DOI: 10.20472/EFC.2024.022.004

DRAGAN CRNOGORAC
School of Economics and Business, University of Ljubljana, Slovenia

IDENTIFYING KEY DRIVERS OF CARBON INTENSITY IN EU SECTORS: INSIGHTS FROM PANEL REGRESSION

Abstract:

This paper investigates the determinants of carbon intensity across various economic sectors in the European Union, focusing on the period that already considers transition policies under the Paris Agreement and the Fit-for-55 initiative. As sectors exhibit diverging emission levels and transition policy implications, understanding the factors influencing carbon intensity has become increasingly relevant. We employ a panel regression analysis using data from 2014 to 2022, examining variables such as brown energy consumption share, total factor productivity, gross value added, employment metrics, energy prices, and environmental taxes. Our findings reveal that carbon intensity is influenced by a complex interplay of factors, with significant variations across sectors. Notably, sectors with high reliance on brown energy show a stronger correlation with carbon intensity levels. The results underscore the necessity for tailored transition policies that consider sector-specific characteristics to effectively reduce carbon emissions within the EU. Furthermore, the study highlights the importance of integrating economic and environmental policies to foster a sustainable transition, providing valuable insights for policymakers aiming to achieve climate targets.

Keywords:

Carbon Intensity, Economic Sectors, Panel Regression Analysis, GMM, EU Climate Policies, Fit-for-55 Initiative, Brown Energy Consumption, Total Factor Productivity, Sector-Specific Transition Policies

JEL Classification: Q50, C23, Q54

Introduction

The Paris Agreement and the EU's Fit-for-55 initiative represent pivotal frameworks aimed at mitigating climate change by reducing greenhouse gas emissions. Transition policies are essential to achieve these ambitious targets, and a plethora of studies has emerged analysing their effectiveness. For instance, the European Union is committed to steering its economy away from high-carbon and pollution-intensive production toward climate-neutral technologies by 2050, emphasizing the need for a just transition that supports regions and sectors most affected by these changes (Vona, 2021).

Recent research underscores the importance of sectoral analysis in understanding the climate impact of these policies, as emissions levels and transition policy implications diverge significantly across different sectors. For example, the Climate Chance Observatory's Global Synthesis Report highlights that sector-specific strategies can lead to substantial reductions in CO2 emissions, indicating that tailored approaches are necessary for effective climate action (Climate Chance Observatory, 2023). This study aims to contribute to this growing body of research by investigating the factors influencing carbon intensity across various economic sectors in the EU.

Carbon intensity, defined as the amount of carbon dioxide emissions per unit of economic output, has become a key indicator in assessing the effectiveness of climate policies. This metric allows for the evaluation of how efficiently an economy produces goods and services while managing its carbon emissions. The United Nations Environment Programme (UNEP) emphasizes that monitoring carbon intensity is crucial for understanding progress in reducing greenhouse gas emissions and achieving climate targets (UNEP, 2023). Numerous studies have utilized carbon intensity to evaluate emissions forecasts and the impact of transition policies. For example, the EU Emission Trading Scheme (ETS) plays a crucial role in determining carbon prices for energy-intensive industries, influencing their carbon intensity (Delbeke, 2021).

This study hypothesizes that carbon intensity is influenced by a complex interplay of factors, including the share of brown energy consumption, total factor productivity, gross value added, employment levels, energy prices, environmental taxes, and climate variables such as heating and cooling days. By employing a panel regression analysis using data from EU countries from 2014 to 2022, we aim to identify the most significant determinants of carbon intensity across different sectors. The aim of this research is to contribute to the development of tailored transition policies and transmission channels for assessment tools both considering sector-specific characteristics and effectively reduce carbon emissions within the EU.

The remainder of this paper is organized as follows: Section 2 reviews the existing literature and develops the hypotheses. Section 3 describes the data and methodology used in the analysis. Section 4 presents the results and discusses the findings. Section 5 outlines the extensions and robustness tests conducted. Finally, Section 6 concludes the paper and suggests avenues for future research.

