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Evaluating Environmental Taxes and CO2 Emission Reduction in the UK: A Neural Network Approach

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Abstract

This paper aims to determine the effects of environmental taxes on CO2 emissions in the United Kingdom (UK). To determine their effectiveness in reducing carbon emissions depending on Neural Networks algorithms as a machine learning algorithm. The paper approved the strong negative relationship between CO2 emissions and Taxes on Pollution, Taxes on Resources, Taxes on Transport, and Taxes on Energy. This indicates the potential of these taxes and their positive results in reducing carbon emissions in the United Kingdom. Also, the paper approved that the taxes on pollution have the highest effects on CO2 emissions at 28.6%, followed by taxes on resources at 25%, taxes on transport at 23.7%, and taxes on energy at 22.8%. So, the UK policymakers should maximize depending on taxes on pollution compared to other taxes And rely on other types in order of influence.

Keywords: *Environmental Taxes, CO2 Emission, Neural Network, machine learning, taxes on pollution.*

JEL-Codes: *Q15, C63, C80, C81, C87*

Introduction

A primary global concern is climate change, primarily driven by carbon dioxide (CO2) emissions contributing to global warming. Ecological taxes are a crucial element of the environmental policies the United Kingdom (UK) has enacted to reduce CO2 emissions. These levies, often called green taxes, target activities that harm the environment, especially those that generate greenhouse gas (GHG) emissions (OECD, 2020). These taxes promote more sustainable practices by raising the costs linked to polluting activities (Heine et al., 2012). Nevertheless, there remains ongoing debate among researchers and policymakers regarding the effectiveness of these taxes in cutting CO2 emissions.

The UK has introduced several environmental taxes, such as the Climate Change Levy (CCL), Carbon Price Floor (CPF), and fuel duties. By 2050, these initiatives aim to help the nation reach its net-zero emissions target. Prior research has explored how these taxes influence energy consumption, emissions, and economic growth. Traditional econometric models may not adequately capture the intricate and nonlinear relationships between taxation and CO2 emissions.

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Recent advances in artificial intelligence (AI) and machine learning (ML) offer new avenues for better analyzing these interactions.
Artificial Neural Networks (ANNs) have become key predictive modeling and pattern recognition tools, especially in environmental and economic studies (Zhang et al., 2022). Unlike linear regression models, ANNs can capture complex relationships and interactions among variables, leading to more precise insights regarding the effects of environmental taxes on CO2 emissions. This study's use of neural networks seeks to address the drawbacks of conventional statistical methods by utilizing data-driven techniques to evaluate policy effectiveness (Goodfellow, Bengio, & Courville, 2016).
In the United Kingdom, the four primary types of environmental taxes are energy taxes (covering transportation fuels), pollution taxes, resource taxes, and transport taxes (excluding transportation fuels). Energy taxes, including fuel tariffs and carbon pricing, aim to encourage the adoption of renewable energy sources and decrease fossil fuel use. By raising the costs associated with carbon-heavy energy sources, these taxes motivate both industries and households to switch to cleaner energy alternatives, thus aiding in reducing CO2 emissions.
Pollution taxes target specific environmental externalities, including industrial emissions, landfill waste, and chemical pollutants. As financial incentives, these levies encourage companies to adopt greener manufacturing practices and improve waste disposal. Pollution taxes effectively lower industrial emissions and foster sustainable practices (Heine et al., 2012). In this strategy, artificial neural networks are crucial because they enable policymakers to analyze large volumes of data to identify optimal tax rates and forecast future environmental impacts.
Taxes on natural resources are designed to manage limited resources like water, minerals, and forest products. They aim to foster efficiency and sustainable extraction methods, lessening environmental harm. Similarly, transport taxes (not including fuel charges) encompass fees related to vehicle emissions, congestion charges, and tolls, all meant to alleviate traffic congestion and encourage the use of public transport. Neural network models can enhance the evaluation of these taxes by revealing complex relationships between taxation strategies and how economic sectors respond.
This study uses a neural network approach to evaluate how environmental taxes affect CO2 emissions in the UK. It employs artificial neural networks (ANNs) to examine historical tax and emission records, seeking patterns to forecast future trends. The findings will contribute to ongoing discussions about environmental taxes and provide essential new insights to lawmakers aiming to enhance tax legislation with sustainable development goals. Furthermore, this research will emphasize the significance of AI-driven methods in environmental economics, underscoring their role in policy assessment and decision-making.
This paper is organized as follows: Section 2 reviews pertinent literature on environmental taxes and CO2 emissions reduction. Section 3 discusses data sources and the neural network framework. Section 4 outlines the methodology. Section 5 presents the results and analysis. Finally, Section 6 emphasizes the recommendations for future research and policy enhancements.

RELATED WORKS

The impact of environmental taxes on reducing CO2 emissions has been extensively analyzed in different economic settings. This section assesses previous studies regarding ecological taxation's effectiveness in lowering emissions, focusing primarily on the UK and comparable economies.

