Environmental consequences of technology and industrial agglomeration in emerging economies: Evidence from a MMQREG new approach

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Abstract

Aggregation and concentration of industries and the production of more complex products due to economies of scale can cause technology spillover. The development of industrial and complex processes requires energy, and the use of energy causes carbon emissions. This raises the question: what impact do technology and industrial agglomeration have on the environment? The aim of this research is to assess the influence of economic complexity and industrial agglomeration on carbon emissions within a panel of emerging economies from 1990 to 2022. To achieve this, industrial agglomeration was initially measured using the location entropy index. Following this, a method of moments quantile regression (MMQREG) was applied within a new panel approach to examine the impact of economic complexity and industrial agglomeration on carbon emissions. The findings revealed that increases in the economic complexity index have varying effects on carbon emissions. The results of parameter estimation showed that industrial agglomeration increases carbon emissions in high quantiles. The results show that economic growth and energy consumption increase carbon emissions in all quantiles, and urbanization helps to preserve the environment. The results of Dumitrescu and Hurlin's panel causality test show a two-way relationship between industrial agglomeration and carbon emissions and a one-way relationship between economic complexity and carbon emissions.

key words

Complex products

consolidation of industries

environment

MMQREG approach

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1. Introduction

Today, energy is a crucial factor in driving the development and advancement of societies, serving as a fundamental requirement for industrialization and technological progress. However, the energy demands of most societies, particularly in developing and emerging economies, have largely been fulfilled by fossil fuels, leading to environmental challenges such as climate change and global warming. This environmental pollution not only poses risks to human health but also undermines the sustainable economic and social development of these societies. Therefore, it is necessary to study the factors affecting environmental pollution.

Today, industrial concentration is an inevitable process of economic development due to economies of scale [1]. Industrial agglomeration leads to the concentrated distribution of companies that produce homogeneous products or similar products in different quantities [2]. In the initial stage of economic development, factors such as reducing transaction costs, increasing returns to scale, and reducing transportation costs expand the scale of agglomeration, which leads to improved local efficiency of resource allocation and promotes economic growth [3]. The spread of pollution in countries with large areas and different development areas creates an imbalance of pollution in different places, and these imbalances cause industrial density to have different effects on the environment in different regions [4]. On the one hand, profit maximization causes firms to aggregate to create economies of scale, which may contribute to the development of environmentally friendly technologies to reduce environmental damage [2, 5]. On the other hand, with the expansion and development of industrial density, companies are prone to increasing growth. Faster growth requires more energy consumption, which results in the emission of pollution [6]. Therefore, density can have different effects on environmental sustainability.

Some studies showed that industrial density increases the emission of environmental pollutants [2, 7, and 8]. Some researchers contend that industrial density can enhance the efficiency of resource allocation and promote the use of renewable energy, thereby reducing environmental pollution [9]. Additionally, the scale effect of industrial density can drive regional economic growth and improve energy efficiency [1]. It can be seen that the studies did not reach a single conclusion regarding the impact of industrial density on the environment. According to [10], industrial density may have an innovation spillover effect. Hence, agglomeration may also contribute to the production of more complex and high-knowledge products through knowledge spillovers. Therefore, it is also worth considering the effects of technology and economic complexity on the environment.

The economic complexity index evaluates the ability of countries to produce complex products that require higher knowledge and better technologies [11]. A complex structure refers to a production structure that produces diverse high-tech products through a wide range of highly skilled people [12]. Countries with a lower complexity index produce fewer products. Producing fewer products reduces energy demand [13, 14]. However, a country with a high complexity index indicates a high level of knowledge of advanced technologies that can increase investment in clean technologies and the development of alternative energy sources due to the availability of financial resources for research and development activities [12, 15, and 16]. Moreover, countries with a higher ECI enjoy a competitive edge on the international stage compared to those with lower ECI. As a result, more complex economies tend to engage in greater trade, and the income generated from this trade provides the financial resources to develop green technologies, undertake eco-friendly innovations, and utilize more renewable resources, all of which contribute to environmental preservation [17]. Although previous studies examined the relationship between economic complexity and the quality of the environment, they did not reach a single conclusion in this regard [5, 18, and 19]. In addition, countries with higher innovation may also move towards developing industrial density to reduce costs.