Existing Literature and Hypotheses Development

Research indicates that several factors significantly affect carbon intensity. A key component is total factor productivity (TFP), which serves as a measure of technological advancement. Improvements in TFP can lead to lower carbon emissions per unit of output, thus reducing carbon intensity. Studies suggest that higher productivity is often associated with cleaner technologies and more efficient energy use (Zhou et al., 2023). Economic output influences carbon intensity, as sectors with higher gross value added may exhibit different emissions profiles depending on their energy consumption patterns (Khan et al., 2023). Additionally, population size, energy consumption, and industrial structure are critical factors affecting carbon emissions in various regions (Ma et al., 2013; Pan et al., 2017).

In the context of China, for example, Zhao et al. (2020) found that the energy structure has the greatest impact on carbon intensity, followed by demographic factors like total population and urbanization rate, as well as economic factors such as industrial structure and GDP per capita. Similarly, the study by Song et al. (2020) highlights that the industrial sector is the primary contributor to carbon emissions, accounting for a significant proportion of total emissions in regions with high coal dependence. This underscores the necessity of optimizing energy structures and transitioning towards cleaner energy sources to effectively reduce carbon intensity.

Findings from non-EU countries further support the relevance of these factors. For instance, research conducted in the United States indicates that states with higher renewable energy shares experience lower carbon intensity levels, reinforcing the importance of transitioning to cleaner energy sources (Liu et al., 2023). In India, the electricity, gas, and water supply sector has been identified as a major contributor to carbon emissions, emphasizing the need for targeted policies to address high-carbon sectors (Sun, 2020).

Panel fixed effects regression models have been widely utilized in climate studies to analyze the impact of various factors on carbon intensity across different sectors. For example, studies have shown that fixed effects models effectively control for unobserved heterogeneity and time-invariant characteristics, allowing researchers to isolate the effects of time-varying variables on carbon emissions (Edokpayi et al., 2018). The use of panel data enables researchers to capture the dynamic relationships between climate variables and economic outcomes, providing insights into the causal mechanisms at play (Blanc and Schlenker, 2020).

In terms of modelling approaches, recent literature suggests that panel models can be effective in assessing the causality between various factors and carbon intensity across sectors and countries. For example, Khan et al. (2019) use a panel regression approach to investigate the impact of environmental regulations on firm-level productivity and emissions, providing insights into the mechanisms through which policy interventions can influence carbon intensity.

The findings from these studies collectively highlight the need for a more comprehensive approach to modelling carbon intensity, incorporating a broader range of factors and considering the complex interactions between economic agents, policies, and the environment. This research aims to contribute to this growing body of literature by employing a panel regression framework to identify the key determinants of carbon intensity across economic sectors in the EU, providing valuable insights for policymakers and modelers alike.

 ISBN 978-80-7668-014-2, IISES

Data and Methodology

Collected data and characteristics

This study examines the determinants of carbon intensity (CO2 emissions) across 21 economic sectors[1] and 27 EU member states from 2014 to 2022. Using data from Eurostat and focusing on the period following the Paris Agreement, the analysis considers factors such as energy usage, technological advancements, labour intensity, market conditions, policy actions, and weather metrics. While most data series are available from 2008 onwards, energy usage data is only available from 2014.

Variables include[2]:

- **Brown Energy Share (brwn_shr):** Proportion of energy consumption from non-renewable sources, calculated by subtracting electricity, nuclear, and renewable energy from total energy consumption.
- **Gross Value Added (gva):** Economic contribution of each sector, measured in million EUR.
- **CO2 Emissions (emissions):** Total carbon dioxide emissions, the primary indicator of carbon intensity, measured in billion tonnes.
- **Employment Metrics (employment):** Labour intensity, measured in thousand hours worked.
- **Energy Prices (electricity_price and gas_price):** Prices for electricity and gas for small to mid-sized enterprises, measured in EUR per MWh and EUR per GJ, respectively.
- **Environmental Taxes (environmental_tax):** Fiscal measures implemented to influence environmental outcomes, measured in million EUR.
- **Weather Variables (heating_days and cooling_days):** Number of days requiring heating or cooling, capturing extreme weather impacts.
- **Total Factor Productivity Growth (tfp)[3]:** Productivity changes, calculated as the difference between GVA growth and weighted labor and capital productivity growth, expressed as a percentage.

