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Analysis of environmental sustainability and economic development from electricity consumption based on the modified spatial Durbin model

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ABSTRACT

The study investigates the impacts of financial development, electricity use, and technology innovation on CO_2 emissions. International trade also plays an essential role in the economic development of Pakistan. Studying the relationship between ecological parameters, technological innovation, electricity use, and CO_2 emissions is necessary to formulate the country's reasonable and practical energy policies. Based on the study's use of data from 292 Pakistani firms from 2006 to 2021, the paper investigates the mechanism of the role between financial development, electricity use, technological innovation, international trade, and CO_2 emissions using the spatial Durbin model. The results reveal that the effect of economic growth, electricity use, and technological innovation on CO_2 emissions has a spatial spillover effect. The results verify that international trade and the transport sector promote the country's carbon emissions. The typical speculation spike on technology innovation enhanced and financial development should concentrate more on protective ecological parameters. The research provides theoretical guidance for solving the contradictory problem of renewable energy use growth and CO_2 emission limitation while promoting green and low-carbon development in the country.

1. Introduction

The research on carbon dioxide emissions has been popular in academic circles in Asia and beyond as the issue of global warming worsens, and many academics are concerned about the status of the environment. Pakistan has promised to increase its nationally determined contribution, the highest CO_2 emissions, as a responsibly developing country. The quantity of various age sources affected the economy, the environment, human welfare, and the climate [1]. Using fossil fuels like coal, flammable gas, and oil for transportation and energy has resulted in rising CO_2 that depletes the ozone layer in the atmosphere [2]. According to the spatial econometric approach's data analysis, a country's economic development impacts CO_2 emissions [3]. There is a negative correlation between financial products, energy usage, and the expansion of financial industry sectors, increasing CO_2 emissions. According to Ref. [4], the oil consumption per person moves along a stable path with a long main break and nonlinear unbalanced change. Fossil fuel production, consumption, and byproducts are three energy-related topics that still need more attention [5]. The tourism

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development index, derived from a principal component analysis, significantly determines CO_2 emissions [6]. According to Ref. [7], the increased demand for coal and oil exacerbates climate change and greenhouse gas emissions. The study addresses the gaps and needs for more cohesion in research related to technological innovation, electricity use, financial development, and CO_2 emissions. While some evidence exists in these areas, there is a need for a more comprehensive understanding of the underlying mechanisms at play. The research efforts to explore the technological innovation for energy production mechanism of electricity use, transportation sector, and international trade affecting CO_2 emissions. The followings are the contributions and advances made by the study. First, the spatial impact of technological innovation and electricity use energy capacity aggregation on county CO_2 emissions is analyzed. Second, ecological parameters, financial development, international trade, the transport sector, and CO_2 emissions are integrated into a unified analytical framework. The results contribute to understanding how energy consumption in different sectors affects CO_2 emissions. Third, in terms of research methodology, given the significant spatial correlation of CO_2 emissions, a Spatial Durbin model is selected in the study to determine the spatial spillover effects among the variables.

The research is organized as follows: Section 2 consists of a literature review, and methodology with research framework is provided in Section 3. Section 4 clarifies the results and discussions, while conclusions and future suggestions are discussed in Section 5.

2. Literature review

According to Ref. [8], hydropower sources produce green, sustainable energy while reducing CO_2 emissions. According to Ref. [9], China's new technology to make renewable energy will soon cut pollution from fossil fuels [10]. says that not using enough renewable energy to make electricity harms the environment [11]. claim that CO_2 emissions are produced due to the energy used to produce commodities for import and export. The relationships between fossil fuel usage, economic growth and eco-economics research provide insights into the long-term sustainability of economic systems [12]. Foreign direct investment (FDI) that uses fossil fuels to make energy has almost no effect on pollution in China [13]. The direct and indirect impact of financial events on the byproducts of fossil fuels causes CO_2 emissions to go up [14]. According to Ref. [15], the quadratic economic development variable and CO_2 emissions make a "U"-shaped pattern with some changes. The increasing receptivity reduces CO_2 emissions by 0.003 units for every unit increase [16]. Unexpected environmental changes are brought on by imports and commodities production using fossil fuels in China, so international trade also plays an essential role in changing the country's ecosystem [17]. International trade has negatively impacted the environment since more energy is being consumed and fossil fuels are being burned [18]. [19] found that the relationship between CO_2 emissions, international trade, and the byproducts of fossil fuels is not a straight line [20]. claim that China's energy usage increased due to globalization, and international trade's impact on byproducts of fossil fuels varies throughout time and place [21]. [22] claim that 20–30% of CO_2 emissions around the globe come from economic activities. Technology innovation helped lessen the consequences of modern fossil fuels [23]. Technological innovations reduced the CO_2 emissions in the long run by improving green energy production resources [24]. By fostering energy-saving and discharge-reducing innovations, green technology progress promotes natural betterment and economic growth [25]. Transportation sector substances formed from fossil fuel burning are predicted to rise substantially in the short and intermediate future but slowly in the long run [26]. Non-parametric sensitivity analysis connects transportation infrastructure to increased CO_2 emissions [27]. The activity of monitoring and measuring the impact of tourism on the environment and implementing policies aimed at improving the sector's sustainability [28]. The participation of the tourism sector promotes carbon emission reduction [29]. The tourism sector contributed to the CO_2 emissions, and tourism development contributed to decreased carbon emission intensities [30].

3. Research methodology

3.1. Variable descriptions

The measuring scale for the research variables is displayed in Table 1.

