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ORIGINAL PAPER

Environmental effect of green technology innovation and industrial structure aspects

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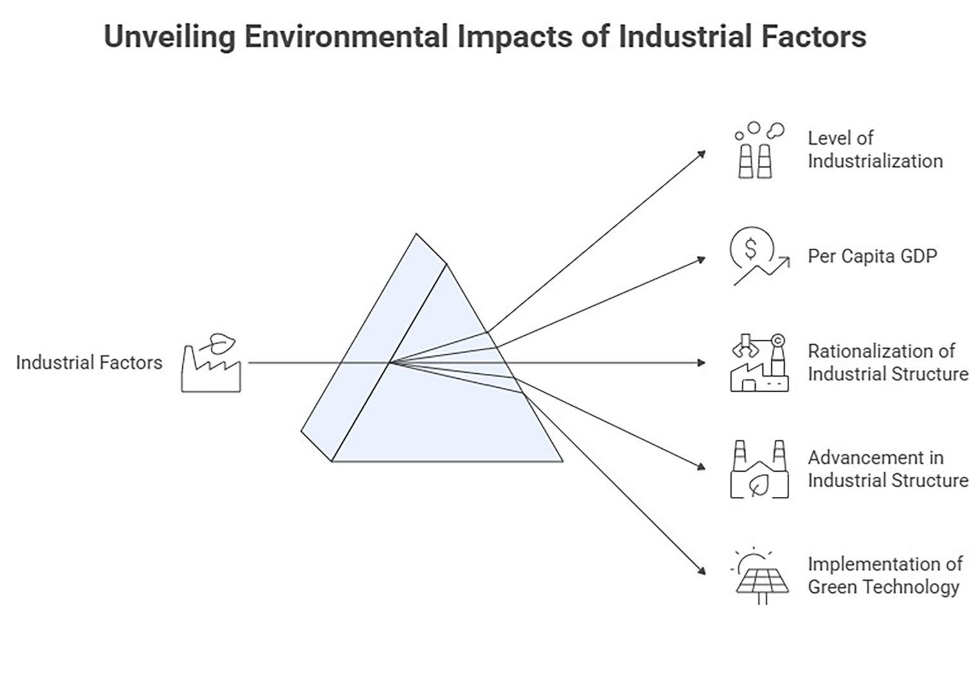
Abstract
With the motivation to explore China's nationally determined contributions (NDCs) toward a net zero emission future, we examine whether green technology innovation mitigates carbon dioxide (CO_2) emission thereby improving environmental quality across five of the most populous provinces (consisting of 85 cities) for the period between 2007 and 2019 in a multi-dimensional panel approach with an endogeneity robustness from two-step system generalized method of moments (GMM). The results show green technology innovation, economic output (GDP), and financial development spur CO_2 emission in the across the provinces. Meanwhile, especially in the whole panel, green technology innovation is dependent on the level of industrial structure (a moderation effect), but this interaction effect fails to show desirable outcome in the province-specific cases. Additionally, in each of Guangdong, Henan, Hunan, Shandong, and Sichuan provinces, carbon emission is triggered by an increase in GDP and financial development. Additionally, green technology innovation (i) worsens carbon emission through the moderating effect of advanced industrial structure and industrial structure rationalization in Guangdong and Sichuan provinces (ii) worsens carbon emission through the moderating effect of rationalization of industrial structure in Henan, Sichuan, and Shandong provinces. These findings have vital policy insight toward improving the quality of green innovations in China.

Graphical Abstract



Extended author information available on the last page of the article

Keywords Technology innovation · Industrial change · Financial development · Income level · Carbon emission · Chinese provinces