---

[1] Statistical Classification of Economic Activities in the European Community (NACE) level (see Appendix 1).

[2] All variables are available at the sectoral level, except for market conditions and weather metrics, which are observed at the country level.

[3] Calculation of total factor productivity from Eurostat observed data is as follows:
TFP Growth=GVA Growth−(α×Labour Productivity Growth+β×Capital Productivity Growth), where Labour Productivity Growth is Real labour productivity per hour worked, α is the share of compensation of employees in total output, Capital Productivity Growth is productivity of net fixed assets in relation to GVA and β is the share of operating surplus in total output.

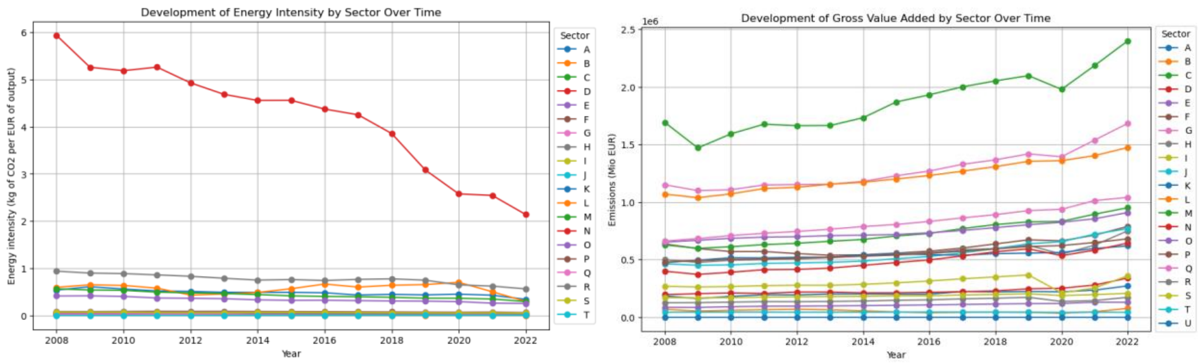
ISBN 978-80-7668-014-2, IISES

Due to limited data for sectors J, K, M, N, Q, R, S, and U, these were excluded. The study provides a detailed view of the factors affecting carbon intensity across the EU, considering macroeconomic differences.

Sector-level data

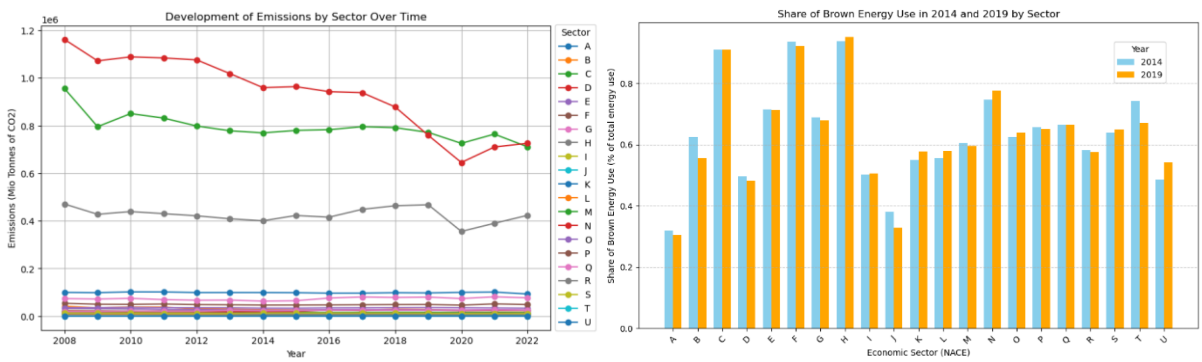
The analysis reveals significant sectoral differences in energy intensity, CO2 emissions, economic contribution, and brown energy usage across the EU. The Electricity, Gas, Steam, and Air Conditioning Supply sector (Sector D) has the highest energy intensity, though it has reduced from 5.93 in 2008 to 2.14 in 2022. Sectors like Financial and Insurance Activities (Sector K) and Real Estate Activities (Sector L) show lower energy intensities. The trend overall is a gradual reduction in energy intensity, signaling progress in efficiency. The Manufacturing sector (Sector C) remains the largest economic contributor, while information and communication sectors show substantial growth, highlighting the digital economy's rise.