The results of previous studies on the environmental consequences of industrial density and economic complexity are not uniform. The reason for this variety of findings is related to the experimental methods applied and the diverse samples of the considered data. Therefore, in this study, the new approach of the MMQREG panel has been used to estimate the parameters. The new technique overcomes the limitations of traditional quantitative regression approaches by addressing concerns about heterogeneity, endogeneity, and sample selection biases. The mentioned approach provides robust and reliable results, especially for outliers and heterogeneous data, using a unified framework characterized by flexibility, robustness, and computational efficiency [20, 21]. This research focuses on a sample of 24 emerging economies. Climate

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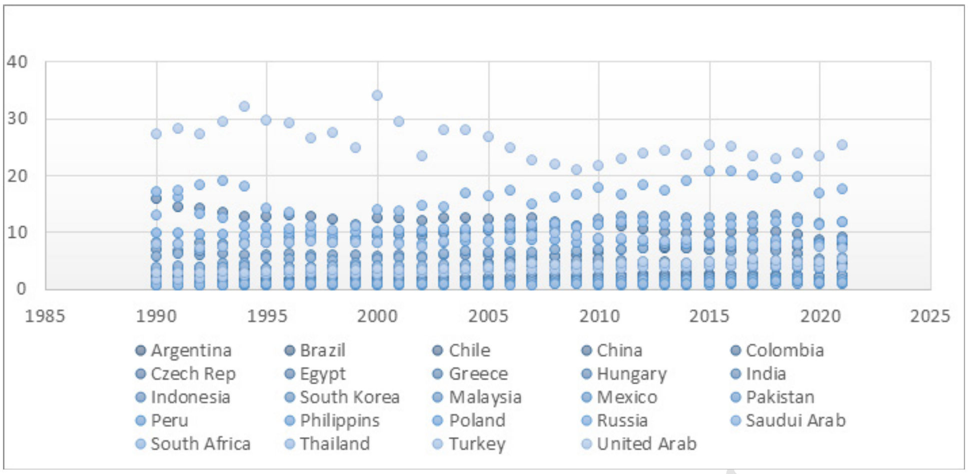

Fig 1. Scatter chart, CO_2 emissions per capita of 24 emerging economies

change is weakening the economic resilience of these nations due to rising greenhouse gas emissions. Several emerging economies, including China, India, and Brazil, have been intensifying their economic activities, contributing to this issue [19]. As a result, the demand for fossil fuels in these countries is very high, which leads to more carbon emissions. Therefore, examining the factors affecting carbon emissions in emerging economies can provide significant policy implications for the environment. In the following, the per capita CO_2 emissions of the studied countries are presented in Fig. 1.

The main objective of this study is to investigate the effect of economic complexity and industrial agglomeration on CO_2 emissions per capita as an indicator of environmental degradation for a panel of 24 emerging economies using a quantitative approach called MMQREG. This study presents several innovations. First, to the best of our knowledge, no prior research has examined the impact of industrial density and economic complexity on carbon dioxide emissions in a panel of emerging economies. Second, this study calculates industrial density using the location coefficient (location entropy) specifically for emerging economies. Third, the parameters are estimated using the new method of MMQREG panel approach, which offers robust and reliable results, particularly for outliers and heterogeneous data. Fourth, the study enhances result reliability through the use of the Driscoll-Kraay (D-K) fixed effects method and the Dumitrescu-Hurlin panel causality test. The empirical findings of this study can provide policymakers in emerging economies with significant implications for sustainable development. The structure of the remaining sections of the research is listed below: The next section describes the literature review. In Section 3, the study data and applied model are presented. Section 4 talks about the empirical findings. In Section 5, the conclusions and their policy implications are discussed.

2. Literature review

This section presents the fundamentals and literature on the relationship between ECI, industrial agglomeration, and per capita carbon dioxide emissions.

2.1 CO_2 emissions and Economic Complexity

The economic complexity index is an evaluation of the capacity of an economy based on production, export, knowledge, and quality [22]. In addition, the measures of economic complexity are the capacity and variety of exporting nations' goods and services in terms of their knowledge, skills, and technological advancement [23]. The economic complexity index can affect the state of the environment through the scale effect [24].

He et al. [25] investigated how ECI affects carbon emissions among the highest energy-transitioning economies. They found that economic complexity aids in enhancing environmental quality. Likewise, Boleti et al. [26] found in 88 countries that increasing the complexity of export goods helps to protect the environment. In addition, Kezri et al. [27] observed that economic complexity in 29 countries in Oceania and Asia leads to a decrease in CO_2 emissions. Abdi [28] suggested that ECI and environmental quality show a positive relationship for African countries. Similarly, the findings of Balsalobre-Lorente et al. [22] support that a higher ECI in BRICS countries helps to reduce carbon emissions. Shah et al. [24] discovered that in G7 countries, there is a substantial and negative relationship between economic complexity and

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ecological footprint. Dogan et al. [29] demonstrated how a country's income level affects the environmental effects of economic complexity. They demonstrated that while economic complexity improves environmental sustainability in high-income nations, it degrades environmental quality in low- and middle-income nations. Additionally, some studies presented disparate findings [30, 31]. Rafque et al. [31] found in 10 developed countries of the world that economic complexity degrades the environment's quality. Similarly, Adebayo et al. [32] showed that more complex structures in MINT countries cause a rise in the emissions of CO_2. In addition, the connection between economic intricacy and carbon emissions is unidirectional.

