively analyzed the relationship between carbon emissions, foreign direct investment (FDI), and trade openness. The results indicate a strong positive correlation between CO_2 emissions and trade openness and FDI, with FDI playing a slightly more significant role. The findings suggest that increased foreign direct investment (FDI) inflows, especially in energy-intensive and industrial sectors, significantly elevate carbon emissions. Similarly, while trade openness can foster economic growth, it contributes to increased emissions from more significant energy usage in production and transportation.

The neural network model employed in this study exhibited impressive predictive accuracy ($R^2 = 0.93$, MSE = 0.004), highlighting its ability to understand the complex, nonlinear dynamics between economic globalization and environmental sustainability. In contrast to conventional econometric models that typically presume linear relationships, the neural network algorithm adeptly identified detailed dependencies. It offered a strong framework for predicting emissions trends influenced by economic indicators. This underscores the significance of employing AI-driven analytical tools in environmental economics.

From a policy perspective, the results emphasize the necessity for a balanced approach to FDI and trade liberalization. Regulators must establish rules that attract sustainable and environmentally conscious investments while addressing the environmental impacts of foreign capital. Initiatives such as promoting clean energy investments, imposing ecological standards on polluting industries, and refining trade policies to support eco-friendly practices can encourage green growth without increasing pollution levels. Furthermore, global cooperation will be crucial for establishing international environmental standards relevant to FDI and trade.

Future studies must investigate the differences in the FDI-emissions relationship across various sectors and regions. This research has highlighted a general connection between economic factors and environmental degradation, but more detailed analyses utilizing sector-specific and region-focused neural network models could reveal richer insights. Moreover, incorporating climate policies, green finance strategies, and technological innovations into the modeling framework could improve the predictive power of AI-driven methods, ultimately providing more focused policy suggestions for sustainable economic development.

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