Introduction

China being a leading player on global scale in terms of industrialization and green technology has remained one of the major countries of focus in the global push for the world's carbon neutrality agenda. The country has witnessed a monumental transition from a traditional agrarian society to the manufacturing hub of the world and hosting some of the largest industrial chains in the twenty-first century (Wen 2021; Dutta 2005). Moreso, in a very proactive approach, the Chinese government came up with "carbon peaking" and "carbon neutrality" plans as essential strategies to address and mitigate climate change effects as well as ensure that China moves on a sustainable development path. The Chinese "carbon peaking" and "carbon neutrality" goals are laudable goals for not just China's environmental sustainability alone but global sustainability considering that a significant proportion of global emission comes from China. As at the end of 2020, emissions from the Chinese economy alone represent about 32.6% of approximate 33,566,428kt of kt of global CO_2 emissions in 2020 (WDI 2022). This massive level of emissions is more than the total amount of reported emissions from the USA, India, and the European Union combined within the same year (WDI 2022). Therefore, to ensure the attainment of these goals, there is a need to work toward transitioning the environmentally unstainable economic structure of the past few decades into an economic approach that prioritizes ecological sustainability, or a green development-based economic approach. An economic model that is centered on green development emphasizes the roles innovations that do not only boost economic prosperity but most importantly ensure improvements in the quality of the environment via the reported innovations or progress in environmental-related technologies (Xu et al. 2021a; Du & Li 2019).

Economic progress that is based on green development would ensure that available natural resources are optimality allocated and utilized in such a way that there will be a minimal environmental destruction by leveraging on technological innovations in production and processes, as well as harnessing other market solutions (Wang et al. 2021). Meanwhile, it has been established that economic activities over the past decades have worsened global environmental quality considering that fossil energy utilization has dominated energy supply for growing industrial activities. However, within the context of technological innovation and green development, the argument postulated in theenvironmental Kuznetscurve (EKC) hypothesis highlights the relevance of technological innovation as one of the bedrocks upon which the emission-inducing impact of the historical economic growth can be overturned for environmental gains. In line with the theory, the Chinese industrial awakening that has spearheaded country's economic boom would have induced carbon emission levels from the initial state of the nation's economic boom. However, the Kuznets effect will set in overtime as more technological innovations are achieved in the society (Kuznets 1955). As economic activities expand overtime, the more such innovations address environmental challenges by putting the country on the path of zero-carbon transitions, the wider the level of green development. Therefore, a proper consideration of the impacts of economic components is of great significance for governments to formulate differentiated green development strategies. Hence, for the current study in the case of China, credence was given to the economic development levels across Chinese provinces while assessing the roles of green innovation amidst dynamics of low-carbon development across the provinces.

Aside from the duo of the state of technology innovation and the possible impacts of the disparity in economic development levels among countries or regions, the industrial structural upgrading is arguably among other crucial factors that can potentially modulate the dynamics of low-carbon development (Pan et al. 2023; Zhou et al. 2013; Chen et al. 2016). Industrial structure can be upgraded to improve efficiency in energy utilization as well as to enhance production culture that more environmentally friendly (Brannlund and Persson 2012; Sohag et al. 2015). In this regard, China is actively adjusting its industrial structure as the available data from the China Bureau of Statistics show that China's tertiary industry has increased significantly from 23.9% in 1979 to 54.6% in 2023, essentially completing the transition from a predominantly industrial and agricultural sector to a balanced industrial composition (including primary, secondary, and tertiary industries). Green innovations have also been identified as the essential drivers for achieving this balanced industrial structure for the desired low-carbon transition (Zhu et al. 2021). There influences on low-carbon transition are even more prominent in the case of advanced and large-scale industrial arrangements as observed by Zhang et al 2023 and Wang et al 2022. As such, the aspects of green innovations should not be sidelined when analyzing a carbon emissions–industrial structure nexus.

Based on these motivations, we scrutinize two questions; (a)have green innovations promoted emission mitigations across different provinces in China? (b)how do green innovations influence industrial structure's roles and their rationalization in carbon mitigations? A multidimensional approach that was adopted for the analysis was based on a dataset of the five most populous provinces in China (Guangdong, Henan, Hunan, Shandong, and Sichuan). Importantly, these mega provinces with each accounting for over 60 million people represent the country's economic and cultural powerhouse and their selection justifies regional spread given that the provinces all span South, Central, East, and West China. The outcomes outlined substantial implications for low-carbon development at industrial levels as well as providing insights on intriguing questions of how to correctly combine economic expansion with environmental protection. Compared to previous studies, this paper makes several significant contributions. Firstly, most existing studies consider industrial structure upgrading, while fewer studies examine its internal components in detail. This study meticulously distinguishes between the aspects of advanced industrial structure and industrial structural rationalization during the process of industrial structural upgrading. The empirical model further entails the integration of green technology innovation (GTI), advanced industrial structure, and industrial structure rationalization into a unified analytical framework, thereby comprehensively examining their interactions and their combined impact on CO_2 emissions. This not only tests the applicability of the EKC hypothesis in China, but also expands the theoretical framework and academic achievements in related fields. Secondly, given the significant disparity in the levels of resource endowment, economic development, and industrial structure among Chinese regions, detailed studies at the provincial level are particularly crucial. Existing research predominantly focuses on macro-level analysis or discussions of specific industries, lacking systematic studies on regional disparities and the industrial activity environmental effects at the provincial level. This study focuses on regional- and provincial-level analysis, and the results demonstrate that the environmental impacts of green innovations differ across the region.