2.2 CO_2 emissions and Industrial Agglomeration

Industrial agglomeration has different definitions. In one definition, industrial concentration is the concentration of a large number of companies from one industry in one region [33], although, in another definition, the concentration of different companies and industries in a specific region is also called industrial concentration [34]. Industrial density generally refers to the geographic concentration of related activities within a specific industry, a common occurrence in industrial development. Essentially, industrial concentration describes the process by which an industry increasingly clusters in a particular region, attracting key resources such as talent, capital, and technology to that area [35]. Industrial agglomeration not only facilitates the transfer of knowledge within the industry but also facilitates the exchange of knowledge between industries, which leads to technological advancement and industry upgrading. This increases added value and improves the level of technology [2]. Collaborative accumulation enables various industries to simultaneously act as sources of knowledge and technology diffusion. This dynamic fosters a two-way exchange of knowledge and technology between interconnected industries [36]. The knowledge and technology spillover generated by agglomeration is very useful for innovation and is very important for improving energy efficiency. In addition, the competitive effect of the agglomeration area encourages companies to find ways to upgrade production equipment, thereby improving energy consumption [12].

A high level of industrial density within a key industrial cluster is often seen as a significant driver of economic development. However, the environmental impact of industrial agglomeration is both profound and complex, with researchers yet to reach a clear consensus. On one hand, industrial density can stimulate regional economic growth and capacity building, which often leads to increased energy consumption and a substantial rise in pollution emissions, as industrial density is associated with negative environmental externalities [2, 37 and 38]. On the other hand, industrial density can improve regional technology and productivity levels, thereby reducing resource and energy waste and, in turn, improving environmental quality [39, 40]. In other words, industrial density also has positive environmental externalities. Industrial density can increase efficiency improvement in the early days of economic development, but after reaching a certain level, the positive effect decreases or even reverses [41]. Some studies show that industrial density improves the scale and distribution efficiency of energy, which leads to positive effects on energy efficiency [1]. However, some researchers believed that such effects could only be achieved after the density reached a certain level [3]. However, other studies emphasized that excessive accumulation may lead to various problems (such as increased prices of production factors and excess capacity), which can lead to negative effects. This result means that there may be a non-linear and inverse U-shaped relationship between industrial density, production, and environmental efficiency [42].

Xu [2], in a study, investigated the effect of industrial density on CO_2 emissions in 30 Chinese provinces with a dynamic spatial panel approach and discovered a positive relationship between industrial density and carbon emissions.

Liu & Wu [43] in a study for Chinese provinces, investigated the effect of high-tech industrial density on green innovation efficiency with a dynamic spatial panel approach. They found that there is a significant relationship between high-tech industrial density and green innovation efficiency. Cui et al. [44] found that, in the long run, the promotional effects of industrial density on ecological welfare performance gradually weaken. As seen, previous studies about the environmental consequences of industrial density and economic complexity on CO_2 emissions did not reach a single conclusion. Therefore, this study investigates the environmental effects of industrial density and economic complexity in a group of emerging economies with a new panel approach, MMQREG. The mentioned approach, in addition to providing a more complete and comprehensive plan of data distribution,

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removes the limitations of traditional quantitative regression approaches regarding things like heterogeneity, endogeneity, and sample selection biases. Therefore, it provides reliable results.

3. Materials and methods

This section includes two subsections. In the first subsection, variables and data are introduced and the method of calculating industrial density is described. In the second subsection, the econometric model will be presented.

3.1 Data

constant dollar prices), i: country and t: time. According to Eq.1 in emerging economies in the studied period, the highest average industrial agglomeration in the United Arab Emirates is about 1.07 and the lowest average industrial density in China is about 0.956. Table 1 describes the definition and source of dependent and independent variables used in this research.