3.2. Data collection

The study used data from Pakistan's four provinces (Punjab, Sindh, Baluchistan, and Khyber Pakhtunkhwa) and two states (Kashmir & Gilgit Baltistan) from 2006 to 2021. The research used a data set of 292 Pakistani firms (including textiles, steel, chemical, and Cement industrial firms). The study collected the data from World bank databases "https://data.worldbank.org.com" and IMF

Table 1
Explanation of variables with measurements.

Variables	Descriptions	Measurements
CO2	Carbon dioxide emissions	The total amount of CO_2 emissions
EP	Ecological parameter	Including temperature, rain intensity, soil acidity, salinity, nitrogen pollutants, and solar irradiance.
TI	Technological innovation	Investments in technological innovations
EU	Electricity Use	Total electric consumption
FD	Financial development	financial institutions, financial markets, and products are developed with an investment
TA	International trade	The total volume of imports and exports
TS	Transport sector	Pollution due use of the transportation industry

Database "https://www.imf.org.com." The environmental data is collected from the Compendium on Environment Statistics database of Pakistan https://www.pbs.gov.pk.com.

3.3. Research design

Traditional econometric models are basically "mean reversion" models. Although economic activities are often spatially interrelated, traditional econometric models. Therefore, to compensate for general econometric models' shortcomings, the study uses spatial econometric models to examine the relationship between variables. Financial development (FD) and international trade (TA) are utilized as a certain quantity of electricity use (EU) based on the fundamental model. When financial development in the fundamental model needed to be squared, the environmental Kuznets Curve phenomenon came into play. International trade (TA) and CO_2 emissions are central to the model's structural ramifications. The technology innovation (TI) and the transportation sector (TS) functions. Equation (1) is the study's formulation for the economic, structural, and technological innovation effects:

$$CO_2 = E\left(EU, Y, Y^2\right).\ S(TA).\ T\left(TI, TS\right) \tag{1}$$

The study used the extended version of Equation-1's logarithm (ln) to apply to both sides of equation-1 to get equation-2, reducing heteroscedasticity and the variance among the data.

$$lnCO_{2it} = \beta_0 + \beta_1\ lnEU_{it} + \beta_2\ lnFD_{it} + \beta_3\ lnFD_{it}^2 + \beta_4\ lnTA_{it} + \beta_5\ lnTI_{it} + \beta_6\ lnTS_{it} + \theta_i + \lambda_t + \mu_{it} \tag{2}$$

Since historical events have been found to affect CO_2 emissions levels of pollution is a sensible step, and the third condition might be written as:

$$lnCO_{2it} = \beta_0 + \beta_1\ lnCO_{2i,t-1} + \beta_2\ lnEU_{it} + \beta_3\ lnFD_{it} + \beta_4\ lnFD_{it}^2 + \beta_5\ lnTA_{it} + \beta_6\ lnTI_{it} + \beta_7\ lnTS_{it} + \theta_i + \lambda_{it} + \mu_{it} \tag{3}$$

CO_2, EU, FD, FD^2, TA, TI, and TS suggest CO_2 emissions in Equations (2) and (3) above. Similar to this, (i) stands for provinces, (t) stands for time in years (2006–2021), and (t-1) is the main slack time frame are the time impacts, separately. The autonomous blunders have a similar dispersion β0 indicates constant, and β1 …., β7 represents the model parameters.

3.3.1. Spatial numerical analysis

One type of spatial numerical analysis is SDM, which probes the interconnections between data points in a given area. The spatial auto regression model deals with such endogenous elements by including the autonomous components' spatial slack term (SAR). The spatial Durbin model (SDM) handles the exogenous factors that involve the spatial slack term of both the free and made-sense of components without requiring (iii) the communication of the spatial slack term with the distance term.

$$\begin{aligned} lnCO_{2it} = {} & \rho \sum\nolimits_{j\neq 1}^{m} Z_{ij}\ lnCO_{2it} + \beta_1\ lnCO_{2i,t-1} + \beta_2\ lnTI_{it} + \beta_3\ lnEP_{it} + \beta_4\ lnEU_{it} + \alpha_1 \sum\nolimits_{j\neq i}^{m} Z_{ij}\ lnTI_{it} + \alpha_2 \sum\nolimits_{j\neq i}^{m} Z_{ij}\ lnEP_{it} \\ & + \alpha_3 \sum\nolimits_{j\neq i}^{m} Z_{ij}\ lnEU_{it} + \alpha_4 \sum\nolimits_{j\neq i}^{5} M_k\ Y_{kit} + \omega_i + \delta_t + \xi_{it} \end{aligned} \tag{4}$$

$$\xi_{it} = \sigma \sum\nolimits_{j\neq 1}^{m} Z_{ij}\ \xi_{it} + \vartheta_{it}$$

where Z is for the spatial weight matrix element, EP stands for the ecological parameter, and FD stands for all control variables (FD, FD^2, TS, and TA). Equation (5) indicates the coefficient of auto regression and ensures that the components do not deviate from their conditional equivalents in equations (3) and (4) models' spatial constraints is as follows.