Figure 1: Energy intensity and GVA development by sector



CO2 emissions data highlight the Electricity, Gas, Steam, and Air Conditioning Supply sector (Sector D) as the largest emitter, with emissions decreasing from 1.16 billion tonnes in 2008 to 0.73 billion tonnes in 2022. The Manufacturing (Sector C) and Transportation and Storage (Sector H) sectors have also reduced emissions but remain significant contributors. Despite these reductions, more progress is needed to meet climate targets. Brown energy usage shows that sectors like Transportation and Storage (Sector H) and Construction (Sector F) heavily depend on non-renewable energy, with Manufacturing (Sector C) also relying significantly on brown energy. The transition to sustainable sources remains a challenge, though Sector D has made some progress in reducing its brown energy dependence.

Figure 2: Emissions and “brown” energy usage development by sector



ISBN 978-80-7668-014-2, IISES

The analysis underscores the need for sector-specific policies and interventions to address the unique challenges each sector faces in transitioning to a more sustainable and low-carbon economy. The varying levels of energy intensity, emissions, and brown energy reliance across sectors highlight the complexity of achieving broad-based improvements in energy efficiency and carbon reduction.

Methodology

To examine the effects of various observed variables on energy intensity, we specify the following dynamic panel data model using the Instrumental Variables Generalized Method of Moments (IV-GMM) estimation:

$$I_{j,k,t} = \alpha I_{j,k,t-1} + \beta Variables_{j,k,t} + \gamma X_{j,k,t} + \delta Z_{k,t-1} + \lambda_j + \theta_t + \epsilon_{j,k,t}$$

where $I_{j,k,t}$ presents energy intensity in sector *j*, country *k*, and time *t*. The term $I_{j,k,t-1}$ is the lagged dependent variable, included to capture the autoregressive process. The observed variables $Variables_{j,k,t}$ include factors such as brown energy share, gross value added (GVA), CO2 emissions, employment metrics, energy prices (electricity and gas), environmental taxes, and weather variables (cooling and heating days). $X_{j,k,t}$ includes contemporaneous variables, and $Z_{k,t-1}$ contains lagged exogenous variables. The fixed effects for sectors (*const*) and time periods are captured by λ_j and θ_t, respectively, while $\epsilon_{j,k,t}$ is the error term.

The IV-GMM model was chosen for its ability to address potential endogeneity issues, particularly those associated with lagged variables. This method helps mitigate biases from omitted variables and reverse causality, which are common in panel data regressions (Arellano and Bond, 1991; Wooldridge, 2010). The inclusion of the lagged dependent variable highlights the model's dynamic nature, reflecting the persistence of energy intensity over time. This approach recognizes that historical energy use significantly affects current levels, providing a more accurate assessment of energy intensity trends (Blundell and Bond, 1998).

In addition, we analyse energy efficiency changes using a similar model structure without the autoregressive term. This approach allows us to focus on short-term variations and immediate responses to recent policy measures, rather than long-term persistence captured by the lagged variable (Roodman, 2009). The choice of the IV-GMM method is particularly suitable for our small T and small N panel data, addressing endogeneity concerns and potential biases from environmental regulations (Levinsohn and Petrin, 2003). By concentrating on sector-level data, our analysis reduces endogeneity issues that are more pronounced in macro-level studies, making our findings more relevant and reliable for policy evaluation (Hsiao, 2003).

