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The impact of energy prices and socio-economic factors on CO_2 emissions in OECD countries: A STIRPAT and machine learning analysis

Cosimo Magazzino [a,b], Tulia Gattone [c,d], Parisa Pakrooh [e], Mehmet Akif Destek [f,g,h,i,*]

[a] ARUCAD Research Centre, Arkin University of Creative Arts and Design, Northern Cyprus, Mersin 10, Turkey
[b] Economic Research Center, Western Caspian University, Baku, Azerbaijan
[c] Department of Economics, John Cabot University, Rome, Italy
[d] Syracuse University in Florence, Florence, Italy
[e] Department of Economics, Business, and Statistics, University of Palermo, Italy
[f] Department of Economics, Gaziantep University, Gaziantep, Türkiye
[g] Research Methods Application Center of UNEC, Azerbaijan State University of Economics, Baku, Azerbaijan
[h] Department of Economics, Korea University, Seoul 02841, South Korea
[i] Baku Eurasian University, Economic Research Center (BAAU-ERC), Baku, Azerbaijan

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ABSTRACT

Climate change presents a major hurdle for OECD countries, which have accounted for substantial historical greenhouse gas emissions and now face the task of reducing carbon dioxide (CO_2) emissions while sustaining economic growth. This research investigates the influence of oil price dynamics, Brent, OPEC, and West Texas Intermediate, and socio-economic factors on CO_2 emissions in OECD countries from 1990 to 2020. Using the STIRPAT framework, we estimate static and dynamic panel regression models to assess the effects of oil price benchmarks alongside variables such as Gross Domestic Product (GDP), urbanization, and education. Granger causality tests evaluate directionality, while artificial neural networks serve as robustness checks. Results show a significant inverse relationship between oil prices and CO_2 emissions, signifying that increased oil prices are associated with lower emissions, as they encourage conservation, efficiency, and cleaner energy transitions. Socioeconomic factors are also essential, with GDP growth and urbanization contributing to variability in emissions across countries. These findings highlight the significance of designing differentiated, context-sensitive mitigation strategies. Policy recommendations include adopting energy pricing reforms, such as carbon taxes, to internalize environmental costs, while also supporting education, urban planning, and the adoption of renewable energy to strengthen long-term emission reduction efforts.

1. Introduction

Tackling climate change remains one of the most urgent challenges facing humanity, requiring a concerted global effort to reduce greenhouse gas (GHG) emissions while maintaining economic stability. Recent international commitments, such as the Paris Agreement, have intensified pressure on countries to design effective mitigation strategies that balance environmental goals with economic and social needs [1]. At the same time, volatile global energy markets, shifting oil price dynamics, and growing energy demand complicate policy design, especially for advanced economies seeking sustainable growth pathways. In this context, understanding how energy prices, particularly oil prices, interact with socio-economic drivers to shape carbon dioxide (CO_2) emissions is vital for effective climate policy.

The motivation for this study stems from the need to better understand the complex relationship between energy prices, socio-economic factors, and CO_2 emissions in the Organization for Economic Co-operation and Development (OECD) countries. OECD economies are responsible for a significant share of historical GHG emissions and have the institutional capacity to lead global decarbonization efforts [2]. However, their emissions trajectories differ widely, reflecting heterogeneity in industrial structures, technological development, policy frameworks, and energy market dynamics [3]. Targeting OECD countries is therefore justified because they are both essential contributors to

* Corresponding author. Department of Economics, Gaziantep University, Gaziantep, Türkiye.
E-mail addresses: cosimomagazzino@hotmail.com (C. Magazzino), tulia.gattone@johncabot.edu (T. Gattone), parisa.pakrooh@unipa.it (P. Pakrooh), adestek@gantep.edu.tr (M.A. Destek).

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global emissions and critical testing grounds for mitigation strategies that can be replicated elsewhere.

Socio-economic factors play a central role in determining emissions outcomes within OECD countries. Calbick and Gunton [4] find that differences in energy prices, economic output per capita, and environmental governance explain over 80 % of the variation in per capita GHG emissions across high-income OECD members. Meanwhile, Puertas and Martí [5] highlight the role of eco-innovation, environmental policy, and productivity in mitigating emissions, demonstrating that OECD countries have introduced new technologies to curb global warming, albeit with uneven success.

Energy pricing remains a key but under-explored mechanism for emissions control in OECD contexts. Price signals influence consumer and producer behavior, encourage efficiency improvements, and promote fuel switching. For example, Li et al. [6] document a significant negative relationship between energy prices and CO_2 emissions in China, suggesting the effectiveness of market-based instruments even outside OECD settings. However, oil price dynamics are especially complex, with global shocks creating different impacts across economies and time scales. Kassouri et al. [7] explain how demand- and supply-driven oil shocks have distinct effects on emissions intensity in the United States, revealing subtle co-movements that demand further investigation across OECD economies.

OECD countries also exhibit varied patterns in energy use and industrial activity that shape emissions. Saboori et al. [8] uncover a long-run bi-directional relationship between energy consumption in the transport sector and CO_2 emissions, indicating the importance of sector-specific policies. Mujtaba et al. [9] emphasize that fossil fuel-based energy consumption deteriorates environmental quality in OECD countries, whereas renewable energy consumption enhances it. While Pizarro et al. [10] emphasize that Nationally Determined Contributions under the Paris Agreement vary in their sectoral coverage and ambition, rendering it difficult to track collective progress without the use of harmonized methodologies.

At the same time, advanced economies persist in investigating new pathways for green growth. Wang et al. [3] determine three possible approaches for OECD countries: technological breakthrough orientation, energy-saving and emission-reduction orientation, and balanced growth orientation, pointing out the diverse options available while also underscoring the necessity for tailored approaches. Hickmann [11] highlights the limitations of voluntary business-led climate initiatives, arguing that meaningful reductions require integration within coherent regulatory frameworks. This suggests that market signals, such as oil prices, interact with policy institutions and socio-economic conditions in complex ways, influencing emissions outcomes in OECD settings.

To address these gaps, this study examines the dynamic effects of various oil price benchmarks, specifically Brent, OPEC, and West Texas Intermediate (WTI), in conjunction with key socio-economic factors on CO_2 emissions in OECD countries from 1990 to 2020. While existing studies often rely on aggregated energy price indices or single-country analyses, this research distinguishes itself by explicitly comparing multiple oil price benchmarks, accounting for their potentially divergent effects on emissions across a diverse set of advanced economies. The empirical strategy is based on the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model [12,13], which extends the IPAT framework to allow flexible estimation of the roles of population, affluence, and technology in shaping environmental impacts.

Methodologically, the study combines static and dynamic panel regression models with causality testing following Dumitrescu and Hurlin [14] to assess the direction and persistence of the oil price-emissions relationship. It also incorporates robustness checks using Artificial Neural Networks (ANNs) to evaluate the reliability of the findings. By providing benchmark-specific evidence and systematically accounting for socio-economic heterogeneity within OECD countries, this research offers a more detailed understanding of the mechanisms through which oil price dynamics and socio-economic factors jointly influence CO_2 emissions. Such insights are critical for designing effective, context-sensitive policies that can support the transition to low-carbon economies.

Hence, while the relationship between energy prices and CO_2 emissions in OECD countries has been extensively explored, this study contributes new insights by discriminating the effects of multiple international oil price benchmarks (Brent, OPEC, and WTI) rather than relying on aggregate energy price indices or country-specific analyses. Moreover, by integrating both econometric and Machine Learning (ML) techniques, the study enhances methodological robustness and predictive accuracy, offering a comprehensive assessment of how oil prices interact with socio-economic variables to shape emissions outcomes. This benchmark-specific and methodologically hybrid approach makes a novel contribution to the empirical literature, equipping policymakers with more granular evidence to tailor carbon mitigation strategies in advanced economies.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature and clarifies our contribution to the field. Section 3 describes the methodological framework. Section 4 discusses data sources and descriptive statistics. Section 5 presents empirical findings, while Section 6 details robustness checks. Section 7 concludes with policy implications and recommendations for future research.

2. Literature review

Understanding the drivers of CO_2 emissions has been a major issue in environmental economics for decades, evolving from simple growth–pollution linkages to complex, multi-factor models that account for energy use, technology, demography, and policy. An important starting point for this literature is the Environmental Kuznets Curve (EKC) hypothesis proposed by Grossman and Krueger [15], which suggests an inverted U-shaped relationship between economic growth and environmental degradation. Early evidence supported this pattern in various pollutants, underlining that growth initially increases environmental damage before eventually leading to improvements through technological change and enhanced regulatory capacity. Building on this conceptual foundation, studies have sought to test and extend the EKC across contexts. Liu [16] confirmed the EKC in Chinese regions, showing that CO_2 emissions rise and then fall with income. In contrast, Farouki and Aissaoui [17] demonstrated the EKC for Morocco's ecological footprint, using an extended STIRPAT model that also included urbanization and trade openness. Thio et al. [18] further supported the EKC hypothesis among the world's top CO_2 emitters, finding that income, population, and trade jointly shape emissions, but that technology innovation is critical for mitigation.

Recognizing that growth alone cannot explain emissions trends, research has increasingly turned to the energy mix and price incentives. Shafiei and Salim [19] found that in OECD countries, renewable energy consumption reduces CO_2 emissions, while non-renewable energy use increases them, emphasizing the necessity of transitioning to a more sustainable energy system. Amer et al. [20] provided complementary evidence for Gulf Cooperation Council (GCC) countries, showing that oil, coal, and gas increase emissions while renewable energy lowers them, emphasizing the varied impacts of different non-renewable sources. Similarly, Bilgili et al. [21] employed wavelet methods to illustrate the role of renewables in industrial production cycles, underlining the interdependencies between energy policy and economic outcomes over time.