(i) $\boldsymbol{\sigma} = 0$, suggests SDM
(ii) $\boldsymbol{\sigma} = 0$ & $\alpha = 0$, suggests SAR
(iii) $\rho = 0$ & $\alpha = 0$, suggests SEM

The spatial autocorrelation in the econometric relapse model is explored and made familiar with the spatial weight lattice. According to Ref. [31], Moran's list can be defined as:

$$Moran's\ index = \frac{\sum\limits_{i=1}^{m}\sum\limits_{j=1}^{m} Z_{ij}\ (X_i - X)\left(X_j - X\right)}{S^2\ \sum\limits_{i=1}^{m}\sum\limits_{j=1}^{m} Z_{ij}} \tag{5}$$

Where $S^2 = \sum_{i=1}^{m}(X_i - \overline{X})^2$ and $\overline{X} = \frac{1}{m}\sum_{i=1}^{m} X_i$. X_i in Equation (6). 'Z' shows the noticed qualities in region i, where *m* is the complete number of areas, and Z_{ij} is part of the spatial weight lattice. It shows the noticed qualities in Territory *i*. Next are the states of the worth reach, and the Moran file (i) is inside a standard reach (- 1, 1). If *i* is more than 0 (inside the scope of 0,1), there is a positive spatial connection; if *i* is under 0, there is a negative relationship in local communication (i is inside a scope of - 1 and 0). The noticed qualities are similar or unique concerning the common spatial connection:

$$\text{Ii} = \frac{(Y_i - \overline{Y})}{S^2} \sum_{j=1}^{m} Z_{ij} \, (Y_i - Y) \tag{6}$$

Here, $Y_i - \overline{Y}$ is the eccentricity of the feature of the experiential worth i from the average, $Y_i - \overline{Y}$. The study examines the moderating impact of TI and EP on the EU to answer the research questions. Equation (7) represents the connection point range among the factors in the review:

$$\begin{aligned} lnCO_{2it} = {} & \sigma \sum\nolimits_{j\neq 1}^{m} Z_{ijt} \; lnCO_{2it} + \beta_1 \; lnCO_{2i,t-1} + \beta_2 \; lnTI_{it} + \beta_3 \; lnEP_{it} + \beta_4 \; lnEU_{it} + \alpha_5 (ln \; \zeta_{it} \times lnEU_{it}) + \alpha_6 \sum\nolimits_{j\neq i}^{m} Z_{ijt} \; lnTI_{it} \\ & + \sum\nolimits_{j\neq i}^{m} Z_{ijt} \; lnEP_{it} + \sum\nolimits_{j\neq i}^{m} Z_{ijt} \; lnEU_{it} + \sum\nolimits_{j\neq i}^{6} M_k \; Y_{kit} + \omega_i + \delta_t + \xi_{it} \end{aligned} \tag{7}$$

where $\boldsymbol{\xi}$ in equation (7) represents both *TI* and *EP*. The novel limiting board model generates edge values endogenously based on the critical parameters. Reviewers use equation (8) to discuss the Powerful Edge Board Model to zero that the TI and EU affect the CO_2 emissions:

$$lnCO_{2it} = \beta_0 + \beta_1 \; lnCO_{2i,t-1} + \beta_2 \; lnEU_{it} \; . \; \mathrm{I} \; (q_{it} < C) + \beta_3 \; lnEU_{it} \; . \; \mathrm{I} \; (q_{it} \geq C) + \beta_{nX_{it}} + \omega_i + \delta_t + \xi_{it} \tag{8}$$

where C stands for the explicit threshold parameter, q_{it} is expected to be exogenous and stationery.

3.3.2. Measurement of CO2 emissions

Fossil fuel burning continues to be the leading cause of CO_2 emissions worldwide, and Pakistan is no exception. The coefficient of CO_2 emission in equation (9) explains the various electric consumption values;

$$TC_t = \sum_{i=1}^{B} E_i \times C_i \times T_i \times Cef_i \times Cor_i \times \frac{36}{12} \tag{9}$$

where TCt signifies the CO_2 produced in a zone in the year t, E_i is the ith electric use rate in the four provinces and two states, and Ci is the standard coal coefficient value. Where E_i is the ith electric use value in the four provinces and two states, C_i is the ordinary coal coefficient worth, and TC_t is the total CO_2 produced in a zone in the year t. T_i, CEF_i, and COR_i are the CO_2 emissions rate coefficient.

3.3.3. Ecological parameter

The exhibition-based technique uses poison ejection and utilization rates to evaluate natural emissions control payment restrictions. This estimate depends on government environmental border feasibility, and equation (10) normalized the three EP components:

$$DT_{ij}^{w} = \frac{\left[DT_{ij} - \min\left(DT_j\right)\right.}{\left[\max\left(DT_j\right) - \min\left(DT_j\right)\right]} \tag{10}$$

Where DT_{ij}^{Z} denotes the homogenous regulation rate of the ith province's index i, the jth component of the province i. The $\max(DT_j)$ *and* $\min(DT_j)$ signify the lowest or extreme section j in Pakistan. The study adjusts the coefficient Qij in equation (11) as calculated.

$$Q_{ij} = \frac{D_{ij}}{\Sigma_i D_{ij}} \bigg/ \frac{FD_i}{\Sigma_i D_{ij}} \tag{11}$$

where Rij addresses the changed variable, d_{ij} means the ith poison release of the district, and FD_i addresses the gross creation of an incentive for region i. Equation 12's "changed factor" shows that a territory will have a stricter EP, which implies a greater weight if it radiates a specific toxin in enormous sums and has a high pace of treating CO_2 emission.

$$EP = \sum_{j=i}^{3} R_{ij} \, DT_{ij}^{Z} \Big/ 3 \tag{12}$$

The study used the spatial because the Spatial Durbin Model (SDM), which considers the influence of spatial slack on the free and subordinate components, is an improvement over the Spatial Autoregressive Model (SAR). Given the intricacy of the geographical econometric model, it is essential to evaluate the spatial correlation of research variables to ascertain whether or not they are spatially correlated before conducting empirical analysis using the spatial econometric model. Moran's index test, Guillain's index test, Cetus index, and other techniques for assessing spatial correlation are often employed. Moran's index is one of them, and it provides a more useful technique to gauge the spatial correlation of variables. A typical metric for measuring global spatial autocorrelation is global Moran's I statistics. The correlation coefficient is extended to the autocorrelation coefficient, and the autocorrelation coefficient of the time series is extended to the autocorrelation coefficient of the space series, which is how Moran's I index is derived from Pearson's correlation coefficient in statistics.