Results and Findings

The results are summarised in Tabel 1 indicating that the level-based models with a lagged dependent variable outperform the delta-based models in terms of explanatory power and significance of coefficients across most sectors.

The analysis of energy intensity across various sectors reveals distinct patterns and drivers that shape energy efficiency outcomes. In Agriculture, Forestry, and Fishing (Sector A), energy intensity is notably reduced, with environmental taxes and emission controls emerging as effective drivers of efficiency improvements. This sector's responsiveness to such measures highlights the role of regulatory interventions in fostering energy savings. Mining and Quarrying (Sector B) exhibits high energy intensity, where emissions and GVA are significant

 ISBN 978-80-7668-014-2, IISES

factors. The strong correlation between emissions and energy intensity underscores the urgent need for targeted emission reduction strategies to manage energy use effectively in this sector. Manufacturing (Sector C) shows moderate energy intensity, influenced by GVA and emissions, with brown energy usage playing a significant role. This indicates that a shift towards cleaner energy sources and further emissions reductions could enhance energy efficiency. The Electricity, Gas, Steam, and Air Conditioning Supply sector (Sector D) has high energy intensity, driven by GVA, share of brown energy and electricity prices. Its sensitivity to electricity prices emphasizes the importance of pricing policies in promoting energy efficiency, alongside potential benefits from cleaner energy solutions. Water Supply, Sewerage, Waste Management, and Remediation Activities (Sector E) also demonstrates moderately high energy intensity, with brown energy usage and emissions being crucial factors. Finally, Transportation and Storage (Sector H) reveals high energy intensity with a strong link to brown energy usage, underscoring the need for cleaner energy alternatives. Overall, emissions, GVA, and brown energy usage are key determinants of energy intensity, with reductions in emissions and a transition to cleaner energy sources emerging as pivotal strategies for improving energy efficiency.

When looking at the delta energy intensity, or the change in energy intensity, we can draw some similarities, but there are new factors that have a significant effect. TFP generally exhibits a significant negative relationship with energy intensity across most sectors, indicating that productivity improvements lead to more efficient energy use. This underscores the role of technological advancements and efficiency enhancements in reducing energy intensity. Conversely, the impact of delta brown share, or the proportion of non-renewable energy sources, varies by sector; in some cases, such as in Sectors B and E, an increase in brown energy share correlates with higher energy intensity, highlighting the need for cleaner energy transitions. The effects of energy prices on energy intensity are mixed; while higher gas prices can reduce energy intensity by encouraging more efficient consumption, this effect is not consistent across all sectors. Environmental taxes generally correlate with lower energy intensity, suggesting that these taxes effectively promote energy efficiency by incentivizing reductions in energy consumption and emissions.

Table 1: Summary of GMM models results

GMM model with the lagged dependant variable – Energy intensity as the dependent variable