Another essential strand of work focuses on socio-demographic drivers. Onozaki [22] identified global population growth as a key factor contributing to rising CO_2 levels. Lin et al. [23] demonstrated that in non-high-income countries, while urbanization and development have a limited impact, population, affluence, and energy intensity remain the primary drivers of emissions. Jung et al. [24] employed a dynamic computable general equilibrium model to show that population structure and economic activity, proxied by Gross Domestic Product (GDP), influence future emissions in East Asia. Zhao and Lee [25] confirmed the importance of human capital, urbanization, and Foreign Direct Investment (FDI) in explaining cross-country heterogeneity in CO_2 emissions. In contrast, Nguyen-Thanh et al. [26] found support for the pollution haven hypothesis, demonstrating FDI's role in spreading emissions, particularly in developing countries.

Technological change and innovation are widely regarded as critical to decoupling economic growth from emissions. Osabuohien-Irabor and Drapkin [27] stressed that outward FDI can enable green technology transfer if supported by strong institutions and human capital in the home country. Apeaning and Labaran [28] revealed that in Brazil, Russia, India, Indonesia, China, and South Africa (BRIICS), well-developed financial sectors greatly boost the impact of climate mitigation innovation in reducing CO_2 intensity, showing that economic development moderates the technology–emissions relationship. Bergougui et al. [29] provided city-level evidence from China, revealing complex, non-linear effects of energy transition, environmental technology, and digitalization on energy security, stressing the importance for sophisticated strategies.

Energy prices, particularly oil prices, represent a critical yet often underexplored lever for emissions control. Katircioğlu [30] explained that in Turkey, oil prices and CO_2 emissions are in a long-term equilibrium, with higher oil prices leading to lower emissions, consistent with the oil-induced EKC hypothesis. Abumunshar et al. [31] also confirmed this inverse relationship in Turkey, showing that non-renewable energy use drives emissions while renewable energy mitigates them. Lee and Chong [32] examined the US building sector, finding long-run causal relationships from energy prices to consumption patterns that affect emissions. Li et al. [33] highlighted in China that higher energy prices reduce pollution, while distortions in energy pricing exacerbate it. Magazzino et al. [34] analyzed the interaction between oil prices and investments in biomass, solar, hydro, wind, and geothermal energy in Italy during the early COVID-19 pandemic, employing Partial Wavelet Coherency, Time-Varying Granger Causality, and ML regressions on country-level price and investment series. Their results indicate a dominant in-phase relationship between oil prices and most renewable series, with occasional unidirectional causality from renewables back to oil. Robustness checks identify solar, hydro, and geothermal as the most influential contributors. While Magazzino and Giolli [35] studied daily oil prices and renewable energy production in Italy from January to September 2020 using long memory tests, spectral causality, and wavelet analysis. Their empirical findings show a strong correlation during the pandemic shock and unidirectional causality from solar, hydro, and wind production to oil prices, underscoring the importance of accelerating Italy's energy transition to reduce reliance on fossil fuel imports during periods of volatile oil prices.

Beyond country-specific studies, Ebaid et al. [36] examined the GCC countries, finding that positive oil price shocks reduce CO_2 emissions, although the effects are asymmetric and vary across countries. Okwanya et al. [37] revealed that in Africa, oil price changes have asymmetric effects on emissions, with responses differing between oil-importing and oil-exporting nations. Zou [38] demonstrated that in China, oil prices significantly affect emissions and GDP in both the short and long term. In contrast, Nwani [39] found that higher oil prices can increase energy consumption and emissions over time in Ecuador, reflecting the dependence of oil-exporting economies on fossil fuel revenues. Mahmood et al. [40] and Malik et al. [41] reported similarly mixed results in Saudi Arabia and Pakistan, respectively, with oil prices sometimes reducing long-term emissions while increasing short-term consumption.

Recent macro-level studies also examine the broader nexus between renewable energy, economic growth, and emissions. Gafsi and Bakari [42] investigated these relationships in G7 countries, finding that renewable energy use supports long-term economic growth while reducing emissions; however, the short-term effects are limited.

Critically, while the literature confirms that oil prices and socio-economic factors affect CO_2 emissions, most studies focus on single countries or aggregated price indices, neglecting benchmark-level differentiation (e.g., Brent, OPEC, WTI). Moreover, research rarely accounts for the interaction of oil prices with socio-economic variables, such as urbanization, education, or GDP, across a diverse set of advanced economies. This study addresses these gaps by examining the dynamic effects of different oil price benchmarks and socio-economic drivers on CO_2 emissions across OECD countries from 1990 to 2020, using the STIRPAT framework combined with advanced panel econometric methods and ML robustness checks. By doing so, it provides a more granular and policy-relevant understanding of how market signals and socio-economic structures jointly shape emissions trajectories in high-income contexts that are striving for decarbonization.

3. Methodological framework

Understanding the determinants of CO_2 emissions is critical for designing effective mitigation strategies, particularly in OECD countries that historically contributed substantially to global emissions but now face complex transitions to low-carbon economies. Theoretical and empirical research has identified a broad set of drivers of emissions, including population growth, economic affluence, energy structure, urbanization, technological development, and policy variables such as energy prices. However, disentangling the contributions of these factors is analytically challenging, given the possibility of non-linear interactions, feedback effects, and country-specific institutional contexts.

To address this complexity, the present study adopts an extended version of the Stochastic Impacts by STIRPAT model, a flexible econometric framework designed to assess the environmental impacts of multiple socio-economic drivers while allowing for stochastic variability and non-proportional relationships [43,44]. Unlike the deterministic IPAT identity (see Ref. [45]), which implies strictly proportional effects of its components, the STIRPAT model accommodates non-linear elasticities and interactions, enabling a richer exploration of the role of oil prices, GDP, energy structure, population size, industrial structure, urbanization, FDI, and education levels in shaping CO_2 emissions across OECD countries over time.

This approach is theoretically justified by prior research showing that energy prices can influence emissions both directly and indirectly. For instance, Lee and Chong [32] demonstrate that in the US building sector, energy price changes affect energy consumption patterns and, consequently, CO_2 emissions. However, the magnitude and direction can vary across fuel types and end uses. In Ecuador, Nwani (2017) provides evidence that higher crude oil prices are associated with increased energy consumption and emissions, underlining the role of oil dependency in shaping this relationship. Conversely, Okwanya et al. [37] show that in Africa, oil price shocks have asymmetric impacts on CO_2 emissions, with positive price changes generally reducing emissions in oil-importing countries but exhibiting different effects in oil-exporting contexts.

In addition to energy prices, socio-economic factors such as urbanization and education also have essential implications for emissions, in line with the EKC hypothesis. Lin et al. [23] emphasize that in non-high-income countries, the primary drivers of CO_2 emissions remain population, affluence, and energy intensity, with urbanization exerting a relatively small direct effect. However, Zhao and Lee [25] highlight the role of heterogeneity in these relationships, showing that human capital, urbanization, and FDI differentially influence CO_2 emissions across groups of countries, suggesting that institutional and developmental contexts condition these effects.

The choice of the STIRPAT framework over simpler linear regression models or purely deterministic identities is motivated by its capacity to incorporate these complex, non-linear, and context-dependent dynamics. As York et al. [44] argue, the STIRPAT model improves on the IPAT model by allowing the estimation of elasticities that vary across drivers, making it possible to test hypotheses such as the EKC empirically. Furthermore, by extending the model to include variables such as oil prices, FDI, education, and energy structure, we align with recent empirical work that seeks to disentangle the multifaceted drivers of emissions in ways that can inform policy.

3.1. Conceptual framework

The classic IPAT identity expresses environmental impact (I) as the product of population (P), affluence (A), and technology (T):

$$I = P \times A \times T \tag{1}$$

While conceptually appealing due to its simplicity, the IPAT model has been criticized for its deterministic assumption of proportionality and its inability to account for behavioral and institutional factors [43]. To overcome these constraints, York et al. [44] proposed the STIRPAT model, which introduces a stochastic specification:

$$I = aP^bA^cT^de \tag{2}$$

where a is a scaling constant, b, c, and d are elasticities to be estimated, and e is an error term capturing unobserved variability. This form allows for non-monotonic and non-proportional relationships between drivers and environmental impacts.

In this study, we extend the STIRPAT model to incorporate additional variables relevant to the OECD context and the study period (1990–2020), recognizing that CO_2 emissions in these economies are shaped not only by demographic and economic factors but also by energy market dynamics, technological change, and institutional variables. Specifically, we model CO_2 emissions as a function of oil prices (OP), GDP, energy structure (ENS), population size (P), industrial structure (INS), urbanization (URB), FDI, and education (EDU):

$$CO_2 = \int (OP, GDP, ENS, P, INS, URB, FDI, EDU) \tag{3}$$

This formulation enables us to assess how changes in energy prices, mediated by economic structures and socio-economic conditions, impact emissions outcomes in OECD countries. We hypothesize that higher oil prices reduce CO_2 emissions by increasing the relative cost of fossil fuels, thereby dampening consumption and encouraging investment in energy-efficient technologies and alternative energy sources. We also expect that GDP growth increases emissions through higher overall consumption and production. However, this relationship may be non-linear due to structural change and technological improvement at higher income levels. Energy structure is hypothesized to affect emissions intensity, with a greater reliance on oil generally leading to higher carbon output; however, there is potential for negative correlations where cleaner energy transitions reduce fossil fuel dependence [46]. The industrial structure is expected to influence emissions, depending on the balance between energy-intensive manufacturing and shifts toward less carbon-intensive service sectors, allowing for both positive and negative correlations. Urbanization is hypothesized to have mixed effects, potentially increasing energy demand through transportation and infrastructure needs while also enabling efficiencies through dense development and planning. FDI is expected to influence emissions both by expanding industrial capacity and by transferring cleaner technologies. Finally, education is hypothesized to shape emissions outcomes in complex ways, potentially reducing them over time by fostering environmental awareness and supporting technological adoption, but also possibly increasing them through higher incomes and consumption patterns associated with greater human capital.