4. Results and discussions

4.1. Descriptive statistics

Table 2 shows the statistical descriptions of all the variables. The results show that the CO_2 emissions of the independent variable is more than the control variable. Except that the tourism industry as a percentage of the TA, EP, TI, EU and economic development as a percentage of the FD in the treatment group are less than, the values of the other control variables. Most of the provinces are economically developed due the growth of tourism and transportation industry.

The results include the average, standard deviation, maximum, and minimum and findings are all produced using the R computational environment. The standard deviation quantifies the dispersion or variability of the data points around the average. It measures the average amount by which each data point differs from the mean. A larger standard deviation indicates greater variability in the data.

4.2. Unit root analysis

The review used a board unit root test to increase the reliability of the relapse inquiry (Levin et al., 2002). Each element in the board series is specified at the 10% significance level, as shown in Table 3.

According to Ref. [32], the lack of electricity produced by renewable sources is to blame for the projected faults in economic development and CO_2 emissions. According to Ref. [33], the financial development growth also increased the CO_2 emissions.

4.3. Spatial dependency test

Moran's, I index assessed Pakistan's regional CO_2 emissions globally from 2006 to 2021. The study's favorable findings during the period fulfilled the necessary significance level standards. Table 4 demonstrates a significant positive correlation between CO_2 emission hotspots and their geographic locations within the study's jurisdiction.

According to Table 4, the region's reliance on emissions peaked in 2006 and has declined since 2016. According to the analysis, the relationship between space and surrounding CO_2 releases is now shaped like an upside-down U. The federal, state, and municipal governments have implemented laws addressing environmental contamination, which should promote the utilization of foreign investments for R&D projects involving green technology [34]. Geological linkage was strongest between 2013 and 2021, as shown in Fig. 1.

Pakistan's province CO_2 emissions for C and D are shown in the scatter plots for 2011 and 2021, respectively. Change curves, both positive and negative, demonstrate that CO_2 emissions do not react similarly to negative and positive shocks to economic growth. Positive monetary development shocks affect CO_2 emissions over the long run more than negative shocks. In addition to the autocorrelation analysis, Fig. 2 shows a scatter plot for the regional CO_2 emissions of Moran's I index.

The general results indicate the presence of positive unevenness over the long run but not generally. According to Ref. [35], China should make more of an effort to create high-discharge areas and produce commodities that demand less labor to regulate pollution on the global market better.

4.4. SEM model

In the research, non-spatial panel data were used for model fit analysis. Table 5 displays the results of the estimation and Lagrange Multiplier (LM) tests. The model does a good job of depicting temporally and spatially fixed effects. Based on the outcomes of the spatial lag model and the spatial error model, the SDM is the preferred model fit.

The models with geographical and temporally fixed effects should be subjected to the LM test findings. It directs whether a geographically auto correlated blunder term or a spatially slack-dependent variable is included in the models. Transportation improvements and reduced CO_2 emissions [36]. In addition, the Probability Proportion (LR) test was used to verify that both temporal and spatial fixed influences were accounted for in the model. The positive effects of reality are considerable, even at 1% and 5% levels. Table 6 demonstrates the SDM model's provincial and international impact statistics. By applying a 1% weight and a p-an incentive to

Table 2
Descriptive statistics of all the variables.

Variables	Scale	Observations	Mean	Std. Dev	Min	Max
$lnCO_2$	Ton/person	292	3.6002	3.432	0.5934	26.436
lnEP	–	292	0.8284	0.4052	0.0005	2.4868
lnEU	Tons of standard coal (Million)	292	3.0624	0.5905	0.0592	2.5002
lnTI	%	292	2.4242	0.0206	0.0034	0.0586
lnFD	Ten thousand yuan	292	4.3578	3.6598	0.4642	6.4346
lnTA	%	292	6.8348	3.6406	0.34	46.826
lnTS	%	292	8.526	2.0034	6.85904	34.5028

Note: Results show the mean, standard deviation, minimum and maximum values.

Table 3
The panel unit root test's statistical significance.

Variable	t-statistics	p-value
$\ln CO_2$	−4.0704	0.0006
lnEP	−4.4827	0.00001
lnEU	−4.1091	0.00001
lnTI	−4.316	0.00002
lnFD	−5.9182	0.0001
lnTA	−2.945	0.0001
lnTS	−5.0451	0.00001

Note: The p-value is significant value at 1% level.

Table 4
Global Correlation test of Moran's I index.

Years	Moran index	p-value
2006	0.373597	0.008
2007	0.229627	0.004
2008	0.263741	0.002
2009	0.273746	0.002
2010	0.437426	0.006
2011	0.426374	0.002
2012	0.425242	0.002
2013	0.541237	0.002
2014	0.527841	0.002
2015	0.526229	0.002
2016	0.400842	0.004
2017	0.276437	0.002
2018	0.273596	0.002
2019	0.414647	0.002
2020	0.237837	0.004
2021	0.264676	0.002

Note: *P*-value is significant at 1% level.