Variable/Sector	A	B	C	D	E	F	G	H	I	L	O	P
lagged_energy_intensity	0.7422*** (0.1010)	0.9024*** (0.0487)	0.8128*** (0.0484)	0.7675*** (0.0725)	0.7430*** (0.0599)	0.8687*** (0.0333)	0.6192*** (0.1299)	0.5592*** (0.0571)	0.7347*** (0.0949)	0.5934*** (0.0773)	0.6626*** (0.0780)	0.6545*** (0.0685)
const	0.0880* (0.0416)	0.3470*** (0.1103)	0.1132** (0.0422)			-0.0514* (0.0228)	0.0299*** (0.0101)	-1.6279** (0.5552)	0.0272*** (0.0102)			0.0056* (0.0030)
brwn_shr			0.0699** (0.0337)	2.9089* (1.2992)	0.1042** (0.0364)	0.0878*** (0.0283)	0.0205** (0.0088)	1.8880** (0.5982)			0.0147** (0.0069)	0.0106*** (0.0028)
employment					-1.348e-07* (0.5646e-07)	-5.06e-09** (1.91e-09)		-1.078e-07* (0.4636e-06)	-1.359e-08*** (4.829e-09)	-1.357e-08*** (2.994e-09)		5.854e-09*** (1.769e-09)
electricity_price		-1.4292*** (0.4908)		-10.597** (3.8052)	0.1359 (0.1802)		-0.0947*** (0.0280)				0.0275* (0.0161)	
gas_price					1.7208* (0.7573)				-0.2110* (0.1096)	-0.1221*** (0.0405)		
environmental_tax	-9.249e-05** (3.558e-05)		-1.352e-05* (0.6351e-05)		-5.294E-09		-7.944e-06** (2.787e-06)			-5.192e-05*** (1.168e-05)	-1.259e-05* (7.393e-06)	
heating_days					-4.179e-05** (1.56e-05)					2.838e-06*** (9.754e-07)		
cooling_days	-0.0002* (0.0000907)											
gva	-3.114e-06** (1.334e-06)	-2.974e-05*** (7.612e-06)	-3.066e-07*** (9.075e-08)	-1.698e-05*** (4.213e-06)	-1.95e-06* (0.9706e-06)	-3.139e-07*** (9.388e-08)	-1.818e-07*** (5.642e-08)	-4.441e-06** (1.252e-06)	3.438e-07** (1.363e-07)		-3.312e-07*** (9.812e-08)	-3.304e-07*** (7.946e-08)
emissions	1.827e-05** (6.762e-06)	6.054e-05* (2.585e-05)			2.633e-05*** (7.793e-06)	6.156e-06** (2.168e-06)	5.193e-06** (1.777e-06)	7.367e-06** (2.305e-06)	1.982e-05*** (5.779e-06)	2.68e-05*** (5.343e-06)	8.287e-06** (3.335e-06)	7.137e-06*** (1.705e-06)
Observations	1343	1312	1368	1347	1335	1344	1330	1330	1336	1337	1281	1337

GMM model with deltas – Delta energy intensity as the dependent variable

Variable/Sector	A	B	C	D	E	F	G	H	I	L	O	P
const			-0.0068*** (0.0017)	-0.0917** (0.0371)			-0.0005** (0.0002)					
delta_brwn_shr		0.4597* (0.2675)		6.9389*** (1.3771)	0.2170*** (0.0735)	0.1009*** (0.0343)						0.0279** (0.0103)
tfp	-0.2292*** (0.0394)	-0.2082*** (0.0519)	-0.0356* (0.0197)	-0.8233* (0.4513)	-0.0487* (0.0262)	-0.0401*** (0.0091)	-0.0181** (0.0072)	-0.3890** (0.1737)	-0.0203** (0.0067)	-0.0088*** (0.0028)	-0.0233*** (0.0064)	-0.0181*** (0.0044)
delta_employment			-7.971e-08*** (2.867e-08)		-4.739e-07* (2.637e-07)			-6.313e-07** (2.553e-07)	-4.67e-08*** (1.739e-08)	-3.611e-08* (1.892e-08)		-2.893e-08** (1.409e-08)
delta_electricity_price				-8.5962* (5.0732)							-0.1481*** (0.0491)	
delta_gas_price		-4.0306** (1.8309)			-0.8109** (0.3657)							
delta_environmental_tax		-0.0026*** (0.0008)	-2.122e-05** (8.471e-06)		-0.0002*** (8.329e-05)	-4.579e-05* (2.62e-05)	-1.416e-05*** (4.972e-06)				-3.034e-05* (1.72e-05)	
delta_heating_days		0.0001** (6.145e-05)	-5.161e-05*** (1.932e-05)	0.0008** (0.0003)								
delta_cooling_days												
delta_emissions	6.542e-05* (3.662e-05)	0.0003*** (2.459e-05)	8.583e-06*** (2.276e-06)	3.287e-05*** (1.193e-05)	0.0002*** (3.078e-05)	2.764e-05*** (7.133e-06)	1.501e-05*** (1.748e-06)	2.698e-05*** (8.894e-06)	8.48e-05** (3.446e-05)	5.072e-05*** (4.338e-06)	3.905e-05*** (6.15e-06)	2.562e-05*** (6.564e-06)
Observations	359	349	357	349	357	359	354	354	357	357	342	357