3.2. Econometric models

To capture both contemporaneous and dynamic effects, we estimate both static and dynamic panel data models. The static model is specified as:

$$\begin{aligned} \ln C_{i,t} = {} & \alpha_0 + \alpha_1 \ln Op_{i,t} + \alpha_2 \ln GDP_{i,t} + \alpha_3 \ln ENS_{i,t} + \alpha_4 \ln P_{i,t} \\ & + \alpha_5 \ln INS_{i,t} + \alpha_6 \ln URB_{i,t} + \alpha_7 \ln FDI_{i,t} + \alpha_8 \ln EDU_{i,t} + \alpha_9 Z_{i,t} \\ & + \varepsilon_{i,t} \end{aligned} \tag{4}$$

where $C_{i,t}$ denotes CO_2 emissions in country i at time t, $Z_{i,t}$ represents country-specific fixed effects, and the α coefficients measure the elasticities of the explanatory variables concerning emissions.

The use of logarithmic transformation in the panel regressions is motivated by several theoretical and econometric considerations. First, expressing variables in natural logs allows for the interpretation of estimated coefficients as elasticities, directly quantifying the percentage change in CO_2 emissions (C) associated with a one-percent change in the explanatory variables. This is consistent with the underlying multiplicative nature of the STIRPAT model derived from the IPAT identity, which posits that environmental impacts result from the joint proportional effects of population, affluence, and technology. Second, log transformation helps stabilize the variance of the residuals (addressing heteroskedasticity), improves the linearity of parameters, and mitigates the influence of extreme values, thereby enhancing the reliability of estimated relationships across countries with diverse economic and demographic profiles. Similarly, for the ML analysis, variables are transformed into standardized (scaled) form rather than logarithmic form. Standardization involves centering variables at their mean and scaling by their standard deviation, ensuring all input features are on a comparable numerical scale. This is essential for the training of ANNs and other ML models, as it prevents variables with larger magnitudes from disproportionately influencing the learning process and improves the convergence properties of optimization algorithms such as resilient backpropagation. Unlike econometric regressions, ML models do not rely on linear-in-logs specifications to estimate elasticities; instead, they flexibly capture nonlinear relationships and complex interactions among predictors.

The dynamic panel model includes a lagged dependent variable to capture path dependence in emissions:

$$\begin{aligned} \ln C_{i,t} = {} & \beta_0 + \beta_1 l.\ln C_{i-p,t} + \beta_2 \ln Op_{i,t} + \beta_3 \ln GDP_{i,t} + \beta_4 \ln ENS_{i,t} \\ & + \beta_5 \ln P_{i,t} + \beta_6 \ln INS_{i,t} + \beta_7 \ln URB_{i,t} + \beta_8 \ln FDI_{i,t} + \beta_9 \ln EDU_{i,t} + \upsilon_{i,t} \end{aligned} \tag{5}$$

The inclusion of the lagged dependent variable reflects the well-documented persistence of CO_2 emissions over time [47]. It helps address potential omitted variable bias due to unobserved, time-invariant country characteristics.

3.3. Theoretical rationale for methodological choices

Static models provide estimates of average cross-sectional elasticities, helpful in understanding long-run equilibrium relationships between drivers and emissions. However, they cannot account for the dynamic adjustment processes through which policy changes or price shocks influence emissions over time. Dynamic models, by contrast, capture short-term adjustments and inertia in emissions patterns, which is particularly relevant given the gradual nature of technological adoption and infrastructure transitions.

The use of panel data methods also offers significant advantages. Fixed effects estimators control for unobserved, time-invariant heterogeneity across countries, which might otherwise bias estimates. Dynamic panel estimators, such as System Generalized Method of Moments (GMM-Sys), are specifically designed to handle endogeneity arising from the inclusion of lagged dependent variables and potential reverse causality [48,49].

3.4. Pre-estimation and diagnostic procedures

Before estimation, unit root tests are conducted using the Levin et al. [50] and Pesaran [51] Cross-sectional Augmented Dickey-Fuller (CADF) tests to assess the stationarity of the panel data series. To verify the existence of long-run relationships among variables, the Kao [52] cointegration test is applied, which is suitable for heterogeneous panel data structures with cross-sectional dependence [47].

We also evaluate cross-sectional dependence using the Cross-sectional Dependence (CD) test proposed by Pesaran [53], recognizing that economic integration among OECD countries can induce contemporaneous correlation in shocks. Where cross-sectional dependence, heteroskedasticity, or serial correlation is detected, Feasible Generalized Least Squares (FGLS) estimation is employed to obtain efficient estimates by modeling the error covariance structure directly [54]. Multicollinearity diagnostics are conducted using the Variance Inflation Factor (VIF), with interpretation guided by Shrestha [55]. Values exceeding 10 indicate problematic collinearity, which can potentially inflate standard errors and undermine inference.

3.5. Post-estimation checks and causality analysis

Post-estimation diagnostics include the Wald test for heteroskedasticity, the Wooldridge test for serial correlation, and additional checks for cross-sectional dependence. For dynamic models, the validity of the instrument set in GMM-Sys estimation is assessed using the Hansen [56] test of over-identifying restrictions. Failure to reject the null hypothesis suggests instrument validity. Finally, to explore directional relationships among variables, the Dumitrescu and Hurlin [14] Granger non-causality test for heterogeneous panels is applied. This test allows us to assess whether, for example, oil prices Granger-cause changes in emissions while accounting for cross-country heterogeneity.

3.6. Robustness via ANNs

Recognizing that traditional econometric models may impose restrictive functional forms and overlook complex, non-linear interactions, we complement panel regressions with ANNs as a robustness check. Following Babatunde et al. [57], we employ multilayer perceptron architectures trained using the resilient backpropagation algorithm, known for its effectiveness in handling noisy, high-dimensional data. The ANN framework comprises an input layer with socioeconomic and energy variables, hidden layers that capture non-linear transformations, and an output layer that predicts CO_2 emissions. Model performance is evaluated using mean squared error and R-squared metrics across training, validation, and testing subsets. This approach provides an additional validation of the relationships identified in econometric models and offers insights into potential non-linearities or interaction effects that may be policy-relevant.

By combining theoretically grounded econometric analysis with ML methods, the study aims to provide a comprehensive, robust examination of the drivers of CO_2 emissions in OECD countries, yielding insights of direct relevance to policymakers seeking to design effective, context-sensitive mitigation strategies.

4. Data and descriptive statistics

This study utilizes an unbalanced panel dataset comprising 38 OECD member countries from 1990 to 2020, resulting in 1178 country-year observations. The dependent variable is C, measured in kilotons (kt) and collected from the World Bank's World Development Indicators.[1] CO_2 emissions reflect the volume of fossil-fuel-related and industrial processes contributing to atmospheric greenhouse gas concentrations, making them a central measure for evaluating progress toward climate targets.

A key feature of this research is the inclusion of three distinct oil price benchmarks: Brent (Op2), OPEC Basket (Op4), and West Texas Intermediate (Op6). These indices were deliberately selected to represent the primary regional and global reference prices in the oil market. Brent is the dominant benchmark for Europe and global seaborne trade, reflecting pricing in the Atlantic Basin and beyond. The OPEC Basket price offers a weighted average for a group of oil-producing countries, capturing supply dynamics and policy coordination within the cartel. WTI serves as the benchmark for North America, with its pricing shaped by inland US production, infrastructure, and market conditions. Including all three benchmarks ensures the analysis accounts for both global price signals and regional heterogeneity in energy markets, which can differentially influence energy costs and related CO_2 emissions across OECD countries. Data for Brent prices are sourced from Trading Economics,[2] the OPEC Basket price is from OPEC's official data portals,[3] and WTI prices are obtained from the US Energy Information Administration (EIA).[4] All price series are deflated using the 2010 Consumer Price Index (CPI) to ensure consistency in real terms.

Additional explanatory variables reflect socioeconomic, demographic, and structural factors that drive CO_2 emissions. GDP per capita, in constant local currency units, captures economic activity and affluence, a fundamental driver in the IPAT/STIRPAT framework. P, measured in millions, serves as a scale factor for aggregate energy demand and emissions. ENS is calculated as the ratio of oil consumption to total energy consumption (expressed in terawatt-hours), capturing the carbon intensity of a country's energy mix. INS is measured as the percentage share of industrial value added in GDP, indicating the economy's sectoral composition and its influence on energy demand patterns. URB is the share of the urban population relative to the total, reflecting demographic transitions often associated with energy-intensive infrastructure and consumption. FDI is included as a percentage of GDP, recognizing its role in capital flows, technology transfer, and potentially pollution-intensive production. Lastly, EDU is measured by the gross enrollment ratio, which represents the percentage of the official school-age population enrolled in education and serves as a proxy for human capital and potential environmental awareness.[5]

Table A.1 in the Appendix offers an in-depth mapping of each variable's source and definition, while Table 1 below presents descriptive statistics for all variables in their original measurement units to maintain clarity regarding the sample's characteristics.

C exhibits a mean of approximately 324,832 kilotons, with a large standard deviation of 853,604 kilotons, underlining the significant variation in emission levels across OECD economies, from small economies with minimal industrial emissions to large economies with extensive energy use. The maximum observed CO_2 emissions exceed 5.8 million metric tons, reflecting the highly industrialized and populous countries.

For oil prices, Brent (Op2), OPEC (Op4), and West Texas (Op6) show means of roughly 147 USD, 139 USD, and 150 USD per barrel, respectively, albeit with sizable standard deviations due to a few outliers. This reflects both inflation adjustments and significant price volatility over the period, which included periods of geopolitical shocks, demand surges, and oil market collapses (e.g., the early 1990s price crash and the 2008 financial crisis).

GDP per capita exhibits substantial variation, with a mean of nearly

[1] Available at https://data.worldbank.org. Last accessed on June 2023.