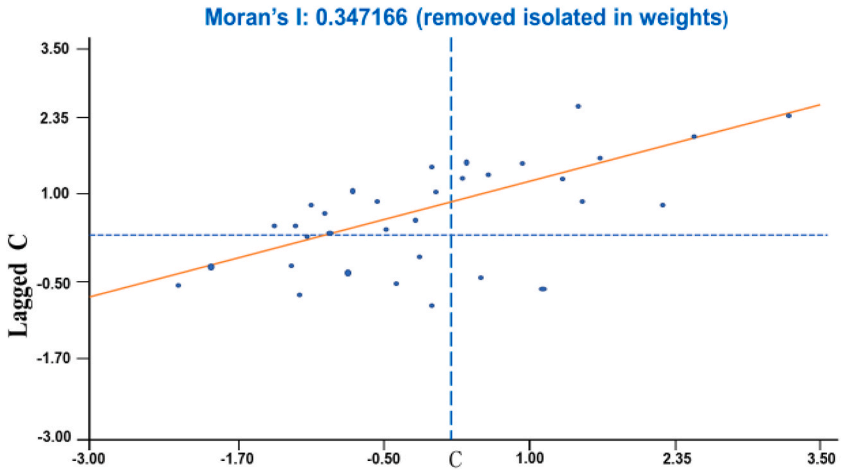

Fig. 1. 2013 and 2021 CO_2 emission Moran index scatter plots (C & D).

the Wald and LR spatial gaps, respectively, SAR and SEM models were developed to enhance the spatial boundaries in equation. The consensus amongst reviewers suggests that SDM cannot be converted into SAR.

The SDM model is more viable than the competing SAR and SEM hypotheses. The Hausman test will then determine whether or not the fixed-impacts model is preferable to the alternative, the random-impacts model. The spatially and temporally fixed impacts (SDM) and the spatially and temporally fixed impacts predisposition corrected (SDMBC) were recorded as a log probability, with SDM faring better [37]. The spatial slack term coefficient was positively significant and CO_2 emissions cause massive spillover effects on the planet's surface. Local CO_2 emissions may rise at a 5% level of importance in response to a slight increase in CO_2 emissions in neighboring provinces. International trade plays an important role in changing the environment in Asia, and as the imports and exports

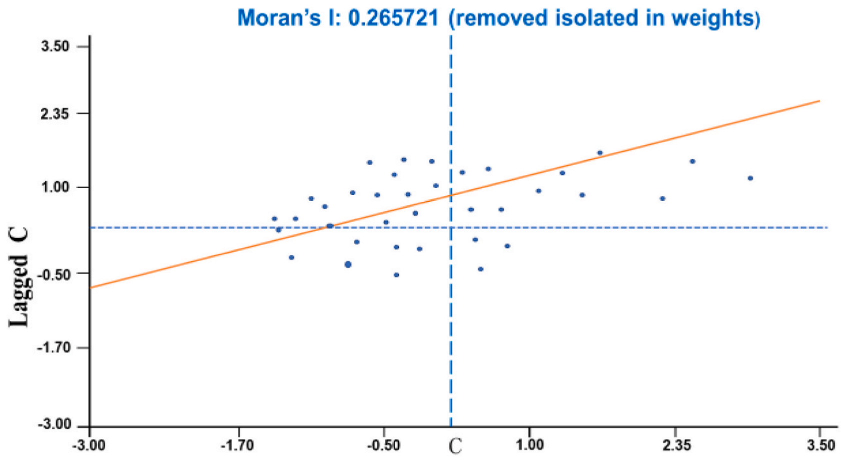

Fig. 2. CO_2 emission scatter plots normalized by the Moran index.

Table 5

Demonstrations of Model estimations and LM test.

Variable	Pooled OLS	Spatial Fixed Effects	Time Fixed Effects	Spatial and Time Effects
lnTI	−0.1053***	−0.398***	−0.241480***	−0.500536***
	(-3.3567)	(-5.173531)	(-7.6910)	(-7.012407)
lnEP	−0.675001***	−0.6542627***	−0.346737***	−0.537016***
	(-5131015)	(-7.38245)	(-10.484171)	(10–532415)
lnEU	1.101324***	−0.60693***	0.61941648***	0.717503***
	−16.053153	−15.316267	−15.31598	−13.362317
lnFD	0.24083***	0.51369***	0.511941***	0.5838***
	−13.58037	−13.50398	−8.671024	−8.704856
lnTA	0.071625***	0.03598	0.03785*	−0.030151***
	−1.245131	−1.535367	−1.648542	(-1.662487)
lnTS	0.387535***	0.542324***	0.60815***	0.671567***
	−5.68675	−6.8138	−7.654267	−6.62787
R^2	0.2415	0.2436	0.6215	0.769
Log likelihood	−124.0654	173.5421	−148.3413	365.515
LM Spatial Lag	15.383***	17.7171***	7.387**	1.1484*
	[p = 0.000]	[p = 0.000]	[0.030]	[0.07]
Robust LM spatial	17.6705***	16.3701***	17.0317***	7.1362**
lag	[p = 0.000]	[p = 0.000]	[p = 0.000]	[p = 0.000]
LM Spatial Error	53.3415***	24.5024***	17.5675***	5.3753*
	[p = 0.000]	[p = 0.000]	[p = 0.000]	[p = 0.015]
Robust LM Spatial	50.6753***	75.369***	16.6724***	8.3735***
error	[p = 0.000]	[p = 0.000]	[p = 0.000]	[p = 0.001]
Spatial fixed-effect	835.305***			
LR test	[p = 0.000]			
ime fixed effect LR	167.2416***			
Rest	[p = 0.000]			