The studies are categorized into themes: carbon taxation, energy taxation, pollution taxation, resource taxation, transport taxation, and broader economic implications.
Obani and Akroh (2024) evaluated the effectiveness of carbon pricing in the UK, confirming that it significantly lowers greenhouse gas emissions while promoting renewable energy adoption. According to Gugler et al. (2023), the carbon tax in Britain resulted in a 40% decrease in emissions from the power sector from 2012 to 2016. Noubissi et al. (2023) explored OECD countries and found a causal relationship between carbon taxes and lower emissions, particularly in the transportation and manufacturing industries.
According to Matusevich et al. (2024), introducing carbon tax programs and other regulatory measures led to a 30% decrease in emissions and a 25% decline in carbon intensity. In a similar vein, Abrell et al. (2019) evaluated the UK Carbon Price Support (CPS) using machine learning techniques, showing a 6.2% decrease in emissions between 2013 and 2016 at an abatement cost of €18 per ton. Adami et al. (2022) pointed out the inconsistencies within the UK's carbon tax framework and recommended simplifying the tax system to improve efficiency and minimize carbon leakage.
Sahi and Lama (2024) investigated carbon taxation in G20 nations and found that successful policies significantly enhance emission reduction effectiveness. Dyshlyk's (2024) analysis of CO2 taxation in the EU shows lower emissions are associated with higher tax rates. On the other hand, Tu et al. (2022) examined the economic and environmental effects of carbon emission levies, demonstrating their efficacy despite early financial challenges.
Yusoff et al. (2024) explored methods to optimize carbon taxes to reduce levels of environmental pollution, showing that effective taxation can lead to substantial reductions in emissions. In contrast, Mehta and Derbeneva (2024) examined African carbon taxes and noted their effectiveness in lowering emissions while bolstering economic stability.
In their 2023 study, Al Shammre et al. utilized a dynamic panel threshold model across OECD nations, revealing that environmental taxes significantly lower CO2 emissions when GDP surpasses certain percentage thresholds. Meanwhile, Zolkover et al. (2024) examined green taxation policies and discovered that these measures foster the modernization of the sustainable industrial sector.
Symons and Proops's 1994 simulation analysis showed that carbon taxes could cut CO2 emissions by about 20% and affect consumer purchasing power.
Bretschger and Grieg (2020) explored the fuel taxation policy in the UK, emphasizing its significance in curbing CO2 emissions from transportation while fostering economic growth. Zhou et al. (2023) affirmed that both environmental taxation and investments in renewable energy play a significant role in lessening the UK's ecological footprint. Koval et al. (2022) pointed out that varied environmental tax rates effectively promote the advancement of clean technology. Addai et al. (2024) showed that environmental taxes in the UK are inversely related to carbon emissions, emphasizing their critical role in promoting ecological sustainability.
Feng et al. (2010) studied multi-GHG taxes in the UK and found them more effective than CO2-specific taxes. However, they noted that these taxes disproportionately impact lower-income households. Zhu et al. (2023) verified that environmental taxes are more effective when supported by a higher share of renewable energy.
Klymenko (2022) emphasized the importance of energy taxation in promoting environmental sustainability by incentivizing cleaner technologies and enhancing energy efficiency.

Máté et al. (2023) analyzed the link between energy supply and environmental taxation, finding that taxation positively affects carbon intensity unless coupled with renewable energy investments.
Adetutu et al. (2020) examined carbon tax impacts on energy intensity in the UK, demonstrating that taxation influences technological progress more than direct energy efficiency improvements.
Dobrowolski and colleagues (2024) studied environmental tax revenues in various countries, revealing a varied effect on decarbonization, notably a slight drop in carbon productivity in the UK. Meanwhile, Kettner-Marx and Kletzan-Slamanig (2018) posited that market-based pollution taxes effectively promote compliance without imposing significant costs on society.
In their analysis of the UK's Climate Change Levy, McEldowney and Salter (2016) emphasized how political and economic considerations impact the findings. He et al. (2019) examined the role of environmental taxes in China and OECD countries, demonstrating that tax laws become more effective when tailored to the economic context and the emissions of specific industries.
Leu and Betz (2016) investigated the current assessment of carbon taxes, emphasizing their pros and cons in measuring effectiveness. Tamura et al. (1995) analyzed the effect of environmental taxes on CO2 emissions via an input-output model and found that such taxes are crucial for reducing overall emissions.
Özarslan Doğan and Güler (2023) examined environmental taxes in G7 nations and discovered a significant inverse relationship between tax rates and carbon emissions.
Brand and colleagues (2013) assessed vehicle tax policies in the UK and found that feebate schemes expedite the shift to low-carbon transportation technologies. Potter and colleagues (2001) stated that a combination of fuel taxes and efficiency initiatives is essential for effectively reducing transportation emissions.
Boardman (2003) examined consumer perceptions of lower-carbon transportation, emphasizing the need for specific fiscal policies that promote sustainable mobility. Sørensen et al. (1994) examined green tax reform and discovered that transitioning from labor to pollution-based taxes can significantly decrease transport emissions.
Barker (1995) investigated fiscal strategies for reducing greenhouse gas emissions, emphasizing how energy taxes can lower emissions without jeopardizing job security. In a study by Bridgen and Büchs (2023), it was revealed that UK carbon tax policies disproportionately affect low-income households, leading them to recommend implementing compensatory measures to assist these vulnerable groups.
Grdinić et al. (2015) showed that transportation-related environmental taxes considerably lower greenhouse gas emissions, particularly with congestion charges.
Numerous studies emphasize the effectiveness of environmental taxation. Moritz and Abdo (2013) studied green taxes in the UK's energy sector, revealing that although these taxes encourage renewable energy, excessively high rates might deter investment. Furthermore, Wolde-Rufael and Mulat-Weldemeskel (2021) evaluated the effects of environmental policies in emerging economies, finding that well-designed environmental taxes can significantly reduce CO2 emissions, thereby supporting the concept of a "green dividend."
Dogan et al. (2022) explored how green growth and environmental taxes function together, revealing that ecological taxes can reduce CO2 emissions when paired with renewable energy strategies. Similarly, Ulucak and Kassouri (2020) examined the non-linear impacts of environmental taxation, indicating that CO2 reductions are more pronounced at elevated levels of globalization.