[2] Available at https://tradingeconomics.com/commodity/brent-crude-oil. Last accessed on June 2023.

[3] Available at https://www.opec.org/opec_web/en/data_graphs/40.htm. Last accessed on June 2023.

[4] Available at https://www.eia.gov/dnav/pet/hist/rwtcD.htm. Last accessed on June 2023.

[5] Values over 100 % indicate enrollment outside the typical age range.

Table 1
Exploratory data analysis.

Variable	Count	Mean	Std. Dev.	Max.	Min.	Skewness	Kurtosis	Variance
C (in Mt)	1178	0.32	0.85	5.80	0.00	5.23	27.81	728.64
Op2	1178	147.07	1341.07	33217.20	12.35	19.52	418.79	1798479.02
Op4	1178	139.35	1253.82	31067.90	11.84	19.51	418.68	1572068.32
Op6	1178	150.55	1391.63	34194.20	13.89	19.30	409.23	1936620.96
GDP (in millions)	1178	1.67	4.67	36.00	0.00	4.34	21.86	21793.22
EDU	1178	104.45	19.23	200.37	43.49	0.57	5.05	369.97
ENS	1178	0.40	0.14	0.79	0.00	−0.10	0.59	0.02
P (in millions)	1178	32.80	53.19	330.00	0.25	3.41	13.73	2829344.96
INS	1178	25.86	5.20	41.11	10.43	−0.02	−0.01	27.00
URB	1178	75.45	11.15	98.08	47.92	−0.29	−0.52	124.31
FDI (in billion)	1178	26.16	71.34	1000.00	−360.00	5.58	53.28	5089904.61

1.67 million constant local currency units. Still, values range from a few thousand to over 36 million units, underlining the economic diversity among OECD members. P has a mean of approximately 32.8 million, with values ranging from under 0.3 million to 330 million, confirming the inclusion of both small nations and large continental economies. ENS, defined as the oil share in total energy consumption, averages approximately 40 %, with values ranging from under 0.2 % to almost 80 %, revealing diverse energy transitions across OECD countries. Moreover, INS averages around 25.9 %, with moderate variation (standard deviation ~5.2 %), showing relatively stable industrial shares typical of advanced economies. URB has a mean of nearly 75 %, with most OECD countries highly urbanized, but ranges from roughly 48 %–98 %, suggesting varied demographic contexts. FDI as a percentage of GDP has a wide distribution, including negative values in some years due to disinvestment, with a mean of 26.16 % and a standard deviation of over 71, underlining the volatility and policy sensitivity of capital flows. EDU typically exhibits high average values consistent with advanced educational systems.

These statistics reveal considerable heterogeneity in economic scale, energy structure, demographic composition, and policy-relevant variables across OECD countries, justifying the use of econometric models that control for country-specific effects and allow for robust estimation of the drivers of CO_2 emissions.

Fig. 1 visualizes oil price trends across the study period using *googleVis*.[6]

Op2 shows notable declines in the early 1990s, consistent with shifts in global market structures and OPEC production strategies. Op4 similarly declines and then stabilizes below 500 USD per barrel for much of the observed period. Op6 displays slightly lower average levels, reflecting North American supply dynamics and transport cost differentials. These price trends justify including all three indices in the analysis, as they capture different market segments and geopolitical risk exposures influencing domestic energy costs and carbon emissions. This triangulated approach enhances the credibility of the empirical strategy by mitigating bias that might arise from reliance on a single benchmark. Fig. 2 presents box plots of the main variables, showing their distributions across countries and years.

CO_2 emissions, GDP, and FDI exhibit pronounced variability and outliers, underscoring the need for econometric approaches that account for heteroskedasticity and cross-sectional dependence. In contrast, variables like ENS, INS, and URB have more concentrated distributions, indicating relative stability within the OECD context. Fig. 3 provides a scatterplot matrix of the main variables, underlining bivariate relationships.

A clear positive association is observed between GDP and CO_2 emissions, reflecting the energy demands of economic activity. Similarly, population size correlates with emissions, consistent with scale effects in the IPAT/STIRPAT framework. The oil price variables display more complex, less linear patterns with emissions, indicating that price effects likely interact with energy mix, industrial structure, and policy variables, motivating the study's inclusion of interaction terms and nonlinear modeling approaches in robustness checks.

Overall, this comprehensive dataset enables an in-depth analysis of the multiple, interrelated drivers of CO_2 emissions across OECD economies, capturing both common trends and country-specific heterogeneity over three decades of economic, energy, and policy change.

5. Results and discussions

Before estimation, rigorous diagnostic tests are performed to confirm the suitability of the econometric approach. The main regression results reveal complex interactions consistent with, and in some cases distinct from, findings in the broader environmental economics literature. Specifically, unit root tests confirm that most variables are stationary at level, except for the ENS, which required differencing, suggesting integration of order one (Tables A.2–A.3). Cointegration analysis via the Kao test (Table A.4) reveals long-run equilibrium relationships among the variables, supporting the inclusion of error correction mechanisms in dynamic specifications. Tests for cross-sectional dependence (Pesaran CD test, Table A.5) indicate significant interdependence across countries, particularly for GDP, consistent with the integrated nature of OECD economies. VIF diagnostics (Table A.6) rule out problematic multicollinearity, with all values comfortably below standard thresholds.

5.1. Static panel results and diagnostics

The static panel regressions are estimated using FGLS, justified by evidence of heteroskedasticity, autocorrelation, and cross-sectional dependence. Table 2 reports key diagnostic tests.

The Hausman test confirms the preference for Fixed Effects (FE) over Random Effects (RE), ensuring consistent control for unobserved heterogeneity. Table 3 reports the FGLS results.

Across specifications using Brent, OPEC Basket, and West Texas oil prices, the coefficients on oil price variables are consistently negative and highly significant. This finding supports the hypothesis that higher oil prices reduce CO_2 emissions in OECD countries, likely by incentivizing energy efficiency and reducing fossil fuel consumption. This result aligns with evidence from Abumunshar et al. [31], who observed that in Turkey, oil price increases are associated with long-run reductions in emissions. Similarly, Ebaid et al. [36] demonstrated that positive oil price shocks have adverse effects on CO_2 emissions in GCC countries. However, they note asymmetric responses, with adverse price shocks not increasing emissions in all contexts, a nuance our aggregate OECD analysis cannot fully disentangle but which emphasizes the significance of price signals in energy transitions.

GDP shows a statistically significant negative coefficient across all

[6] The figures are generated in R using the *googleVis* package. The code calculates yearly averages of oil prices and produces an interactive line chart with customized axes, colors, and layout. The chart was created with the *gvisLineChart()* function.

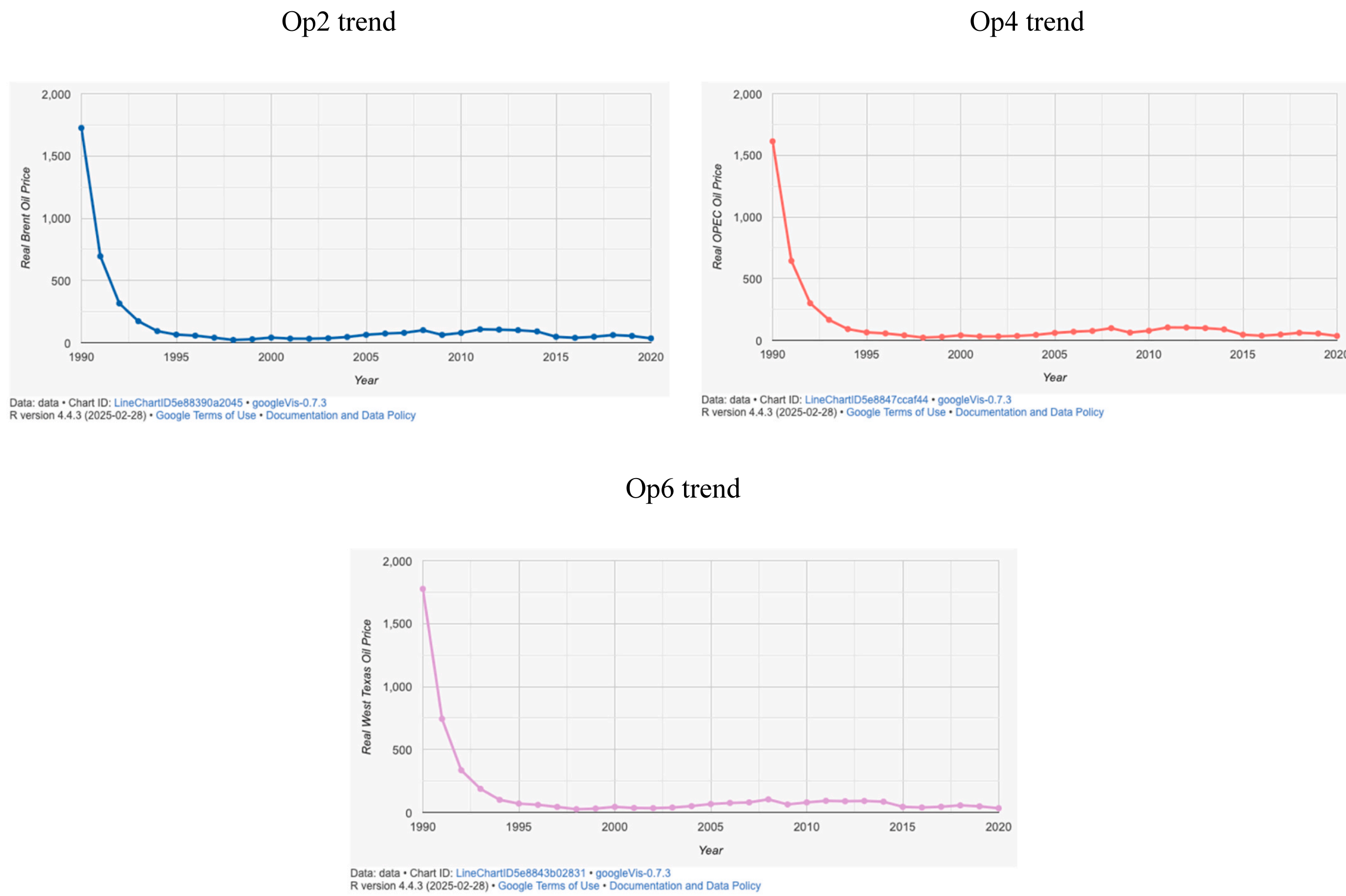

Fig. 1. Oil price trends (Adjusted by CPI = 2010).