3.2. The model of MMQREG

In this study, according to the studies [30, 45], and theories presented in the previous sections, carbon emissions in emerging economies are considered a function of the following factors:

Table 1. Data sources and description of the variables

Abbreviation	definitions	Sources
CO_2	CO_2 emissions (per capita)	WBD
GDP	GDP per capita (constant 2015 US$)	WBD
E	Primary energy consumption (TWh)	WBD
ECI	Economic complexity index	OEC
IA	Industrial agglomeration calculated based on Eq.1	-
UR	Urbanization (%)	WBD
G	Globalization index	WBD

This study aims to investigate the effect of economic complexity and industrial agglomeration on carbon dioxide emissions in 24 emerging economies during the years 1990-2022. In this study, industrial density is calculated based on the location entropy index according to the study [3], which is the best index for estimating industrial agglomeration. The equation of the entropy index of the place of industrial agglomeration is as follows:

$$IA = \frac{\frac{IY_i(t)}{\sum_i^m IY_i(t)}}{\frac{GDP_i(t)}{\sum_i^m GDP_i(t)}} \quad (1)$$

In the above equation, IA: industrial agglomeration, IY: industry sector production (at constant 2015 dollar prices), GDP: total production (at 2015

$$CO_2 = f\,(GDP,E,ECI,IA,UR,G) \quad (2)$$

In this research, the new panel technique method moments quantile regression (MMQREQ) created by Machado and Silva [46] was used to estimate Eq. 2. In addition, the Driscoll-Kraay standard errors regression is also used for the robustness of the results. This regression provides distributional and heterogeneous impacts in different positions of the CO_2 emissions. In Eq. 3 the conditional quantile for the location-scale model is presented:

$$\mathbb{Q}_Y(\tau|X_{it}) = \alpha_i + \delta_i q_i(\tau) + X_{it}^{/}\gamma + Z_{it}^{/}\varphi q(\tau) \quad (3)$$

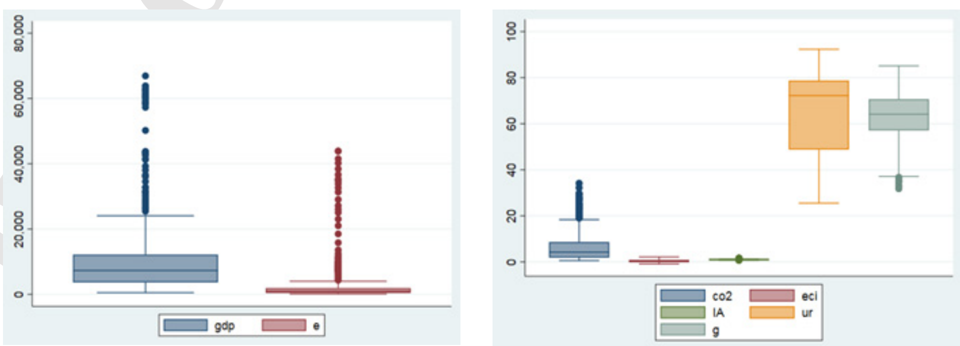

Fig 2. Box plot of research variables

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Table 2. Characteristic statistics

Variables					
	Observations	Mean	Standard deviation	Minimum	Maximum
CO_2	792	6.189	5.899	0.566	34.137
GDP	792	10.122	10723.09	528.898	66911.09
E	792	2429.826	5350.085	103.3548	43873.07
ECI	792	0.366	0.661	-0.883	2.168
AI	792	1.013	0.115	0.714	1.655
UR	792	64.960	18.054	25.547	92.347
G	792	63.842	10.851	31.800	85.134

In Eq.3 $X^{/}$ represents the vector of regressors. $\alpha_i+\delta_i\, q_i\, (\tau)$ expressing the parameters are permitted to be heterogeneous and to differ among the quantiles of Y, as measured by the scalar coefficient of the (τ) quantile. Eq. 3 can be redefined according to Eq. 2, with Eq. 4:

$$\mathbb{Q}_{CO2_{i,t}}[\tau|\alpha_i, \varepsilon_{it}, X_{i,t}] = \alpha_{it} + \gamma_{1a\tau}GDP_{i,t} + \gamma_{2a\tau}E_{i,t} + \gamma_{3a\tau}ECI_{i,t} + \gamma_{4a\tau}IA_{i,t} + \gamma_{5a\tau}UR_{i,t} + \gamma_{6a\tau}G_{i,t} + \varepsilon_{i,t} \quad (4)$$

In In the above equations, Q_{CO2} [├ τ┤| α_i,ε_{it},$X_{(i,t)}$] represents CO_2 emissions conditional quantile that for the distributional effect at τ, has the scalar coefficient ($\alpha_i(\tau)$). For example, to investigate the variable impact of ECI on CO_2 emissions, τ is set between zero and one, which creates the effect of the independent variable at the chosen point in the dependent variable's conditional distribution. For example, if τ= 0.25 is equivalent to the quantile 25th of the distribution of the dependent variable.