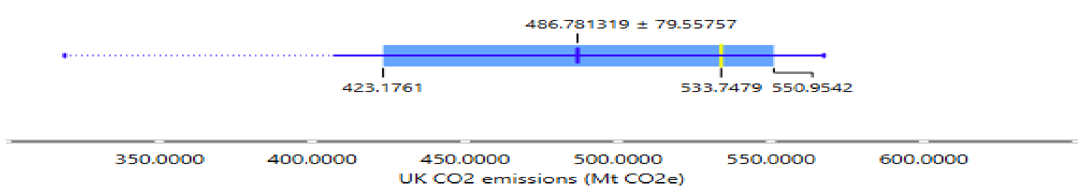
Zolkover et al. (2024) emphasized the role of green taxation in advancing sustainable industrial modernization. Kettner-Marx et al. (2018) validated that carbon taxation leads to enduring emission reductions while sustaining economic stability. Research by Xu and Li (2024) on corporate carbon taxation policies found that these frameworks significantly reduce emissions in highly polluting industries and encourage green innovation.
Mehta and Derbeneva (2024) examined how environmental taxes affect Africa, discovering that carefully crafted tax policies can significantly lower carbon emissions and bolster economic stability. Similarly, Tamura et al. (1995) employed econometric modeling to assess the effects of carbon taxes, validating their success in decreasing total emissions.
In their investigation of ways to enhance the application of the carbon price, Yusoff et al. (2024) found that carefully considered fiscal measures result in more significant emission reductions with less economic compromise. Similar conclusions were drawn by Özarslan Doğan and Güler (2023), who studied environmental taxes in the G7 countries and identified a strong inverse relationship between tax rates and carbon emissions.

Data

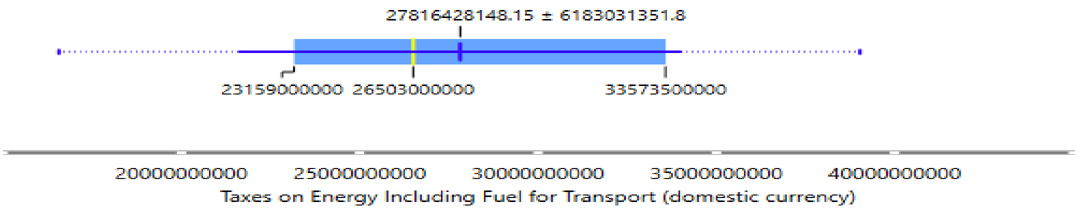
This study employs a comprehensive dataset to explore the connection between environmental taxes and CO2 emissions in the United Kingdom from 1995 to 2021. The dependent variable in this analysis is CO2 emissions, which indicate the level of environmental impact. The International Monetary Fund (IMF) offers a range of ecological taxation types as independent variables. This provides a comprehensive overview of fiscal instruments aimed at reducing emissions. Each category—energy, pollution, resource exploitation, and transportation taxes—uniquely influences economic and environmental practices; the box plot in Figure 1 shows the data stability.
The World Bank's CO2 emissions data has been carefully compiled to ensure accuracy and consistency in monitoring national emission patterns. This study utilizes high-quality data from these two trustworthy sources to provide a solid foundation for empirical analysis. The dataset covers over three decades, allowing for a comprehensive examination of long-term policy impacts and identifying significant environmental and tax legislation changes.
This dataset provides a valuable opportunity to investigate the complex relationship between tax schemes and emission levels, particularly considering the evolving environmental policy landscape in the UK. It is a foundation for employing advanced analytical models—specifically, artificial neural networks—to uncover non-linear relationships and predictive insights that exceed those obtainable through traditional econometric methods.