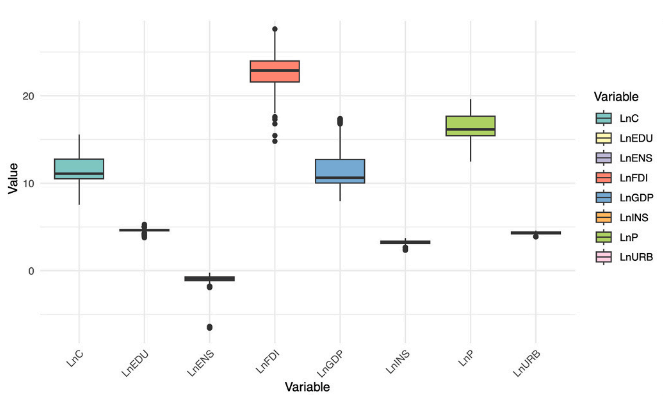

Fig. 2. Box plots.

static models. This inverse relationship is consistent with the EKC hypothesis, which posits that after surpassing a certain income threshold, economic growth is associated with improved environmental outcomes through technological upgrading and structural change [15,16]. This result is comparable to findings from Farouki and Aissaoui [17] in Morocco, who confirmed an EKC relationship for the ecological footprint, and Katircioğlu [30] in Turkey, who specifically validated an oil-price-induced EKC. The OECD context, characterized by high average income levels and stringent environmental regulations, likely reinforces this pattern, suggesting that advanced economies may increasingly decouple growth from emissions.

The coefficient on ENS is positive and significant, indicating that greater reliance on oil in the energy mix leads to higher emissions. This supports findings from Amer et al. [20] in GCC countries, who reported that oil consumption is the strongest non-renewable energy driver of CO_2 emissions. Our results reinforce the policy imperative for energy diversification and the shift toward renewables in the OECD context, aligning with the calls by Shafiei and Salim [19] for developed economies to reduce their reliance on fossil fuels to mitigate climate change.

Population size also has a positive and significant coefficient, underscoring its role as a scale driver of emissions. This finding supports the well-documented linear relationship between global population growth and CO_2 concentration [22]. It is consistent with the STIRPAT literature, which emphasizes population as a core factor [43]. Similarly, industrial structure and urbanization both exhibit positive and significant coefficients. The role of industry is expected, given its energy-intensive production processes, while urbanization is likely to reflect higher energy demand for transportation, heating, and infrastructure. Zhang and Lin [58] similarly found that urbanization increases energy consumption and emissions in China, though they note regional heterogeneity. While OECD member countries may differ in their per capita energy intensity, the positive average effect is plausible given the advanced urban infrastructure and persistent reliance on fossil fuels in transportation.

Interestingly, FDI shows a negative and significant coefficient, suggesting that higher inward investment is associated with reduced emissions. This result contrasts with concerns about pollution havens and instead aligns with the pollution halo hypothesis, whereby FDI can transfer cleaner technologies and practices to host countries. Nguyen-Thanh et al. [26] revealed that FDI affects emissions across developed and developing countries, suggesting that attracting cleaner multinational investments is essential for achieving long-run environmental stability. For the OECD sample, high institutional quality may enable

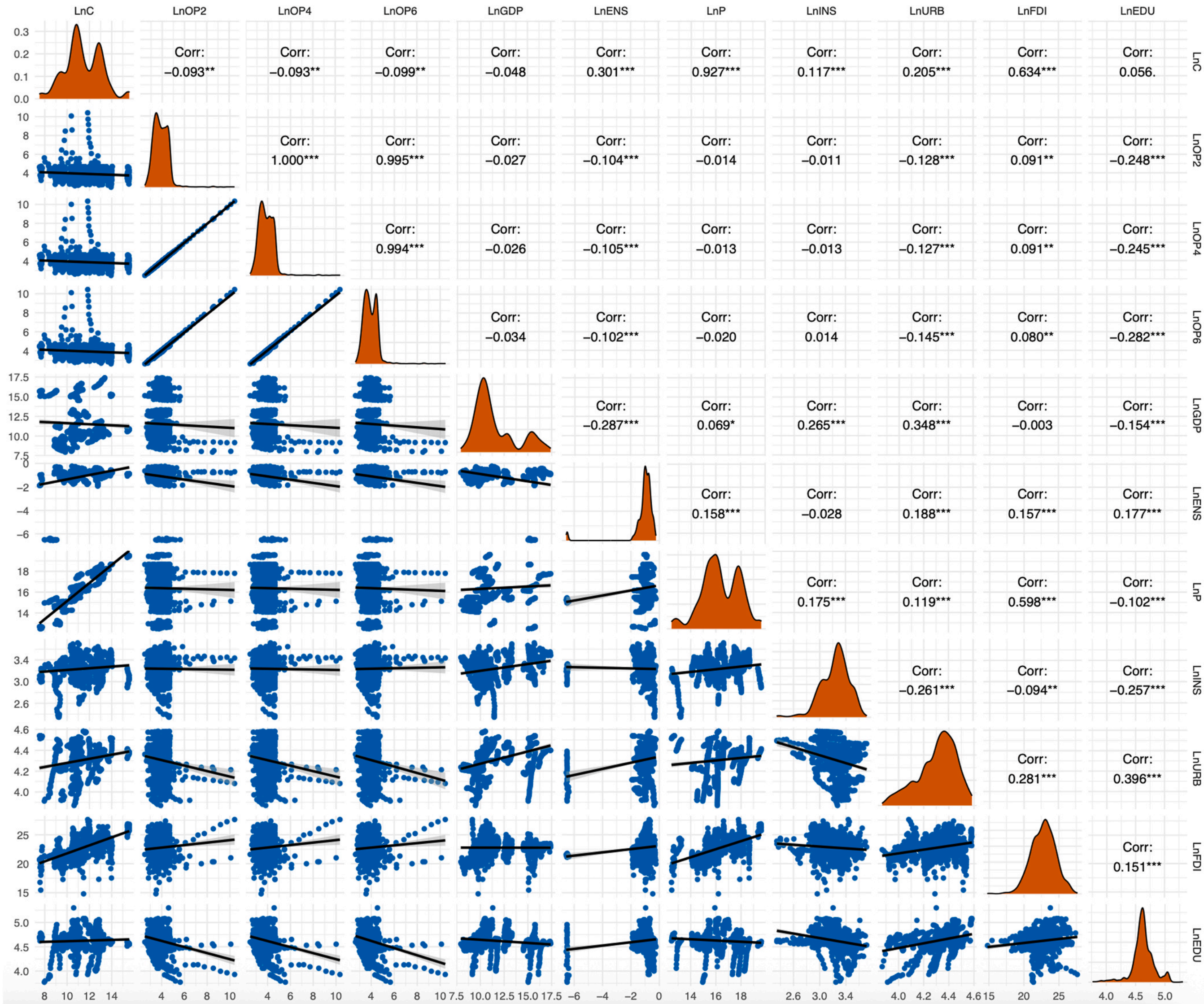

Fig. 3. Scatterplot matrix.

Table 2
Diagnostic tests.

Test	Model 1		Model 2		Model 3	
	Statistic	P-Value	Statistic	P-Value	Statistic	P-Value
Hausman (Between FE and RE)	19.61***	0.00	19.64***	0.00	19.44***	0.01
F-Limer (Between FE and PLS)	344.50***	0.00	344.30***	0.00	345.74***	0.00
Autocorrelation (Wooldridge)	116.40***	0.00	113.53***	0.00	121.30***	0.00
Heteroscedasticity (Wald)	21799.30***	0.00	22030.80***	0.00	19622.00***	0.00
Weak Cross-Sectional Dependence (Pesaran)	18.89***	0.00	18.88***	0.00	18.93***	0.00
Final Model	FGLS		FGLS		FGLS	

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

FDI to contribute to emissions reduction by fostering green investment and technology transfer. Lastly, EDU also emerges as a significant negative driver of emissions, suggesting that higher levels of human capital reduce environmental pressure. This aligns with findings that illustrate how human capital moderates CO_2 emissions (e.g. Ref. [25]), enabling environmentally conscious behavior and supporting policy effectiveness. In OECD countries, this channel likely includes public support for regulation, sustainable consumption patterns, and the development of low-carbon technologies.

5.2. Dynamic panel results (system GMM estimates)

Dynamic panel estimates using the GMM-Sys approach (Table 4) account for path dependence in emissions, as indicated by the highly significant lagged dependent variable with coefficients ranging from 0.95 to 0.97.

Oil prices remain negatively associated with emissions, though the magnitude of the coefficients is smaller than in static models, and significance levels are somewhat weaker (often at the 10 % level). This attenuation is expected, given the inclusion of lagged emissions and the

Table 3
FGLS estimates.