4. Results and Discussion

This section includes their subsections. First, the required pre-tests are presented and then the estimation results of the model are discussed. Finally, the results of the panel causality test are presented.

4.1 Pre-tests Results

4.1.1 Normal distribution test & VIF test

In any econometric model, conducting pre-tests is essential to ensure the reliability of the results. Since the quantile approach requires the variables to follow a non-normal distribution, this study begins by checking the normality of the variables. To assess this, two tests—the Shapiro-Wilk and Shapiro-Francia tests—are applied. The results of normality tests are presented in Table 3.

The findings of Table 3 indicate that all the variables of this study have a non-normal distribution which is the concept of having a significant deviation from the symmetrical pattern. In addition, the result of the Variance Inflation Factor (VIF) test is

Table 4 the obtained data from SimaPro analysis for each scenario

Indicator	**Unit**	**Incineration**	**Recycling**	**Landfilling**	**Composting**
Abiotic depletion	kg Sb eq	1.438	2.54	4.872	2.25
Global Warming	kg CO2 eq	6247.71	2908.28	4293.54	2995.14
Ozone Layer Depletion	kg CFC-11 eq	0.000995	0.000348	0.0000753	0.0000246
Human Toxicity	kg 1.4-DB eq	328.542	268.964	658.951	286.275
Fresh Water Ecotoxicity	kg 1.4-DB eq	86.5154	73.6135	98.6862	67.5646
Marine Ecotoxicity	kg 1.4-DB eq	3.546318	2.458634	5.9875	1.7341
Terrestrial Ecotoxicity	kg 1.4-DB eq	3.598798	2.938645	5.538987	2.146523
Photochemical Oxidation	kg C2H4 eq	1.255889	0.987878	1.985623	0.975585
Acidification	kg SO2 eq	475.5985	355.9854	657.6841	301.9852
Eutrophication	kg eq	94.6897	105.6864	245.8955	90.5985

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Table 3. Test of normal distribution

Variables	Shapiro-France test	Shapiro-Wilk test	VIF
CO_2	0.80440 (0.00000)	0.80448 (0.00001)	-
GDP	0.69251 (0.00000)	0.69208 (0.00001)	1.48
E	0.39309 (0.00000)	0.39118 (0.00001)	1.11
ECI	0.96462 (0.00000)	0.96572 (0.00001)	1.44
AI	0.88787 (0.00000)	0.88662 (0.00001)	1.16
UR	0.91554 (0.00000)	0.91708 (0.00001)	1.57
G	0.98782 (0.00000)	0.98878 (0.00002)	1.87

listed in Table 3. Since all of the variables' VIF values are less than 10 and the mean is 1.44, there is no multicollinearity issue.

4.1.2 Test of cross-sectional dependence

Today, due to the development of globalization, common global shocks, and technological development, cross-sectional dependence exists in panel data analysis [47]. CD shows the contagion effects of a shock from one country to another, and ignoring it leads to biased estimates. The developed CD test of is used to verify cross-sectional dependence [48]. Table 4 presents the findings. The absence of CD is the null hypothesis.

Table 4's findings show that the null hypothesis was disproved. In the sense that our panel exhibits cross-sectional dependence (CD) is present in all variables in the countries under study. This indicates a connection between these nations. This finding implies that the interdependence of these economies is what causes the spillover effect.

4.1.3 Test of slope homogeneity

To verify the slope's homogeneity in this paper, the [49] test is employed. Homogeneous slopes, or slopes with the same slope coefficients across all cross-sectional units, are the null hypothesis in this test. This test's outcomes are shown in Table 5.

Table 5 findings demonstrate that there is slope heterogeneity and rejects the null hypothesis. Therefore, the following helps to improve the results by determining the unit root tests and other appropriate methods despite dependency on cross sections and heterogeneity in slope.

4.1.4 Tests of panel unit root

Due to the existence of dependence on CS, and to avoid biased estimates, to obtain the properties of the variables' stationarity, the unit root tests of second-generation (CIPS), created by [50], and the pescadf test, evolved by [51] are used in this investigation. Table 6 displays the results of the CIPS and CADF tests.

Table 6's findings demonstrate that except for urbanization and industrial density, the rest of the variables are static at the level of 10% or lower.

Table 4. Test of cross-sectional dependence.

Variables	CD-Test	P-Value	Average joint T
CO_2	14.998	0.000	33.00
GDP	66.407	0.000	33.00
E	53.256	0.000	33.00
ECI	20.449	0.000	33.00
AI	13.838	0.000	33.00
UR	50.236	0.000	33.00
G	90.906	0.000	33.00

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Fig. 3: the results of the final environmental indicator

Pesaran and Yamagata's Test	
Delta	2.156**
Delta adj.	2.629***

Notes: *** and ** indicate statistical significance at 1% and 5%.