Figure 1: Data Box Plot

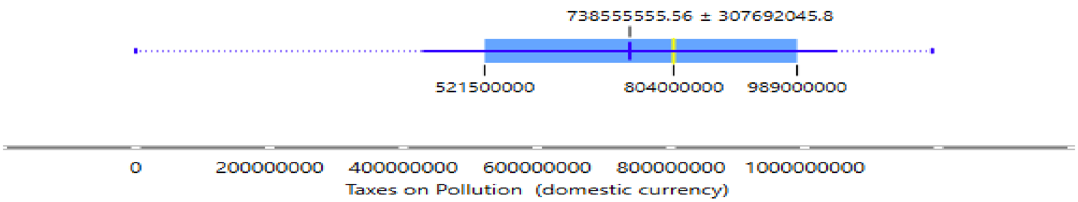
(A)



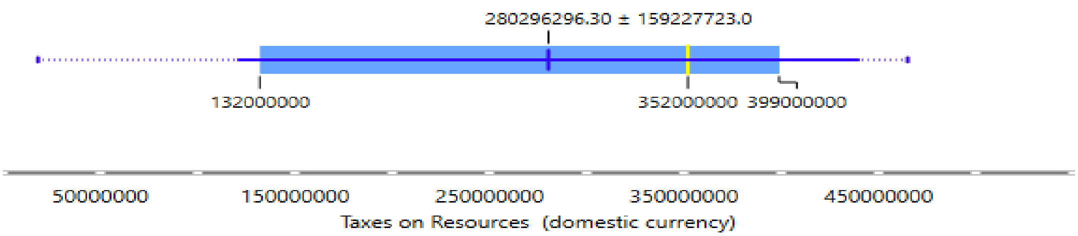
(B)



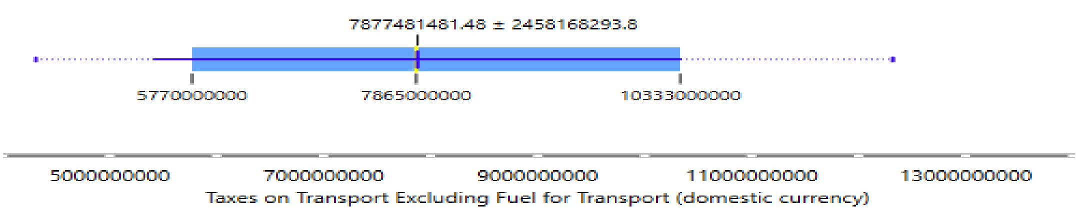
(C)



(D)



(E)



The statistical charts depicting the distribution of environmental taxes and CO_2 emissions in the United Kingdom reveal variations in these factors over time. The first chart, centered on CO_2 emissions, shows that average emissions are around 486.78 million metric tons of CO_2 equivalent, with a standard deviation of 79.56 million metric tons. The majority of values fall between 423.17 million and 550.95 million metric tons, indicating moderate variations in emission levels that are likely a result of shifts in environmental and economic policies.

The data indicates that energy taxes, which include transportation fuel, average approximately $2.78 trillion, with a significant standard deviation of $618 billion. Total tax revenues range from

\$2.31 trillion to \$3.35 trillion, reflecting significant variations that may be connected to changes in energy prices or tax policies regarding fuel and energy consumption.
The data on pollution taxes reveal that the average revenue is £738 million, with a standard deviation of £307 million. The values range between £521 million and £989 million, indicating considerable differences in pollution-related taxation, which could be attributed to shifts in environmental legislation and the enforcement of stricter regulations on emissions.
Regarding taxes on resource exploitation, the average tax revenue stands at £280 million, with a standard deviation of £159 million. The data reveals a value fluctuation between £132 million and £399 million, emphasizing revenue differences tied to varying economic activities in resource extraction and usage.
In conclusion, transport taxes, excluding fuel, generate an average revenue of £787 million, with a standard deviation of £245 million. The reported figures show considerable variation, ranging from £577 million to £1.03 billion, indicating shifts in policy and changes in demand for transportation services.

METHODOLOGY

Artificial neural networks (ANNs) emulate the neural networks found in animal brains. They comprise interconnected components called "artificial neurons," allowing systems to identify complex data patterns through adaptable and layered adjustments. ANNs have greatly influenced machine learning, propelling advancements in autonomous systems, computer vision, and natural language processing (NLP).
The fundamental concept of artificial neural networks (ANNs) originated in the 1940s with Warren McCulloch and Walter Pitts, who created the first mathematical model of a neuron (McCulloch & Pitts, 1943). The introduction of backpropagation in the 1980s (Williams et al., 1986) and the rise in deep learning's prominence in 2010 (Hinton et al., 2015) significantly advanced ANNs, transforming them into potent tools for addressing intricate, high-dimensional problems.

Synaptic Importance Score

$$S_{ij} = \underbrace{\mathbb{E}\left[\left(\frac{\partial \mathcal{L}}{\partial w_{ij}}\right)^2\right]}_{\text{Fisher Information}} + \underbrace{\lambda \cdot \text{Activation}(w_{ij})}_{\text{Activation Frequency}}$$

Where,

- *Sij*: The synaptic relevance score for the connection between neurons *i* and neuron *j*.
- E: The average expectation is computed throughout the training data distribution.
- $\left(\frac{\partial \mathcal{L}}{\partial w_{ij}}\right)$ Loss function gradient related to weight *wij*. Assess the sensitivity of the loss to changes in *wij*.
- $\left(\frac{\partial \mathcal{L}}{\partial w_{ij}}\right)^2$: squared gradient to ensure non-negative values of and measure the "importance" of *wij*.
- λ: The regularization hyperparameter balances activation frequency and Fisher information.
- Activation (*wij*): *wij* activation frequency of the weight during training.