Model	Variable	Coefficient	Std. Dev.	P-Value
1	LnOp2	−0.12***	0.02	0.00
	LnGDP	−0.08***	0.01	0.00
	LnENS	0.14***	0.01	0.00
	LnP	0.99***	0.01	0.00
	LnINS	0.32***	0.08	0.00
	LnURB	0.84***	0.13	0.00
	LnFDI	−0.07***	0.01	0.00
	LnEDU	−0.54***	0.09	0.00
	Wald Test	11372.30***		0.00
	RMSE	0.46		
2	LnOp4	−0.12***	0.02	0.00
	LnGDP	−0.08***	0.01	0.00
	LnENS	0.14***	0.01	0.00
	LnP	0.99***	0.01	0.00
	LnINS	0.32***	0.08	0.00
	LnURB	0.84***	0.13	0.00
	LnFDI	−0.07***	0.01	0.00
	LnEDU	−0.54***	0.09	0.00
	Wald Test	11378.70***		0.00
	RMSE	0.46		
3	LnOp6	−0.12***	0.02	0.00
	LnGDP	−0.08***	0.01	0.00
	LnENS	0.14***	0.01	0.00
	LnP	0.99***	0.01	0.00
	LnINS	0.33***	0.08	0.00
	LnURB	0.85***	0.13	0.00
	LnFDI	−0.07***	0.01	0.00
	LnEDU	−0.52***	0.09	0.00
	Wald Test	11339.6***		0.00
	RMSE	0.46		

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

dynamic nature of adjustment; however, the direction of the effect remains robust. This finding is consistent with long-run equilibrium results in Turkey [31] and with the asymmetric responses to price shocks observed by Ebaid et al. [36] and Okwanya et al. [37] in developing country contexts.

GDP continues to show a strong, significant negative relationship with emissions, supporting the EKC hypothesis even in dynamic specifications. This finding aligns with evidence from Liu [16] and Farouki and Aissaoui [17], who demonstrate that rising income can lead to lower environmental pressure in the long term. ENS remains a positive driver of emissions, reinforcing the importance of fossil fuel dependence as a structural constraint. Population, however, loses significance in the dynamic models, suggesting that much of its effect is captured by the lagged dependent variable, consistent with the scale effect being persistent but slow to adjust.

URB remains a significant positive driver, with even larger coefficients in dynamic models. This finding aligns with Lin et al. [23], who argue that, in non-high-income countries, urbanization exerts only a small effect on emissions. Yet, its cumulative effect remains substantial in higher-income settings, particularly through transport and consumption patterns. FDI continues to exhibit a negative and significant impact, further supporting the argument for a pollution halo in advanced economies with strong regulatory frameworks and absorptive capacities [26,27]. Additionally, education remains negatively associated with emissions, underscoring the role of human capital in facilitating environmental sustainability.

Lastly, the diagnostic tests confirm model validity: Hansen tests indicate instrument appropriateness, and Arellano-Bond AR(2) tests show no second-order autocorrelation, confirming reliable dynamic specifications.

5.3. Granger causality analysis

The Dumitrescu-Hurlin panel causality tests (see Table 5) confirm bidirectional causality between oil prices and CO_2 emissions, reinforcing

Table 4
GMM-Sys estimates.

Model	Variable	Coefficient	Std. Dev.	P-Value
1	l.LnC	0.97***	0.09	0.00
	LnOp2	−0.01*	0.01	0.06
	LnGDP	−0.60***	0.16	0.00
	LnENS	0.19*	0.11	0.08
	LnP	0.04	0.05	0.51
	LnINS	0.13	0.14	0.35
	LnURB	1.02 ***	0.32	0.00
	LnFDI	−0.01***	0.00	0.01
	LnEDU	−0.27***	0.11	0.01
	Wald Test	5.6×10^{8}***		0.00
	Arellano Bond AR(2)	0.07		0.94
	Hansen test of overid. restrictions	23.86		1.00
	Diff. in the Hansen Test (GMM)	0.00		1.00
	Diff. in the Hansen Test (IV)	4.29		1.00
2	l.LC	0.95***	0.09	0.00
	LnOp4	−0.01*	0.01	0.07
	LnGDP	−0.56***	0.17	0.00
	LnENS	0.16**	0.10	0.04
	LnP	0.02	0.05	0.70
	LnINS	0.15	0.15	0.32
	LnURB	3.86 ***	1.61	0.01
	LnFDI	−0.01***	0.00	0.01
	LnEDU	−0.18*	0.10	0.09
	Wald Test	9.12×10^{8}***		0.00
	Arellano Bond AR(2)	−0.09		0.93
	Hansen test of overid. restrictions	26.17		1.00
	Diff. in the Hansen Test (GMM)	0.00		1.00
	Diff. in the Hansen Test (IV)	–		–
3	l.LnC	0.94***	0.08	0.00
	LnOp6	−0.02***	0.01	0.00
	LnGDP	−0.56***	0.16	0.00
	LnENS	0.17*	0.10	0.10
	LnP	0.02	0.05	0.71
	LnINS	0.12	0.15	0.41
	LnURB	4.33 ***	1.61	0.00
	LnFDI	−0.01***	0.00	0.00
	LnEDU	−0.19*	0.11	0.07
	Wald Test	1.35×10^{9}***		0.00
	Arellano Bond AR(2)	−0.29		0.77
	Hansen test of overid. restrictions	25.58		1.00
	Diff. in the Hansen Test (GMM)	0.00		1.00
	Diff. in the Hansen Test (IV)	–		–

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 5
Dumitrescu-Hurlin causality test results.

Hypothesis	Z-bar
LnOp2 does not cause LnC	14.14***
LnOp4 does not cause LnC	14.29***
LnOp6 does not cause LnC	13.29***
LnGDP does not cause LnC	10.25***
LnENS does not cause LnC	8.52***
LnP does not cause LnC	11.57***
LnINS does not cause LnC	8.28***
LnURB does not cause LnC	9.74***
LnFDI does not cause LnC	4.12***
LnEDU does not cause LnC	2.54**
Hypothesis	**Z-bar tilde**
LnC does not cause LnOp2	7.21***
LnC does not cause LnOp4	6.72***
LnC does not cause LnOp6	6.99***
LnC does not cause LnGDP	3.19***
LnC does not cause LnENS	10.73***
LnC does not cause LnP	69.70***
LnC does not cause LnINS	3.63***
LnC does not cause LnURB	56.63***
LnC does not cause LnFDI	8.71***
LnC does not cause LnEDU	7.42***

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

the dynamic interaction between energy markets and environmental outcomes. This aligns with evidence from Abumunshar et al. [31] and Nwani [39], who document feedback loops between oil prices, energy consumption, and emissions in developing country contexts.

GDP is also found to cause emissions, supporting the EKC framework, whereby income changes drive environmental outcomes; however, emissions also influence economic trajectories through regulation, energy costs, and health impacts. ENS, INS, and URB all cause emissions, confirming that energy mix, industrial composition, and demographic transitions are key drivers. Conversely, causality from emissions to GDP, population, and FDI indicates the possibility of feedback effects, such as regulatory responses or shifts in investment attractiveness in response to environmental performance.

These findings echo the complexity highlighted in previous work. For example, Wang et al. [59] document bi-directional causality between economic growth, energy consumption, and emissions in China, emphasizing the challenge of disentangling drivers in integrated economies. Similarly, Magazzino [60] emphasizes the role of energy in driving GDP in GCC countries, reinforcing the importance of sectoral and regional heterogeneity.

5.4. Discussion

Overall, the results highlight that OECD countries face both challenges and opportunities in decarbonization. The consistent adverse effect of oil prices suggests that carbon pricing and fossil fuel taxation can effectively reduce emissions by altering consumption patterns and incentivizing the use of clean energy. However, the positive role of fossil energy structure emphasizes the need for deep transitions in the energy mix to achieve sustained reductions. The EKC-type relationship with GDP suggests that further economic development, when coupled with environmental regulation and technological change, can support emissions reductions. Yet this transition is neither automatic nor uniform, as evidenced by heterogeneity across OECD countries. Education and FDI emerge as critical enablers of sustainability, facilitating technology transfer, cleaner production, and behavioral change. Policies that enhance human capital, strengthen environmental regulation, and encourage green investment are therefore central to achieving long-term climate goals.

6. Robustness checks via ANNs

To strengthen the validity and credibility of the findings obtained from the econometric models, this study adopts ANNs as an additional and complementary modeling approach. The purpose of employing ANNs is to investigate whether the relationships identified in the linear panel data framework remain robust when evaluated with methods capable of capturing potential non-linear interactions and complex dependencies among the variables. This approach directly addresses concerns about the need for methodological complementarity and provides a rigorous test of model stability.

To determine an appropriate neural network architecture, the study employed a systematic cross-validation strategy. Specifically, stratified cross-validation was performed within the training data.[7] To evaluate candidate multi-layer perceptron architectures. Three configurations were tested: a simpler two-layer network (with four neurons in the first hidden layer and two in the second), a moderately complex two-layer network (six neurons in the first hidden layer and four in the second), and a deeper three-layer network (six, four, and two neurons). Performance was assessed using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The architecture minimizing average RMSE across folds was selected as optimal, ensuring the model complexity is neither excessive nor insufficient for the problem. The final architectures chosen for the three oil price variants (Brent, OPEC, and West Texas) were retrained on the entire training set.[8] This optimizer was chosen for its ability to adapt weight updates without requiring manual tuning of learning rates and for its robustness in the presence of local minima.

The integration of ANNs into this analysis serves not to predict oil prices themselves but to investigate the broader mapping between socioeconomic variables (including oil price indices) and CO_2 emissions. By leveraging the flexibility of ANN, the analysis tests whether the same variables found necessary in regression models retain their explanatory power in non-linear specifications. This comparison enhances the credibility of the conclusions and provides evidence about the stability of identified drivers.

Fig. 4, presented as a unified representation, illustrates both the structure of the ANN models and the importance scores for the independent variables across all three models. Each model in Fig. 4 is differentiated by the oil price variable being tested: Brent (Model 1), OPEC (Model 2), and West Texas (Model 3).