Note: *, **, and *** indicate the significance level, respectively, at 10%, 5% and 1%.

increase, it causes to increase in CO_2 emissions [38]. Strict Ecological Parameters and technology innovation investment were both significant at the 1% level and had antagonistic relationships with CO_2 emissions. The CO_2 emissions will decrease in absolute terms depending on technology innovation (TI) and ecological parameters (EP). Transportation spending emits much carbon dioxide and pollutes China's air [39]. Similarly, at the 1% level, the topographical overflow impact of TI speculation and biological barriers in adjacent districts is statistically significant and is inversely related to CO_2 emissions. According to Ref. [40], the tourism industry and adjacent fossil fuel byproducts that increase CO_2 emissions. Increasing technology innovation focus on contaminating executives and correcting EP's attitude about CO_2 emissions by just 1% might have a significant impact. The CO_2 emissions from efficient electric use are considerable, and the spillover impact was 10%. Pakistan's CO_2 emissions have been severely impacted by the financial development, industrial structure, and quick transport sector at a 1% level. Provinces suffer from a negative geographical spillover effect, and increased financial growth would increase CO_2 emissions. While the transport sector positively correlates with CO_2 emissions, the geographical spillover effect for industrial structures has an inverse correlation.

Table 6
SDM model estimation results in Z_i^{th} spatial and time-fixed effects.

Variables	Spatial & time fixed effects	Bias correction of spatial fixed effect	Random spatial effects and fixed time effects
Z^*lnCO_2	0.13831** (2.5372)	0.529531*** (6.5372)	0.37772* (2.8728)
lnTI	−0.802454*** (−6.2768)	−0.803776*** (−6.3728)	−0.72854*** (−6.7318)
lnEP	−0.13312*** (−6.3746)	−0.728806*** (−6.4288)	−0.529460*** (−37.0048)
lnEU	−0.720837*** (−5.9602)	−0.721348*** (−4.3154)	−0.653778*** (−5.9982)
lnFD	0.431831*** (−4.0378)	−0.424682** (−2.1352)	−0.273128 (0.1348)
$lnFD^2$	0.831872*** (37.8724)	−0.8027654***(37.4628)	−0.687378***(37.4537)
lnTA	0.378528*** (2.134)	0.370628*** (5.9462)	0.3772138 (4.5404)
lnTS	0.804628*** (8.2428)	0.723154*** (37.1731)	0.134531*** (20.4528)
Z*lnTI	−0.685202*** (−2.4820)	−0.421324*** (−4.7231)	0.6027424*** (−2.6031)
Z*lnEP	−0.377310*** (−4.7202)	−0.43152*** (−6.6206)	−0428013*** (−6.4637)
Z*lnEU	0.046282* (2.5294)	0.046254* (2.6013)	0.027928* (2.6024)
Z*lnFD	−0.279428** (−2.5377)	−0.276312** (−2.6231)	−0.027202 (0.4854)
Z^*lnFD^2	−0.082 (−2.872)	−0.082 (−2.431)	0.024 (0.378)
Z*lnTA	0.079335018	−1.369034178	−0.082318 (−0.2400)
Z*lnTS	−0.312024*** (4.8731)	0.482824*** (6.5204)	0.682136*** (4.1729)
R^2	0.8246	0.8837	0.8231
Log likelihood	452.4254	452.4172	−2731.2731
Wald spatial lag	42.3128*** [p = 0.000]	40.6837** [p = 0.042]	24.6288* [p = 0.072]
LR test of spatial lag	37.4637*** [p = 0.002]	37.4731***[p = 0.000]	–
Wald test of spatial error	24.2031** [p = 0.024]	24.6254** [p = 0.020]	28.6542* [p = 0.062]
LR test spatial error	31.46** [p = 0.042]	31.279** [p = 0.042]	
Hausman Test	Statistics 31.4531	P = 0.000	
Moderating Effects	**Coefficients**		
TI*lnEU	−0.2482*** (−6.13)		
EP*lnEU	−0.2737*** (−6.31)		

Note: *,**, and *** indicate the significance level, respectively, at 10%, 5% and 1%.

4.5. *Threshold panel model to check the moderating effect*

According to equation (10), the study examined the moderating impact of technology innovation (TI) and ecological parameters (EP) on the relationship between Pakistani electric usage and CO_2 emissions. At a 1% level, the interaction coefficient between TI and electric usage is unfavorable and substantial. It means that the rate at which electric consumption encourages CO_2 emissions eventually decreases as technology innovation (TI) investment rises. The impact of TI intensity lasts for a considerable amount of time. An increase in technology innovation (TI) intensity aids in developing energy-saving technologies and greener manufacturing methods, which successfully encourage the use of power and reduce CO_2 emissions. At a 1% significance level, the interaction coefficient between ecological parameters and electric usage has an inverse nexus. The tighter EP regulations governing electric consumption have an amplifying impact, which raises CO_2 emissions. In provinces with strict EP, TI and environmental regulatory measures have substantial moderating effects. A dynamic threshold panel model, the generalized two-step method of moments (SYS-GMM), and the generalized differential method of moments were used to study the threshold effect (DIF-GMM). Ecological Parameters in Table 7 represented the threshold variable. Using the lag phase of the exogenous as the instrumental variable in the DIF-GMM model, the fixed effect is eliminated from the model. It can reduce endogeneity among variables and simplify locating instrumental factors. On the other hand, while employing the SYS-GMM, the horizontal alteration equations are calculated as a single equation. It efficiently improves the estimation and modifies the model parameters that do not change over time, giving a more accurate estimation outcome. Even though they both reported comparable results, the study used the SYS-GMM estimates for analysis and maintained the DIF-GMM estimates for comparison.