4.1.5 Test of cointegration

Since cross-sectional correlation is ignored by the cointegration analysis suggested by previous studies, in this study, we use [52] cointegration test to address this issue. The cointegration test developed by [53] is used. The test results are displayed in Table 7:

The results of Table 7 showed that three of the four factors verify the existence of a long-term relationship.

Table 6. Tests of unit root

Variables	CIPS	CADF	Variables	CIPS	CADF
	(Zt-bar)	(t-bar)		(Zt-bar)	(t-bar)
CO_2	-2.083*	-2.179**	LCO2	-2.237**	-2.387***
GDP	-1.570	-2.095*	LGDP	-2.342***	-2.525***
E	-2.102*	-2.050*	LE	-2.542***	-2.160**
ECI	-2.548***	-2.539***	LECI	-2.662***	-2.553***
AI	-1.766	-1.775	LAI	-2.302***	-2.288***
UR	-1.334	-1.794	LUR	-2.445***	-2.414***
G	-2.183**	-2.378***	LG	-2.439***	-2.641***

Notes: Critical values -2.3, -2.16, and -2.08. Statistical significance at the 1%, 5%, and 10% levels is indicated by the symbols ***, **, and *, respectively.

4.2 MMQREG Model Results

The approach has been used to investigate the environmental consequences of industrial density and economic complexity. The model estimation results are presented in Table 8.

The findings in Table 8 demonstrate that economic growth has a positive and significant impact on carbon emissions across all quantiles. Specifically, a one percent increase in economic growth leads to a rise in carbon emissions ranging from 0.928 to 1.246 percent, regardless of a country's position in the distribution. Furthermore, the data indicate that in countries with lower carbon emissions (i.e., lower quantiles), the effect of economic growth on CO_2 emissions is more pronounced, with the highest coefficient, 1.246, observed at the 10th quantile. These results are justifiable, as higher economic growth typically demands increased energy consumption. Several studies from various countries corroborate these findings [23, 38, and 53].

There is a positive and significant relationship between the variables of energy consumption and carbon emissions in all quantiles (see Table 8). To achieve sustainable development, societies need to invest in infrastructure, and improving infrastructure and investing in advanced technologies require energy consumption. Voumik et al. [53] also discovered a positive relationship between fossil energy and CO_2 emissions. Several studies in different countries support our results [23, 38].

The results of estimating coefficients with MMQREG regression in Table 8 show that economic complexity has different effects on carbon emissions at different quantile levels. An increase in economic complexity in the 10th quantile causes

Table 7. Test of Westerlund ECM panel cointegration.

Statistics	Value	Z-Value	Robust p-Value
Gt	-3.521	-4.783	0.010
Ga	-23.717	-8.884	0.000
Pt	-15.954	-6.278	0.010
Pa	-10.302	-4.314	0.110

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Table 8. Results of FE-DK & MMQREG

Vari-ables	DK regression with fixed effects	MMQREG regression						
		Location	Scale	Qtile_10	Qtile_25	Qtile_50	Qtile_75	Qtile_90
LGDP	0.249 (0.030) [8.16]***	1.097 (0.0318) [34.41]***	-0.093 (0.021) [-4.38]***	1.246 (0.045) [27.43]***	1.180 (0.035) [32.81]***	1.126 (0.032) [35.11]***	1.025 (0.037) [27.53]***	0.928 (0.051) [17.85]***
LE	0.551 (0.026) [20.53]***	0.551 (0.026) [20.53]***	0.073 (0.014) [5.12]***	0.077 (0.030) [2.56]**	0.129 (0.023) [5.44]***	0.171 (0.021) [8.07]***	0.250 (0.025) [9.95]***	0.326 (0.035) [9.31]***
LECI	-0.271 (0.061) [-4.44]***	0.146 (0.108) [1.35]	0.324 (0.072) [4.48]***	-0.373 (0.154) [-2.41]**	-0.141 (0.122) [-1.16]	0.047 (0.109) [0.43]	0.399 (0.127) [3.14]***	0.737 (0.177) [4.16]***
LAI	0.354 (0.057) [6.17]***	0.337 (0.170) [1.98]**	0.116 (0.113) [1.02]	0.150 (0.244) [0.62]	0.233 (0.194) [1.20]	0.301 (0.172) [1.75]*	0.428 (0.195) [2.19]**	0.549 (0.273) [2.01]**
LUR	-0.125 (0.049) [-2.52]**	-0.801 (0.094) [-8.53]***	0.456 (0.062) [7.27]***	-1.531 (0.131) [-11.62]***	-1.207 (0.102) [-11.72]***	-0.941 (0.093) [-10.12]***	-0.447 (0.113) [-3.93]***	0.027 (0.158) [0.18]
LG	-0.477 (0.084) [-5.68]	-0.069 (0.149) [-0.47]	-0.228 (0.099) [-2.29]**	0.296 (0.214) [1.39]	0.133 (0.170) [0.79]	0.0004 (0.151) [0.01]	-0.247 (0.172) [-1.44]	-0.486 (0.241) [-2.02]**
CONS	-2.847 (0.364) [-7.81]***	-6.194 (0.524) [-11.82]***	-0.694 (0.349) [-1.99]**	-5.082 (0.750) [-6.77]***	-5.577 (0.597) [-9.34]***	-5.981 (0.529) [-11.29]***	-6.733 (0.602) [-11.18]***	-7.457 (0.842) [-8.85]***