Cross-validation for all three models resulted in a three-layer ANN structure with 6, 4, and 2 nodes, respectively. Model 1 in Fig. 4, corresponding to Brent (Op2), reveals that ENS and URB exhibit the highest positive contributions to emissions predictions, indicating strong reinforcing effects even in non-linear contexts. GDP and Op2 demonstrate a negative relationship, supporting the hypothesis that higher oil prices and economic development in OECD countries act as mechanisms that reduce CO_2 emissions, consistent with market-based theories of energy efficiency gains and decoupling trends. Model 2 in Fig. 4, representing OPEC prices (Op4), confirms the dominant positive influence of ENS, while also showing that P and EDU contribute positively, underlining the persistent impact of demographic and human capital factors on emissions profiles. The negative importance of GDP and Op4 reflects their role as stabilizing factors, consistent with regression findings suggesting that higher oil prices reduce demand for fossil fuels through price signals. Model 3 in Fig. 4, focusing on West Texas prices (Op6), exhibits an especially pronounced negative importance for Op6, underscoring its significant role in reducing predicted emissions through price-induced consumption adjustments. It is also vital to understand that the negative association for INS in the Op4 model and ENS in the Op6 model can plausibly reflect cases where a higher industrial share or a lower reliance on oil within the energy mix signals a shift toward more efficient or cleaner production processes that mitigate carbon emissions.

The results derived from the ANN models confirm and reinforce the main conclusions established through the panel regression analyses. Although the relative importance of specific variables varies somewhat across the different oil price specifications, the underlying patterns remain consistent. In particular, the ANN models consistently indicate that higher oil prices are linked to reductions in carbon emissions, supporting the notion that price increases encourage energy efficiency and the adoption of cleaner technologies. At the same time, the models highlight energy structure and urbanization as persistent and significant

[7] The dataset was divided into training and testing sets, with 72 percent allocated to training. This split ratio was selected after evaluating alternative partitions to balance two key objectives: ensuring sufficient data for the model to learn complex patterns while maintaining an adequate testing sample for robust out-of-sample validation. Missing values were removed to ensure the ML model could operate correctly.

[8] The ANN models were implemented in R using the *neuralnet* package. Candidate network architectures (with 2–3 hidden layers) were selected via three-fold stratified cross-validation to minimize RMSE. The choice of three folds reflected a deliberate balance between computational efficiency and reliable error estimation, given the dataset's moderate size and the need to maintain representative fold stratification. The final models employed resilient backpropagation (*rprop*+), logistic activation functions in hidden layers, and linear output for regression. Training used a single replication per fold to mitigate overfitting.

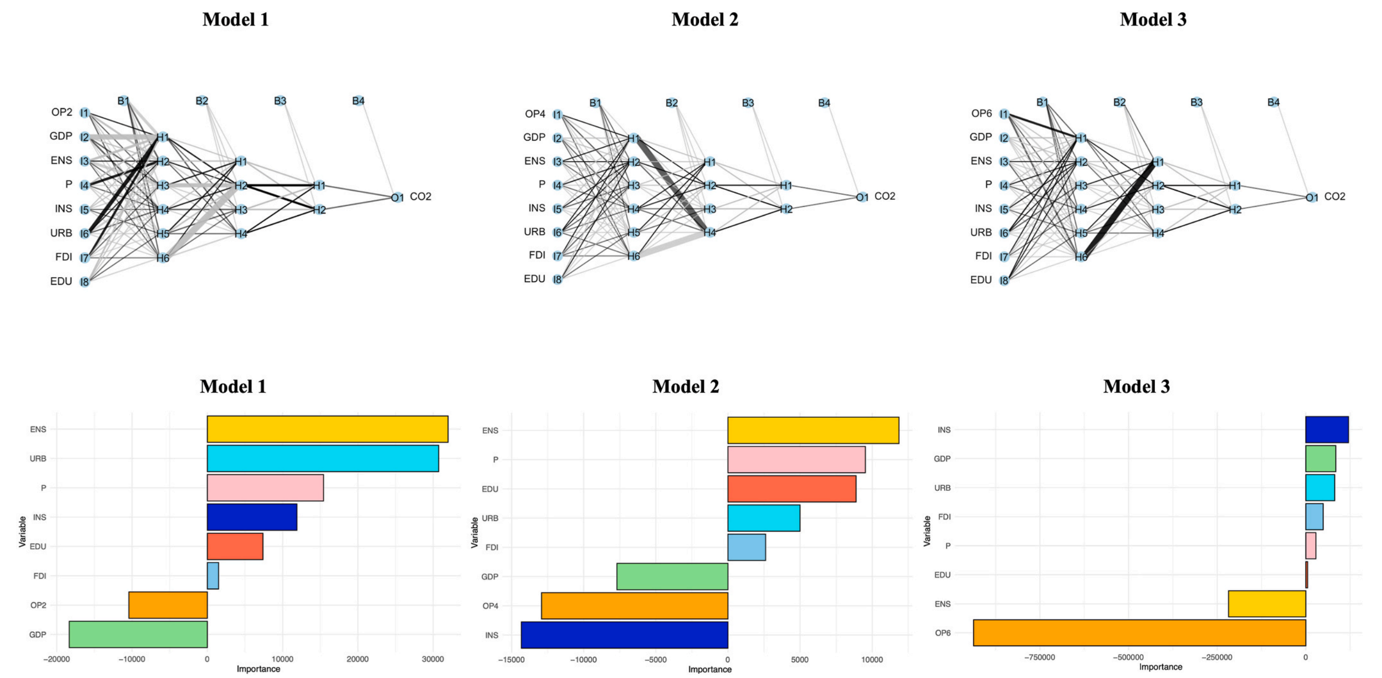

Fig. 4. ANN models' results.

drivers of higher emissions, underscoring their central role in explaining carbon dynamics within OECD countries. This alignment between methods strengthens confidence in the robustness of the study's empirical findings.

The predictive performance of the ANN models is rigorously evaluated on the holdout test set. Table 6 reports the key metrics across all three oil price variants.

The models achieve low MSE and RMSE values, indicating precise predictions. MAE values are similarly low, supporting claims of accurate average prediction. The correlation coefficients between the predicted and actual emissions approach unity, confirming a strong alignment and validating the model's accuracy.

Importantly, these results are directly comparable to those of the econometric regressions. While the regression models (see FGLS results) produce RMSE values around 0.5, the ANN models demonstrate slightly greater explanatory power with lower RMSE values, underscoring the stability of the relationships identified in the linear models even when non-linear interactions are accounted for. This complementarity suggests that key variables, such as oil prices, GDP, population, and energy structure, retain their predictive significance regardless of the chosen model specification.

Furthermore, these findings address concerns about the ANN's contribution beyond the scope of regression models. The ANN approach reveals consistent importance rankings for core variables while capturing non-linearities and interaction effects that regressions cannot fully represent. For example, the interaction between ENS and oil prices remains visible in the ANN models, reinforcing the interpretation that energy structure and price policies must be considered jointly in emissions mitigation strategies. The stability of GDP's negative contribution across all ANN specifications further confirms the evidence for decoupling processes in OECD economies.

Table 6
Performance metrics.

Metric	Model 1	Model 2	Model 3
MSE	0.047	0.003	0.007
RMSE	0.218	0.059	0.086
MAE	0.047	0.035	0.039
Correlation Predicted/True Value	0.973	0.998	0.996

Beyond serving as a robustness check, the use of ANNs in this study offers methodological and substantive contributions that enhance the originality of the analysis. ANNs are well-suited to detect complex, nonlinear interactions among variables that traditional econometric models may overlook due to their parametric constraints. In this context, the ANN models uncover consistent patterns across oil price variants but also reveal varying intensities in the influence of key variables, such as energy structure and industrial composition, suggesting nonlinear amplification effects that give us a better grasp of emissions dynamics. For instance, the stronger negative importance of West Texas prices in ANN models suggests threshold effects in how oil price shocks influence consumption behavior. Moreover, the ANN framework allows for the examination of relative variable importance without imposing functional form assumptions, providing practical insights into the comparative strength of predictors.

7. Conclusions and policy implications

7.1. Conclusions

This study sheds light on the drivers of CO_2 emissions in OECD countries by combining theoretical, empirical, and methodological perspectives. We drew on the EKC hypothesis [15], which posits that environmental degradation first rises and then falls with income growth. We operationalized it through the STIRPAT framework to allow flexible estimation of how population, affluence, technology, and policy-relevant variables shape emissions. Our findings provide evidence consistent with a partial decoupling of GDP and emissions in OECD countries, as higher income levels are associated with lower emissions per unit of GDP. This result suggests that advanced economies have begun to internalize environmental costs through technological progress, regulatory measures, and structural shifts toward service-oriented economies. Yet this trend is not uniform across the OECD, reflecting heterogeneous industrial bases, policy regimes, and stages of energy transition.

The significant inverse relationship between oil prices and CO_2 emissions aligns with prior work, which shows that energy price increases can reduce fossil fuel demand and emissions (e.g., Ref. [6,30]).

However, our analysis extends this insight by comparing multiple oil price benchmarks, recognizing that OECD economies are exposed to different market dynamics depending on their energy import mix and contractual structures. This benchmark-level analysis highlights that oil price shocks can have differentiated impacts on emissions trajectories across countries and over time.

Urbanization's positive association with emissions highlights the ongoing challenge of mitigating environmental impacts in rapidly expanding metropolitan areas. This result highlights the complexity of urban dynamics: while cities can facilitate energy efficiencies through density and shared infrastructure, they can also contribute to emissions through construction, transportation, and increased consumption. The OECD context spans dense, transit-oriented European cities and more sprawling urban forms in North America and Oceania, requiring differentiated policy approaches. Meanwhile, education consistently shows a negative association with carbon emissions in the main results, suggesting that higher levels of education are linked to lower emissions, likely reflecting increased environmental awareness and adoption of cleaner technologies. This finding indicates that better-educated populations may adopt more energy-efficient behaviors, support environmental regulations, and facilitate the adoption of new technologies. However, the impact of education is also mediated by cultural values, political institutions, and economic structures.