Weight Update Rule

$$\Delta w_{ij} = -\eta \frac{\partial \mathcal{L}_{\text{new}}}{\partial w_{ij}} \cdot \exp(-\alpha S_{ij})$$

- Δwij: Variation in weight (wij) during training.
- η: controlling the learning pace and step size of the weight updates.
- $\frac{\partial \mathcal{L}_{\text{new}}}{\partial w_{ij}}$: The new task's loss gradient concerning *wij*.
- Exp ($-\alpha Sij$): Weight updates for important synapses are decreased in amplitude by an exponential decay function(high *Sij*).
- α: The preservation of critical synapses is controlled by the decay rate.

Total Loss Function

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{task}} + \beta_1 \sum_i \text{Energy}(i) + \beta_2 \sum_{ij} S_{ij} \left| w_{ij} \right|^2$$

- $\mathcal{L}_{\text{task}}$: task-specific loss (e.g., cross-entropy during classifying).
- $\beta 1$: The weight of the word energy efficiency $\sum$ Energy(i).
- Energy (i): Energy consumption by neurons i.
- $\beta 2$: Term weight for synaptic regularization$\sum_{ij} S_{ij} \left| w_{ij} \right|^2$
- $\sum_{ij} S_{ij} \left| w_{ij} \right|^2$: Regularization penalizing heavyweights based on their importance *Sij*.

Empirical Results

To ensure the correct choice of neural network algorithm compared to other algorithms, it was necessary to compare its performance metrics with the rest of the algorithms, as shown in Table 2. The performance metrics depend on knowing the values of each of the following: RMSE, MSE, MAE, and R^2.

Table 2: Algorithms accuracy metrics

Models	**MSE**	**RMSE**	**MAE**	**R2**
NNs	**371.9**	**19.28**	**14.94**	**0.94**
KNN	**508.2**	**22.54**	**14.83**	**0.92**
DT	**696.87**	**26.39**	**19.88**	**0.89**
GB	**726.9**	**26.96**	**19.01**	**0.885**
RF	**763.2**	**27.62**	**19.12**	**0.87**
SVM	**2913**	**53.97**	**38.86**	**0.54**

Source: Made by author

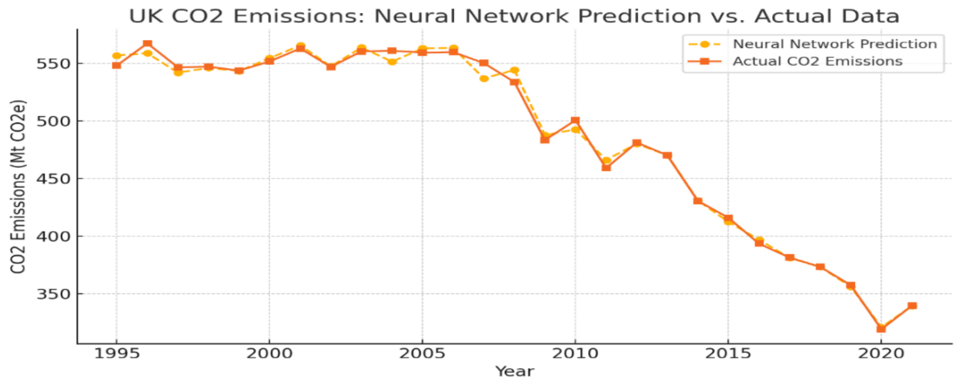
Table 2 shows that the NN algorithm is more accurate than the KNN, DT, GB, RF, and SVM algorithms. NNs have the highest value of R2 and the lowest value of MSE. The next step determines the NNs' prediction performance, and Table 3 shows that.

Table 3: Comparison between CO2 emissions actual values and NN prediction values

year	Neural Network UK CO2 emissions prediction	UK CO2 emissions (Mt CO2e)
1995	556.824	548.0823
1996	558.762	567.3642
1997	541.962	546.4920
1998	545.95	547.1041
1999	543.315	543.7186
2000	554.516	551.6797
2001	565.519	562.9085
2002	547.361	546.9059
2003	563.719	560.4270
2004	551.502	560.9379
2005	562.994	559.3283
2006	563.441	559.7568
2007	537.011	550.2287
2008	544.153	533.7479
2009	487.632	483.3614
2010	492.672	500.6285
2011	466.04	459.0174
2012	480.149	481.1900
2013	470.178	470.1718
2014	430.8	430.4962
2015	412.304	415.8560
2016	396.732	393.3439
2017	380.971	381.2854
2018	373.132	373.2205
2019	356.003	357.3326
2020	320.73	319.0147
2021	339.177	339.4953

Source: Made by author

Figure 1: UK CO2 emissions actual VS. Prediction values



Source: Made by Author

The graph analysis uncovers vital insights regarding the correlation between projected and actual CO_2 emissions in the UK from 1995 to 2021. The overarching trend shows a steady reduction in emissions, highlighting the lasting effects of environmental regulations and economic changes. The Neural Network effectively identifies crucial trends and structural shifts in emission patterns, as evidenced by its forecasts closely aligning with actual emissions. However, the model occasionally overestimates or underestimates emissions significantly when unforeseen economic changes or external shocks influence actual outcomes.