Note: Dependent variable, LCO_2. () indicate standard errors; [] indicate t-statistics. *, ** and *** show respectively, statistical significance at 1%, 5% and 10% levels.

a decrease in carbon emissions, but an increase in complex products in the 75th and 90th quantiles causes an increase in carbon emissions. From one side, countries with a higher economic complexity index produce a wider range of products with higher knowledge, which can require more energy to produce more, which causes pollution. On the other, economic complexity arises through the type of goods produced that comprise the production structure of a country. Countries with higher economic complexity tend to have superior infrastructure, which helps mitigate environmental degradation. These advanced economies often implement more efficient energy consumption systems, boosting overall energy efficiency. Furthermore, the production of more complex goods not only drives economic growth but also contributes to environmental quality improvement. Additionally, rising economic complexity enhances a country's capacity to address environmental challenges. Several previous studies have also highlighted that economic complexity supports environmental preservation by fostering the development of clean technologies and improving energy efficiency [30, 31, and 32]. Some studies also found that the production of complex products destroys the environment [24, 28].

The results of Table 8 show that the effect of industrial agglomeration on CO_2 emissions in the 10th and 25th quantiles is not significant, but it has a positive and significant effect on carbon emissions in the quantiles 50th, 75th, and 90th. These findings show that industrial agglomeration in countries with higher carbon emissions (50, 75, and 90 quantiles) plays an important role in damaging the environment. The highest impact factor is related to the 90th quantile, so with a 0.01% change in industrial agglomeration, 0.549% of carbon emissions increase. Industrial agglomeration can bring energy and environmental problems. First, industrial density can increase capacity and increase energy consumption, and this may be accompanied by a sharp increase in pollutant emissions. Second, local governments may lower their emission standards to attract industry, and then the catchment area becomes a haven for pollution. Thirdly, industrial agglomeration may cause companies not to make efforts to improve the environment. Therefore, with the growth of industrial density, the quality of the environment will deteriorate. Some studies also found a positive and significant relationship between industrial agglomeration and pollution [2, 4].

As can be seen in Table 8, there is a negative and

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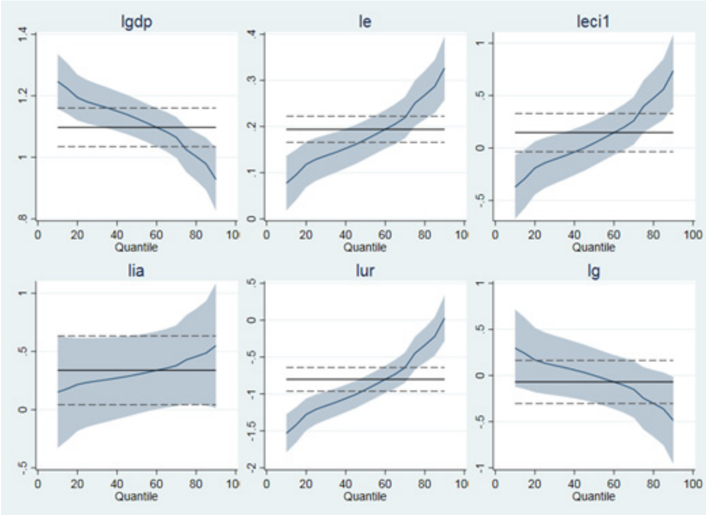

Fig 3 Graphical representation of coefficient of independent variables from OLS regression and MMQREG: shaded areas are 95% confidence intervals for quantile regression estimates. The vertical axis shows the elasticity of the explanatory variables. The red horizontal lines show the 95% confidence intervals for the OLS coefficient. (Source: Research findings)

significant relationship between urbanization and carbon emissions in all quantiles except 90. Therefore, the findings showed that the development of urbanization in emerging economies helps to improve the environment. Some studies support these results [30, 54]. Some studies also showed that increasing urbanization causes environmental degradation [55].