In summary, this study advances the existing literature by providing a differentiated, benchmark-specific analysis of oil price effects on CO_2 emissions across a diverse set of OECD countries, moving beyond the conventional use of aggregated energy price indices. By incorporating Brent, OPEC, and WTI oil prices into a unified empirical framework alongside key socio-economic variables, the study captures the subtle and asymmetric influence of global energy markets across advanced economies. Moreover, the integration of dynamic panel modeling with ANN-based robustness checks strengthens the methodological contribution, demonstrating that combining traditional econometric techniques with ML can enhance the credibility and interpretability of results. These innovations position the study as a novel contribution to the policy-relevant literature on energy pricing and emissions mitigation, particularly by underlining the importance of tailored, evidence-based strategies that reflect the specific energy market exposures and socio-economic contexts of OECD member states.

Nonetheless, limitations remain. Our analysis does not explicitly model technological innovation trajectories, sectoral shifts, renewable energy adoption, or country-level policy differences such as carbon taxes, subsidies, and emissions trading systems. Given the OECD's heterogeneity, these factors likely condition the observed relationships. Additionally, while ANN-based robustness checks confirm the stability of our core findings, they do not explain mechanisms or institutional contexts. Future research should integrate these dimensions using mixed-methods approaches and more granular data.

7.2. *Policy implications*

Our research indicates that oil pricing mechanisms can serve as essential levers for emissions reduction in OECD countries. Policymakers might consider maintaining moderate to high effective fossil fuel prices through targeted energy taxes or carbon pricing systems. For high-income OECD members with established administrative capacity, strengthening existing carbon tax regimes or expanding emissions trading systems could provide predictable long-term signals to investors and consumers.

Given the positive link between urbanization and emissions, urban planning policies should prioritize sustainable transport systems, green infrastructure, and compact city design to mitigate environmental impacts. For middle-income OECD countries experiencing rapid urban growth, investing in public transportation and transit-oriented development can help avoid becoming locked into carbon-intensive patterns. The negative association between education and emissions highlights the value of integrating environmental literacy into national curricula. Beyond general awareness campaigns, targeted education reforms that emphasize energy efficiency, sustainable consumption, and climate change mitigation can build long-term societal support for low-carbon transitions.

Recognizing heterogeneity across OECD members is essential. While high-income countries may focus on refining market-based mechanisms and investing in advanced technologies, middle-income countries may prioritize capacity building, institutional reforms, and incremental improvements in energy efficiency. Overall, aligning oil price policy with socio-economic conditions and sectoral needs can support a more effective and equitable transition toward low-carbon economies.

Credit author statement

C.M.: Data Collection, Methodology, Formal Analysis, Software, T. G.: Conceptualization, Writing - Original Draft, Writing - review & editing, P.P.: Writing - Original Draft, Validation, Visualization, M.A.D.: Supervision, Writing - Original Draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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The views expressed in this paper are those of the authors and do not necessarily represent those of the institutions with which the authors are affiliated. All errors and opinions are ours. All standard disclaimers apply.

Abbreviations

ANNs	Artificial Neural Networks
C	Carbon Dioxide Emissions
CADF	Cross-Sectional Augmented Dickey-Fuller
CD	Cross-Sectional Dependence
CO_2	Carbon Dioxide
CPI	Consumer Price Index
EDU	Educational Rate
EIA	Energy Information Administration
EKC	Environmental Kuznets Curve
ENS	Energy Structure
FDI	Foreign Direct Investment
FE	Fixed Effects

FGLS Feasible Generalized Least Squares
GCC Gulf Cooperation Council
GDP Gross Domestic Product
GHG Greenhouse Gas
GMM-Sys System Generalized Method of Moments
INS Industry Structure
MAE Mean Absolute Error
ML Machine Learning
MSE Mean Squared Error
OECD Organisation for Economic Co-operation and Development
Op Oil Prices
Op2 Brent Oil Prices
Op4 OPEC Oil Prices
Op6 Real West Texas Oil Price
P Population Size
RE Random Effects
RMSE Root Mean Squared Error
STIRPAT Stochastic Impacts by Regression on Population, Affluence, and Technology
URB Urbanization Rate
VIF Variance Inflation Factor
WTI West Texas Intermediate

Appendix

Table A.1
Data sources and variable measurements.

Variable	Definition	Unit	Source
LnC	Logarithm of CO_2 Emissions	Kilo Ton	World Bank
LnOp2	Logarithm of Real Brent Oil Price (Adjusted by CPI = 2010)	$ per Barrel	Trading Economics
LnOp4	Logarithm of Real OPEC Oil Price (Adjusted by CPI = 2010)	$ per Barrel	OPEC
LnOp6	Logarithm of Real West Texas Oil Price (Adjusted by CPI = 2010)	$ per Barrel	EIA
LnGDP	Logarithm of Real Gross Domestic Product (Adjusted by CPI = 2010)	Local Currency Unit	World Bank
LnENS	Logarithm of Energy Structure (Oil Energy consumption/Total Fossil Energy Consumption)	–	World Bank
LnP	Logarithm of Population	Million	World Bank
LnINS	Logarithm of Industry Structure	%	World Bank
LnURB	Logarithm of Urbanization Rate	%	World Bank
LnFDI	Logarithm of Real Foreign Direct Investment (Adjusted by CPI = 2010)	$	World Bank
LnEDU	Logarithm of Educational Rate	%	World Bank

Table A.2
Levin-Lin-Chu unit-root test results.

Variable	Lags	Unadjusted t	Adjusted t*	P-value	Result
LnC	1	−10.62***	−5.53***	0.00	I(0)
LnOp2	1	−13.22***	−2.99***	0.00	I(0)
LnOp4	1	−13.27***	−3.21***	0.00	I(0)
LnOp6	1	−13.20***	−2.75***	0.00	I(0)
LnGDP	1	−11.31***	−10.16***	0.00	I(0)
LnENS	1	−3.43	3.23	0.99	I(2)
LnP	1	−4.03***	−2.52***	0.00	I(0)
LnINS	1	−8.09***	−4.46***	0.00	I(0)
LnURB	1	−15.24***	−13.99***	0.00	I(0)
LnFDI	1	−7.78***	−2.60***	0.00	I(0)
LnEDU	1	−9.00***	−5.20***	0.00	I(0)

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table A.3
CADF unit-root test results.

Variable	Lags	Without Trend		With Trend		Result
		Z [t-bar]	P-value	Z [t-bar]	P-value	
LnC	1	0.44	0.67	−0.74	0.23	I(1)
LnOp2	1	−19.88***	0.00	−21.81***	0.00	I(0)
LnOp4	1	−19.83***	0.00	−21.85***	0.00	I(0)

(continued on next page)

Table A.3 (*continued*)

Variable	Lags	Without Trend		With Trend		Result
		Z [t-bar]	P-value	Z [t-bar]	P-value	
LnOp6	1	−19.65***	0.00	−21.76***	0.00	I(0)
LnGDP	1	−1.26*	0.10	−0.62	0.26	I(0)
LnENS	1	−1.2*	0.10	0.32	0.62	I(0)
LnP	1	−5.32***	0.00	−1.04	0.15	I(0)
LnINS	1	−0.28	0.39	4.40	1.00	I(1)
LnURB	1	1.72	0.95	3.80	1.00	I(2)
LnFDI	1	−4.57***	0.00	−2.37***	0.00	I(0)
LnEDU	1	−3.92***	0.00	−0.27***	0.00	I(0)

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table A.4
Kao cointegration test results.

Equation	Modified Dickey-Fuller t		Dickey-Fuller t		Augmented Dickey-Fuller t		Unadjusted Modified Dickey-Fuller t		Unadjusted Dickey-Fuller t	
	Statistic	P-Value	Statistic	P-Value	Statistic	P-Value	Statistic	P-Value	Statistic	P-Value
1	−1.58**	0.05	−3.2***	0.00	0.46	0.31	−1.78**	0.03	−3.3***	0.00
2	−1.56**	0.05	−3.2***	0.00	0.47	0.31	−1.79**	0.03	−3.4***	0.00
3	−1.42*	0.07	−3.0***	0.00	0.56	0.28	−1.64**	0.05	−3.1***	0.00

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table A.5
Pesaran CD test for cross-section dependence results.

Variable	CD-test	P-Value
LnC	16.65***	0.00
LnOp2	103.51***	0.00
LnOp4	103.04***	0.00
LnOp6	99.99***	0.00
LnGDP	139.15***	0.00
LnENS	30.36***	0.00
LnP	66.75***	0.00
LnINS	65.66***	0.00
LnURB	57.50***	0.00
LnFDI	43.12***	0.00
LnEDU	67.26***	0.00

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table A.6
VIF test results.

Model	Variable	VIF	1/VIF	Mean VIF
1	LnOp2	1.13	0.88	1.81
	LnGDP	2.75	0.36	
	LnENS	1.29	0.77	
	LnP	2.59	0.38	
	LnINS	1.40	0.71	
	LnURB	1.99	0.50	
	LnFDI	1.86	0.53	
	LnEDU	1.50	0.66	
2	LnOp4	1.13	0.88	1.81
	LnGDP	2.75	0.36	
	LnENS	1.29	0.77	
	LnP	2.59	0.38	
	LnINS	1.40	0.71	
	LnURB	1.99	0.50	
	LnFDI	1.86	0.53	
	LnEDU	1.50	0.66	
3	LnOp6	1.15	0.86	1.82
	LnGDP	2.76	0.36	
	LnENS	1.29	0.77	
	LnP	2.59	0.38	
	LnINS	1.40	0.71	
	LnURB	1.99	0.50	
	LnFDI	1.86	0.53	
	LnEDU	1.53	0.65	

Data availability

Data will be made available on request.

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