Between 1995 and 2008, emissions were pretty steady, showing only slight changes as environmental taxation policies were implemented and the transition to cleaner energy started. The financial crisis of 2008-2009 led to a significant drop in emissions, corresponding with the economic downturn and a decrease in industrial activity. Although the decline is more pronounced, the model accurately predicts this decrease, possibly due to unforeseen policy responses or behavioral changes that the training data does not fully capture.

In 2010, emissions decreased notably, particularly from 2014 to 2021. Stricter laws, a greater reliance on renewable energy sources, and the UK's commitment to reducing carbon emissions were the primary factors behind the decline. According to data, the most significant drop occurred between 2020 and 2021, mainly due to the impacts of COVID-19, which led to reduced transportation and a shutdown of the economy, resulting in historically low emissions. The neural network clearly illustrates this downward trend, emphasizing its predictive reliability. However, slight discrepancies suggest that additional economic data could enhance the model's accuracy.

The study emphasizes machine learning's capabilities in monitoring and forecasting ecological events, demonstrating that environmental taxes significantly lower emissions. Incorporating additional economic variables and assessing policy effects can enhance the model's predictive ability, leading to more precise forecasts.

The next step is crucial for policymakers. This step determines the extent of the influence of the independent variables on the dependent variable and thus determines the most important variables, which ultimately leads to making a sound decision. Table 4 determines this.

Table 4: Feature importance scores

variables	Score
Taxes on Pollution	28.557
Taxes on Resources	24.98951
Taxes on Transport (Excluding Fuel for Transport)	23.66029
Taxes on Energy (Including Fuel for Transport)	22.79319

Source: Made by author

Table 4 shows that taxes on pollution have the highest effect on CO2 emissions, by 28.6%, followed by taxes on resources by 25%, taxes on transport by 23.7%, and taxes on energy by 22.8%. Therefore, the UK should tax these contributions to reduce carbon emissions—the type of relationship between the variables, whether positive or negative, is determined in Table 5.

Table 5: Pearson correlation

Independent variables	dependent variables	Pearson correlation coefficient
Taxes on Pollution	CO2 emissions	-0.50
Taxes on Resources	CO2 emissions	-0.65
Taxes on Transport (Excluding Fuel for Transport)	CO2 emissions	-0.80
Taxes on Energy (Including Fuel for Transport)	CO2 emissions	-0.90

Source: Made by author

Table 5 shows a strong negative relationship between CO2 emissions and Taxes on Pollution, Resources, Transport, and Energy. This indicates the potential of these taxes and their positive results in reducing carbon emissions in the United Kingdom.

CONCLUSION

This study uses a neural network technique to assess the effectiveness of environmental levies in reducing carbon dioxide emissions across the United Kingdom. The findings reveal a strong negative correlation between carbon dioxide emissions and various environmental fees, emphasizing their essential role as tools for addressing climate change policy. Environmental taxes resulted in a remarkable 28.6% decline in CO_2 emissions, marking them the most effective among all tax categories. Specifically, transportation taxes reduced emissions by 23.7%, energy taxes by 22.8%, and resource taxes by 25%. These results indicate that governments should focus on pollution taxes to meet carbon reduction goals while implementing a comprehensive strategy that includes other tax types.

The neural network model emerged as an exceptionally effective forecasting tool, surpassing conventional econometric models and machine learning methods like KNN, Decision Trees, and Support Vector Machines. Its capacity to identify intricate, non-linear relationships within the dataset facilitated a more accurate assessment of the impact of taxation policy. The difference between actual and predicted CO_2 emissions reinforced the model's reliability, underscoring its value in shaping environmental policy decisions.

These findings emphasize the need for a comprehensive tax framework beyond increasing tax rates. It should include regulatory actions aimed at enhancing taxation efficiency and reducing

emissions. The UK must keep improving its environmental tax policies to ensure tax levels support economic and ecological goals. Additionally, the research highlights the crucial role of artificial intelligence and machine learning in ecological economics, offering valuable insights into the complex links between taxation and emissions.
Future studies must integrate more economic aspects, such as GDP growth, energy usage, and industrial output, to improve predictive models. Additionally, analyzing the lasting impacts of environmental taxes on businesses and consumers can provide essential insights into how effective policies are. Through ongoing enhancements in tax methods and data-driven analysis, policymakers can create more adaptable and practical approaches to achieve the UK's net-zero emissions target by 2050.