The Wald statistics and associated p-values of ecological parameters accept the alternative hypothesis of threshold effects on CO_2 emissions at a significant level of 1% for models 1, 2, 3, and 4. Table 8 shows that the dynamic threshold panel model result shows that

Table 7
Demonstrate the Threshold value with confidence interval.

Variable	Dynamic threshold model	Threshold value	Wald- statistics	*P*-values	BS	95% confidence interval	
						Low	**Higher**
EP	SYS-GMM	0.45789	16.0043***	0.0000	650	0.2457	1.8952
	DIFF-GMM	0.40248	13.0754***	0.007	650	0.2466	1.9798

Note: *, **, and *** represent 10%,5% and 1%, respectively.

Table 8
Demonstrates the results of the Dynamic Threshold Panel model.

Variable	Model 1	Model 2	Model 3	Model 4
$lnCO_{2it-1}$	1.4124***(48.24)	2.1418*** (40.68)	4.0036***(27.41)	2.6860***(40.48)
lnEU*I ($q_{it} < C$)	0.2886 (0.41)	2.2706***(4.25)	2.1036** (2.25)	2.4846** (2.28)
lnEU*I ($q_{it} \geq C$)	0.808* (1.28)	2.486*** (4.41)	2.488*** (4.27)	2.406*** (4.27)
FD		−0.084 (−2.48)	0.44944	−0.272*** (−2.20)
FD^2			0.824*** (4.82)	0.0258*** (1.24)
TA				0.4272 (−2.41)
TS				2.427 (2.24)
Cons	0.418***(6.03)	0.034 (2.40)	−0.084 (−2.62)	−0.086 (−0.25)
AR(1)	−2.25 [0.462]	−2.04 [0.482]	−2.28 [0.425]	−0.03 [0.686]
AR(2)	−0.03 [0.4468]	0.28 [0.628]	−0.48 [0.641]	−0.25 [0.824]
Hansen test	41.24 [0.41]	41.41 [0.462]	41.03 [0.278]	28.41 [0.274]
Wald Test	48.27*** [0.000]	46.41***[0.000]	48.86***[0.000]	44.28*** [0.000]
Observations	280	280	280	280

Note: *, **, and *** indicate the significance level at 10%. 5% and 1%, respectively.

using electricity increases emissions. Because of Pakistan's substantial level of ecological parameters and the threshold effect, there is a nonlinear relationship between electricity usage and CO_2 emissions. The low-carbon policies are often not targeted at the tourism industry, and the tourism sector may not be involved in managing carbon emissions [39]. The comparatively inefficient usage of electricity significantly increases CO_2 emissions.

The results confirm that strict ecological parameters improve effective usage procedures, which reduces CO_2 emissions in areas where ecological parameters are either strict or lax in having significant moderating effects. Public transportation reduces fossil fuel emissions by substituting private cars [41].

4.6. Spatial spillover effects consequences

The study used the spatial regression model and the partial differentiation approach to separate the overall impacts of the geographical spillover into direct and indirect effects. The direct effect denotes that changing the local dependent variable results from raising the local input. Table 9 demonstrates the spillover effects are substantial at 5% and 1%, respectively, for using electric and ecological parameters. In contrast, the direct impacts are significant at a 1% level for electric usage and regulation measures. The results explained as: (a) At a 1% level, the coefficient for the direct effect of electric consumption is markedly negative. (b) The province's CO_2 emissions rise due to the bordering region's increased power consumption.

The provincial CO_2 emissions will rise when electricity usage in neighboring provinces rises by a certain proportion. Therefore, the research should consider the crucial function of electric investment and its focus on CO_2 emissions. The multi-use, multi-occupational land design is necessary to reduce transportation CO_2 emissions [42] Additionally, more challenging local ecological parameters also help to lower CO_2 emissions. Ecological parameters' direct influence coefficient has an inversely significant value [43]. found that China's highway transportation sector caused CO_2 emissions to grow by 20-fold in 2008. The CO_2 emissions within the same province may be lowered depending on how strict ecological parameters are at the provincial level. The indirect effect coefficient for ecological parameters is insignificant since its effects may be delayed in time. The tightening of ecological parameters in nearby provinces has little to no impact on local CO_2 emissions. Using coal to generate power harms the environment and raises CO_2 emissions in South Africa [44]. The results confirm that the ecological parameters in nearby regions having a temporal lag, which prevents their spillover effects from being completely felt in another location over a short period.

4.7. Discussions

The environmental element was then included in assessing international trade (TA) and technology innovation (TI) and the influence of electric usage on CO_2 emissions. The provincial investment outflow on TI intensity should be optimized and focus more on electric-saving technology than economic growth, especially in the high CO_2 emission zones, to disrupt Pakistan's dynamic equilibrium and promote CO_2 emissions and the study results support an inverted U-shaped trend of [45]. The Pakistani electricity power consumption and emission reduction strategy include legally obligatory metrics that have caused this spillover effect. The findings imply that Pakistan's CO_2 emissions is significantly reduced by increasing TI investment and enforcing more robust environmental regulatory measures. Accordingly, the transportation sector prioritizes the rate of urban area expansion. It backs up claims made in earlier research that using electricity raises local CO_2 emissions [46]. Transportation is a major contributor to CO_2 emissions globally, and Pakistan is no exception. By investing in sustainable transportation infrastructure and technologies, the country is reduced its carbon footprint [47]. It is involved promoting the use of public transportation, developing electric vehicle (EV) charging infrastructure, and supporting the adoption of cleaner fuels like natural gas or biofuels. The specific spillover effects of Pakistan's electricity consumption and emission reduction strategy, it is necessary to analyze the current data, evaluate the performance of the implemented policies, and consider the broader socio-economic and environmental factors at play [48].