*Note: Lagged dependent variable is treated as endogenous, and all other variables as exogenous. All regressions include year fixed effects. Coefficients are presented and standard error in brackets. The following are p-values which indicate the significance level of coefficients: *p < 0.10, **p < 0.05, ***p < 0.01.*

To enhance energy efficiency and reduce energy intensity, several policy recommendations are crucial. First, implement stringent emission reduction policies in high-energy-intensity sectors such as Mining and Quarrying and Transportation, including stricter emissions standards and support for cleaner technologies. Next, promote a transition to renewable energy sources in sectors reliant on brown energy, like Manufacturing and Water Supply, through subsidies for renewable energy projects and investments in clean energy infrastructure. Adjusting electricity prices to better reflect the true cost of energy can drive efficiency improvements in sensitive sectors like Electricity, Gas, Steam, and Air Conditioning Supply. Develop sector-specific strategies that address the unique drivers of energy intensity in each sector, such as focusing on emission controls in Transportation and cleaner energy in Manufacturing. Prioritize technological advancements by supporting innovation and efficiency improvements, as total factor productivity improvements are linked to reduced energy intensity. Finally, expand and optimize environmental tax schemes to further encourage energy efficiency where these taxes have demonstrated significant impacts.

Extensions and Robustness Tests

The analysis demonstrates a robust framework for understanding changes in energy intensity across sectors. The financial analysis shows overall strong robustness and performance. While some sectors exhibit heteroskedasticity, which has been partially addressed through model adjustments, the Breusch-Pagan test confirms these measures. Multicollinearity is observed but remains manageable; however, addressing it through techniques like variable selection or combination could improve model clarity and precision. These issues might affect the interpretation of coefficients and the stability of predictions, but they do not significantly undermine the model's overall effectiveness. The analysis still provides valuable insights and reliable results, though attention to these areas could further enhance its accuracy and reliability.

The delta model analysis provides a robust framework for understanding changes in energy intensity across sectors. Although heteroskedasticity is present in several sectors, the use of robust standard errors addresses this issue. Additionally, multicollinearity is less of a concern when using deltas, enhancing the clarity of the results. Overall, the findings support sector-specific strategies that focus on productivity improvements, emission management, and cleaner energy transitions.

Conclusion

This study explores the determinants of carbon intensity (CO2 emissions) across 21 economic sectors and 27 EU member states from 2014 to 2022, using data from Eurostat. It highlights significant sectoral variations in energy intensity, CO2 emissions, economic contribution, and reliance on brown energy. The Electricity, Gas, Steam, and Air Conditioning Supply sector (Sector D) stands out with the highest energy intensity and CO2 emissions, though both metrics have decreased over the study period. The Manufacturing sector (Sector C) remains a major economic contributor but also heavily relies on non-renewable energy.

The analysis demonstrates that emissions, brown energy usage, and gross value added (GVA) are key drivers of energy intensity across sectors. Sectors with high energy intensity, such as Mining and Quarrying (Sector B) and Transportation and Storage (Sector H), need targeted emission reduction strategies and a transition to cleaner energy sources. The role of environmental taxes and energy prices is significant, with environmental taxes generally promoting lower energy intensity and higher energy prices potentially driving efficiency improvements, though effects vary by sector.

Methodologically, the IV-GMM model used in this study effectively addresses endogeneity concerns and reflects the persistence of energy intensity over time. The findings suggest that policies should focus on stringent emission reductions, support for renewable energy, and technological advancements to improve energy efficiency. Sector-specific strategies and optimized environmental tax schemes are essential for achieving substantial progress in reducing carbon intensity and transitioning to a low-carbon economy.