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References

Parry, I. W., Norregaard, J., & Heine, D. (2012). Environmental tax reform: principles from theory and practice. Annu. Rev. Resour. Econ., 4(1), 101-125.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

OBANI, I. P., & AKROH, T. O. (2024). Evaluating the effectiveness of environmental taxes: A case study of carbon pricing in the UK as a tool to reduce greenhouse gas emissions. International Journal of Science and Research Archive. https://doi.org/10.30574/ijsra.2024.13.2.2126

Sahi, S. V., & Lama, S. (2024). Environmental Taxation and Carbon Emission in G20 Nations. Vision : Journal of Indian Taxation, 11(2), 83–94. https://doi.org/10.17492/jpi.vision.v11i2.1122406

Noubissi, E., Nkengfack, H., Pondie, T. M., & Ngounou, B. A. (2023). Economic impact of the carbon tax: Evaluation of the reduction in CO2 emissions. https://doi.org/10.1111/1477-8947.12348

Gugler, K., Haxhimusa, A., & Liebensteiner, M. (2023). Carbon Pricing and Emissions: Causal Effects of Britain's Carbon Tax. Social Science Research Network. https://doi.org/10.2139/ssrn.4116240

Adami, S., Delestre, I., Levell, P., & Miller, H. (2022). Tax policies to reduce carbon emissions. Fiscal Studies, 43(3), 235–263. https://doi.org/10.1111/1475-5890.12308

Dobrovolska, O., Günther, S., Чернецька, О. В., Dubrova, N., & Качула, С. (2024). Environmentally related taxes and their influence on decarbonization of the economy. Environmental Economics, 15(1), 174–189. https://doi.org/10.21511/ee.15(1).2024.13

Matusevich, A., Hassan, M. M., Vaishnavi, P., Sudan, P., Chhetri, A., Chhabra, S., Sharma, P., Sharma, G., & Deepa, R. (2024). Evaluating the Effectiveness of Carbon Tax Policies with Econometric Modeling. E3S Web of Conferences, 581, 01012. https://doi.org/10.1051/e3sconf/202458101012

Zhou, Y., Adebayo, T. S., Yin, W., & Abbas, S. (2023). The co-movements among renewable energy, total environmental tax, and ecological footprint in the United Kingdom: Evidence from wavelet local multiple correlation analysis. Energy Economics.

https://doi.org/10.1016/j.eneco.2023.106900
Koval, V., Laktionova, O. Yu., Udovychenko, I., Olczak, P., Palii, S. D., & Prystupa, L. (2022). Environmental Taxation Assessment on Clean Technologies Reducing Carbon Emissions Cost-Effectively. Sustainability, 14(21), 14044. https://doi.org/10.3390/su142114044
Abrell, J., Kosch, M., & Rausch, S. (2019). How Effective Was the UK Carbon Tax? A Machine Learning Approach to Policy Evaluation. https://doi.org/10.3929/ETHZ-B-000338148
Bretschger, L., & Grieg, E. (2020). Exiting the fossil world: The effects of fuel taxation in the UK. Research Papers in Economics. https://ideas.repec.org/p/eth/wpswif/20-332.html
Bridgen, P., & Büchs, M. (2023). The climate crisis and taxation (pp. 238–266). Policy Press. https://doi.org/10.1332/policypress/9781447364177.003.0014
McEldowney, J. F., & Salter, D. (2016). Environmental taxation in the UK: the climate change levy and policy making. The Denning Law Journal, 28, 37–65. https://doi.org/10.5750/DLJ.V28I0.1276
Dyshlyk, V. (2024). Efficiency of environmental taxation with an emphasis on CO2 emissions: analysis of the experience of EU countries and prospects for Ukraine. Balanced Nature Using, 1, 60–67. https://doi.org/10.33730/2310-4678.1.2024.302625
Al Shammre, A., Benhamed, A., Ben-Salha, O., & Jaidi, Z. (2023). Do Environmental Taxes Affect Carbon Dioxide Emissions in OECD Countries? Evidence from the Dynamic Panel Threshold Model. Systems, 11(6), 307. https://doi.org/10.3390/systems11060307
Moritz, L., & Abdo, H. (2013). Investigating Effects of Green Taxes on Investments in Renewable Energies: The Case of the UK. 4(2), 39–51. https://doi.org/10.3844/ERJSP.2013.39.51
Leu, T., & Betz, R. (2016). Environmental tax evaluation : what can be learnt so far? 1–24. https://digitalcollection.zhaw.ch/handle/11475/17571
Brand, C., Anable, J., & Tran, M. (2013). Accelerating the transformation to a low carbon passenger transport system: The role of car purchase taxes, feebates, road taxes and scrappage incentives in the UK. Transportation Research Part A-Policy and Practice, 49, 132–148. https://doi.org/10.1016/J.TRA.2013.01.010
Feng, K., Hubacek, K., Guan, D., Contestabile, M., Minx, J. C., & Barrett, J. (2010). Distributional Effects of Climate Change Taxation: The Case of the UK. Environmental Science & Technology, 44(10), 3670–3676. https://doi.org/10.1021/ES902974G
Adetutu, M. O., Odusanya, K., & Weyman-Jones, T. (2020). Carbon tax and energy intensity: assessing the channels of impact using UK microdata. The Energy Journal, 41(2). https://doi.org/10.5547/01956574.41.2.MADE
Boardman, B. (2003). Reducing UK residential carbon emissions by 60. https://www.eceee.org/library/conference_proceedings/eceee_Summer_Studies/2003c/Panel_1/1224boardman/paper
Symons, E., & Proops, J. L. R. (1994). Carbon Taxes, Consumer Demand and Carbon Dioxide Emissions: A Simulation Analysis for the UK. Fiscal Studies, 15(2), 19–43. https://doi.org/10.1111/J.1475-5890.1994.TB00195.X
Tamura, H., Nakanishi, R., Hatono, I., & Umano, M. (1995). Is Environmental Tax Effective for Total Emission of Carbon Dioxide. http://pure.iiasa.ac.at/id/eprint/4508/
Barker, T. (1995). Taxing Pollution Instead of Employment: Greenhouse Gas Abatement through Fiscal Policy in the UK. Energy & Environment, 6(1), 1–29. https://doi.org/10.1177/0958305X9500600101