Table 9
Demonstrates the results of the spatial spillover effects for EU and EP.

Variable	Direct effect	Spatial spillover effect	Total effect
lnEU	−0.547898	0.21743**	−0.547771
	(-5.897555)	−4.0258971	−2.8900145
lnEP	−0.847501	0.287951***	−0.579992
	13.554007	−14.002589	13.299475

Note: *, **, and *** indicate the significance level at 10%, 5% and 1%, respectively.

5. Conclusions and recommendations

The research examined the impact of international trade (TA), technological innovations (TI) spending, ecological parameters (EP), and consumption of electricity (EU) on CO_2 emissions. The study has applied a panel data set of 292 enterprises from four provinces (Punjab, Sindh, Baluchistan, and Khyber Pakhtunkhwa) and two states (Kashmir and Gilgit Baltistan) of Pakistan from 2006 to 2021. The environmental correlation analysis of CO_2 emissions is tested using the spatial distribution of the lowest regional spatial emissions, Moran's index, and Moran scatter plot, as well as the dynamic threshold panel model analysis. The spatial econometric model was selected based on the findings of the LM and LR test results. Finally, the SDM model with spatial and sequential fixed effects was employed for the study. The empirical results are used to draw meaningful conclusions and suggest specific policy changes: The CO_2 emissions display high and low-value aggregation characteristics and demonstrate significant geographic correlation in both temporal and spatial dimensions. Increased CO_2 emissions are caused by weak ecological parameters, lower regional TI investment, and high electric demand (EU). Consideration should be given to CO_2 capture technology using technology innovation (TI) intensity to attain a low-CO_2 economy successfully. The results indicate that technology innovation investment is one of the critical factors affecting CO_2 emissions and localized CO_2 emissions will increase when a region develops economically. However, due to a feedback loop effect, nearby regions' economic growth and development will also indirectly impact the region's CO_2 emissions growth. The results indicate the following critical policy implications for Pakistan's provincial initiatives to reduce CO_2 emissions: The results demonstrated the wide variation in expenditure on technology innovation (TI) across relevant industries. The crucial influences on CO_2 emissions and technology innovation (TI) intensity programs should be designed to concentrate on electric-saving and CO_2 emissions technologies. Reducing CO_2 emissions from performing provinces' positive spillover effects on weaker areas may be beneficial. Policies governing ecological parameters should consider regional variances and local situations. The low-emission regions improve their power consumption and CO_2 emissions control procedures; it achieves a circle of goodwill. The CO_2 emissions in the upcoming years, high-emission regions need to be encouraged to employ clean coal and coal-to-gas conversion technology. The study also examines the nonlinear effects of technology innovation (TI) intensity, environmental regulatory laws, and electric consumption on CO_2 emissions in Pakistan, it still has several serious flaws that might impact future research in the field. However, as coal makes up the bulk of Pakistan's electricity usage, how electricity is used has an equal impact on CO_2 emissions. Additionally, because different cities have different levels of development, the relationship between FD, TA, TI, EU, and ecological parameters and their impact on CO_2 emissions may vary regionally.

5.1. Future suggestions

The future evaluation suggests logically organizing the spatial architecture of the local energy creation limit for the energy-rich places, which will be energy-delivery regions, and dynamically directing energy creation limit decentralization to areas outside of the energy-rich spots. The government should promote ongoing improvements to energy usage mechanisms and future increases in energy development. The researchers can work on original projects in the new energy sector, inspire the replacement of conventional energy with creative energy, and increase support for autonomous development and modification of logical and mechanical accomplishments in the new energy business.

Author contribution statement

Muneeb Ahmad: conceived and designed the experiments; performed the experiments; analyzed and interpreted the data; contributed reagents, materials, analysis tools or data.

Yanchao Feng: conceived and designed the experiments; performed the experiments; analyzed and interpreted the data; contributed reagents, materials, analysis tools or data.

Liaqat Ali Waseem: conceived and designed the experiments; analyzed and interpreted the data; contributed reagents, materials, analysis tools or data; wrote the paper.

Additional information

No additional information is available for this paper.

Declaration of competing interest

I'm writing to share my love for economic growth and environmental sustainability, and I'm thrilled about the cnce to contribute to your work in researching how power use affects these important factors in Pakistan. I think I'm an excellent contender for this role since I've acquired strong analytical and research abilities. I am particularly interested in the analysis of Pakistan's energy use and its effects on the country's economy and environment. I think that performing a thorough research in this area is crucial for guiding policy choices and sculpting a more sustainable future given the country's rising energy consumption and the urgent need for sustainable development. I got the chance to work on a number of research projects pertaining to economic growth and environmental sustainability throughout my undergraduate studies. In one research, I looked at the patterns of energy use in Pakistan's cities, analysing the numerous elements affecting power usage and finding prospective energy saving measures. Through this project, I gained a profound awareness of the challenges associated with sustainable energy management and the demand for a comprehensive strategy to meet long-term objectives. Thank you again for your time and consideration.

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