References

Alves Dias, P., et al. (2021). "The Just Transition: A European Perspective." European Commission.

Annicchiarico, B. and Diluiso, F. (2019). "A multi-sector DSGE model for the Italian economy: Analyzing low-carbon policies under uncertainty." *Energy Economics*.

Arellano, M., and Bond, S. (1991). "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *The Review of Economic Studies*, 58(2), 277-297.

Blanc, E., & Schlenker, W. (2020). "The Use of Panel Models in Assessments of Climate Impacts on Agriculture." *Environmental Research Letters*.

Blundell, R., and Bond, S. (1998). "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics*, 87(1), 115-143.

Climate Chance Observatory. (2023). "Global Synthesis Report on Climate Action." Retrieved from Climate Chance.

Dissou, Y., and Karnizova, L. (2016). "The role of heterogeneous production sectors in the analysis of climate policies." *Environmental Economics and Policy Studies*.

Edokpayi, J. N., O. E. Popoola, and J. O. Odiyo (2018). "Panel Model Analysis of Impact of Climate Change on Crop Yields in Nigeria." *Ilorin Journal of Science*.

Fischer, C., and Springborn, M. (2024). "The Effect of Environmental Taxes and Economic Growth on Carbon Emissions." *Environmental Economics and Policy Studies*.

Hsiao, C. (2003). "Analysis of Panel Data." *Cambridge University Press*.

Khan, M. A., S. H. Syed, and A. Fatima (2019). "Environmental regulations and firm-level productivity: Evidence from panel data." *Journal of Cleaner Production*.

Khan, M. A. (2023). "Investigating the Dynamic Effects of Service Value Added on CO2 Emissions." *Sustainability*.

Levinsohn, J., and Petrin, A. (2003). "Estimating Production Functions Using Inputs to Control for Unobservables." *The Review of Economic Studies*, 70(2), 317-341.

Liu, Y., Y. Hao, and Y. Gao (2023). "Renewable energy and carbon intensity in the United States: A state-level analysis." *Energy Policy*.

Ma, Y., C. Zhao, and Y. Li (2013). "Analysis of influencing factors of CO2 emissions based on different coal dependence." *Environmental Science and Pollution Research*, 20(3), 1888-1899.

Pan, Y., X. Zhang, C. Cai, and Y. Cheng (2017). "Driving factors of carbon emissions in China: Evidence from a multi-regional input-output analysis." *Applied Energy*, 185, 1833-1842.

Song, Y., Y. Wang, and H. Hu (2020). "The industrial structure and carbon emissions in China: A spatial econometric analysis." *Journal of Cleaner Production*.

Sun, M. (2020). "Sectoral analysis of carbon emissions in India: A focus on electricity, gas, and water supply." *Sustainability*.

United Nations Environment Programme (UNEP). (2023). "Sectoral Solutions to Climate Change." Retrieved from UNEP.

Wang, L., et al. (2023). "Assessing the Distribution of Employment Vulnerability to Carbon Intensity." *Journal of Cleaner Production*.

Wooldridge, J. M. (2010). "Econometric Analysis of Cross Section and Panel Data." *MIT Press*.

Zhao, J., et al. (2020). "Spatial network structure and influencing factors of carbon emission intensity in Guangdong-Hong Kong-Macao Greater Bay Area." *Frontiers in Environmental Science*.

Zhou, D., et al. (2023). "Carbon Emission, Air Pollution, and Total Factor Productivity." *Environmental Science & Policy*.

Zhang, X., et al. (2023). "Cooling and Heating Degree Days in the US." *Climate Dynamics*.

 ISBN 978-80-7668-014-2, IISES

Appendix 1: Description of economic sectors in NACE classification

NACE CODE	DESCRIPTION
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning supply
E	Water supply; sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other service activities
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
U	Activities of extraterritorial organisations and bodies