Potter, S., Enoch, M. P., & Fergusson, M. (2001). Fuel taxes and beyond. UK transport and climate change. https://trid.trb.org/view/707025

Kettner-Marx, C., & Kletzan-Slamanig, D. (2018). Carbon taxes from an economic perspective. Research Papers in Economics. https://ideas.repec.org/p/wfo/wpaper/y2018i554.html

Klymenko, M. (2022). “green” policy and environmental taxation as the instruments to tackle climate change. Internauka, 7(63). https://doi.org/10.25313/2520-2294-2022-7-8150

Grdinić, M., Klun, M., & Kotnik, Z. (2015). Environmental Taxation: New Evidence for Energy Taxes. Social Science Research Network. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2719597

Sørensen, P. B., Pedersen, L. H., & Nielsen, S. B. (1994). Taxation, Pollution, Unemployment and Growth: Could there be a “Triple Dividend” from a Green Tax Reform? Research Papers in Economics. https://ideas.repec.org/p/kud/kuiedp/9414.html

Addai, K., Al Geitany, S. H., Athari, S. A., Farmanesh, P., Kırıkkaleli, D., & Saliba, C. (2024). Do Environmental Tax and Energy Matter for Environmental Degradation in the UK? Evidence from Novel Fourier-Based Estimators. Energies, 17(22), 5732. https://doi.org/10.3390/en17225732

Zolkover, A., Лаговська, O. A., VALIHURA, V., Zhelef, G., & Shynkar, T. (2024). Assessing the Impact of Green Taxation Policies on Sustainable Growth. Grassroots Journal of Natural Resources, 7(3), s331–s348. https://doi.org/10.33002/nr2581.6853.0703ukr17

Xu, W., & Li, M. (2024). Green tax system and corporate carbon emissions – a quasi-natural experiment based on the environmental protection tax law. Journal of Environmental Planning and Management. https://doi.org/10.1080/09640568.2024.2307524

Yusoff, Y. H., Nadilah, I., Anwar, M. K., Yustiansyah, R. A., Utama, R. H., & Dahlan, M. (2024). Optimizing the Implementation of Carbon Tax in Reducing the Impact of Environmental Pollution. Accounting and Finance Research. https://doi.org/10.5430/afr.v13n2p89

Mehta, D., & Derbeneva, V. (2024). Assessing the Impact of Environment Tax on Carbon Emissions of African Countries. Journal of Tax Reform, 10(3), 510–523. https://doi.org/10.15826/jtr.2024.10.3.181

Zhu, Y.-G., Taylor, D., & Wang, Z. (2023). The role of environmental taxes on carbon emissions in countries aiming for net-zero carbon emissions: Does renewable energy use matter? Renewable Energy. https://doi.org/10.1016/j.renene.2023.119239

Dogan, E., Hodzic, S., & Šikić, T. (2022). A way forward in reducing carbon emissions in environmentally friendly countries: the role of green growth and environmental taxes. 35, 5879–5894. https://doi.org/10.1080/1331677X.2022.2039261

ÖZARSLAN DOĞAN, B., & Güler, C. (2023). The Importance of Green Tax in Reducing Carbon Emissions: The Case of G-7 Countries. Abant Sosyal Bilimler Dergisi, 23(2), 892–903. https://doi.org/10.11616/asbi.1219062

Wolde-Rufael, Y., & Mulat-weldemeskel, E. (2021). Do environmental taxes and environmental stringency policies reduce CO2 emissions? Evidence from 7 emerging economies. Environmental Science and Pollution Research, 28(18), 22392–22408. https://doi.org/10.1007/S11356-020-11475-8

Ulucak, R., & Kassouri, Y. (2020). An assessment of the environmental sustainability corridor: Investigating the non-linear effects of environmental taxation on CO2 emissions. Sustainable Development, 28(4), 1010–1018. https://doi.org/10.1002/SD.2057

Máté, D., Török, A., & Kiss, J. T. (2023). The impacts of energy supply and environmental taxation on carbon intensity. Technological and Economic Development of Economy,

0(0), 1–21. https://doi.org/10.3846/tede.2023.18871
McCulloch, W. S., & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. The bulletin of mathematical biophysics, 5, 115-133.
Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. nature, 323(6088), 533-536.
LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. nature, 521(7553), 436-444.
World Bank. (2023). World Development Indicators: Energy Use and Emissions. Available at: https://databank.worldbank.org/
IMF climate change indicators. Available at: https://climatedata.imf.org/