The results of Table 8 show that there is no significant relationship between globalization and carbon emissions in emerging countries in quantiles except 90. In the 90th quantile, there is a negative relationship between globalization and carbon emissions. Some studies support our results. They argue that increased globalization through increased gross domestic product can help protect the environment more because wealthier societies can afford green technologies and clean energies [19]. Some studies obtained conflicting results [56].

The findings in Table 8 show that the D-K approach also strengthens our findings. The graphical behavior of the coefficients of the independent variables is presented in Fig. 3.

4.3 Panel causality test

The Panel Causality Test by [57] is employed in this investigation, which is usually suitable for investigating the connection of causation between two variables. Table 9 highlights the results of D-H.

Hypothesis H1 states that the independent variable is, at least in one panel, the cause of the dependent variable in this test, while the null hypothesis states that the independent variable is not the cause of the dependent variable. The results of Table 9 show that there is a one-way relationship between economic complexity and carbon dioxide emissions and a two-way relationship between industrial agglomeration and carbon emissions.

5. Conclusion and policy implications

Economic growth requires energy consumption, but if growth is to be created by industries, it requires more energy consumption. At the same time, energy consumption leads to more pollution of the environment. As societies grow, the development and consolidation of industries are encouraged to leverage economies of scale. Moreover, these economies of scale can facilitate the production of more complex products. Consequently, examining the environmental implications of industrial density and economic complexity could offer valuable insights for policymakers and researchers seeking solutions to address climate change and pollution-related issues. Therefore, this study investigated the effect of industrial agglomeration and economic complexity on CO_2 emissions in a panel of 24 emerging economies from 1990 to 2022 with the new mmqreg panel approach. In this research, industrial density is assessed using the location entropy index. The results indicate that economic complexity exerts varying effects on the environment. Furthermore, the findings reveal that industrial density does not significantly impact carbon emissions in lower quantiles; however, it contributes to an increase in CO_2 emissions in higher quantiles. The panel test of D-H causality showed a two-way relationship between industrial agglomeration and CO_2 and a one-way relationship between economic complexity and carbon emissions.

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Table 9 Panel causality D-H test results

D-H Causality Test				
	W-Bar	Z-Bar	Z-Bar Tilde	decision
LGDP	3.1691	7.5140***	6.3846***	Bi-directional
LE	3.0738	7.1840***	6.0943***	Uni-directional
LECI	1.1830	0.6340	0.3320	Uni-directional
LIA	2.3771	4.7705***	3.9711***	Bi-directional
LUR	3.3817	8.2503***	7.0324***	Bi-directional
LG	2.6773	5.8102***	4.8858***	Bi-directional

Note: For the 1%, 5%, and 10% levels of significance, use ***, **, and *.

While industrial density can facilitate technological advancements and contribute to achieving a circular economy—potentially reducing energy consumption and pollutant emissions—it can also lead to energy and environmental challenges. The increased production capacity associated with industrial density often necessitates greater energy consumption, which can result in higher carbon emissions. Consequently, this study recommends that policymakers in emerging economies implement emission standards for environmental pollutants and enforce relevant environmental regulations when attracting industries. Additionally, the introduction of green taxes on industries could further enhance environmental quality. In addition, governments can allocate the revenues from green taxes to the purchase of environmentally friendly technologies. Although tax exemptions and subsidy payments to low-carbon industries can also increase the environmental motivation of other industries. Also, the findings of this study show that policymakers should consider the heterogeneity of the environmental consequences of the production of complex and high-tech products in emerging countries with high and low shares of carbon emissions. Therefore, for each country to adopt appropriate policies according to the effects of technology on the environment. The findings of this study emphasize that emerging countries can improve the environment by using modern production techniques, effective transportation systems, and appropriate standards for various sectors. In addition, the different lifestyles of citizens and urban consumption patterns of communities also exert different pressures on environmental sustainability, and policymakers can encourage them to adopt sustainable behaviors and lifestyles by making citizens aware of environmental consequences. In addition, the authorities of the studied countries can help to improve the environment and achieve sustainable development goals by developing the research and development sector. This study suggests future researchers examine the intensifying effects of industrial density through technology spillover on environmental quality. In addition, future studies can focus on the effects of industrial density on other indicators of environmental quality such as ecological footprint.

Statements and Declarations:

Data Availability: The data presented in this study are available upon reasonable request to the corresponding author.

Conflict of interest: The authors declare that there is not any conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

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