Our findings identify the interactions between GTI, advanced industrial structure, and industrial structure rationalization in different regions and provide specific recommendations for policymakers in different regions with the perspective of influencing net-zero emission targets. Finally, we constructed and applied a multidimensional panel data model, which can capture both time-series and cross-sectional variability, to identify the heterogeneous characteristics of the impacts of GTI, advanced industrial structure, and its rationalization more accurately on CO_2 emissions. Overall, the research provides new evidence for the environmental effects of innovations and industrial transformation in achieving the goal of zero carbon emission and provides a scientific basis for environmental policymaking in China, and globally by extension. The order of the rest of the sections is: summarized literature review in Sect. "Related Literature: a synopsis", data and presentation of empirical results in Sect. "Data and Empirical Analysis", discussion of results in Sect. "Results and Discussion", and conclusion with policy reflection in Sect. "Conclusion".

Related literature: a synopsis

Considering the carbon reduction drive of the Chinese economy in recent times, the environmental effects of GTI have become a hot research topic on China among scholars (Chen et al. 2021; Godil et al. 2021; Shao et al. 2021; Su et al. 2023). We provide a summary of some of the existing studies in Table 1.

Overall, Fig. 1 shows a simple Sankey diagram that demonstrate the summarized studies. As seen in the diagram, elements such as renewable energy, industrial structure, income, and trade openness are often combined when scholars examine the relationship between green technology innovation and CO_2 emissions. However, the environmental impacts of GTI cannot be completely generalized (Lin and Ma 2022). Most of the studies concluded that GTI is environmentally beneficial, but there are also studies that arrive at a different view.

Contributions to the literature

Although some existing works have explored the impact of industrial structure upgrading on carbon emissions (Chang et al. 2023; Zheng et al. 2023; Zhou et al. 2013; Du et al. 2019; Yin et al. 2024), there are still existing gaps, especially regarding the multidimensional impact of industrial structure. Therefore, based on the multidimensional perspective, this paper subdivided industrial structure upgrading into two variables, industrial structure advancement and industrial structure rationalization, to comprehensively analyze the environmental impacts of industrial structure upgrading and green technological innovation, and the results of the study offer more insight on the aspects of technological innovation, industrial structure, and environmental policy.

Furthermore, the environmental effect of green technology innovation is still largely debatable (Bilgili et al. 2016; Li et al. 2023). While there are multiple supports for the emission reduction impacts of GTI, some scholars found that GTI may not always produce these beneficial environmental effects (Khan et al. 2020; Rennings 2000; Villanthenkodath and Mahalik 2022). Hence, to answer the questions of "whether GTI's roles are beneficial to China's sustainable development and whether their environmental impacts differ across regions or regional development levels", this paper examines the impact and heterogeneity of green technology innovation on CO_2 reduction through empirical analysis, thus engendering

Table 1 Existing literature

Author	Samples	Sample countries/Approach	Empirical methods	Summary of findings
Green technological innovation (GTI) and the environment				
Sharif et al. 2022	1995 to 2019	G7 countries/Traditional panel approach	CS-ARDL	GTI and green financing reduce CO_2 emissions
Raihan and Tuspekova 2022	1996 to 2018	Kazakhstan/Traditional time-series approach	DOLS	GTI and renewable energy reduce CO_2 emissions while energy consumption and economic growth act otherwise
Tan and Cao 2023	1990 to 2019	G7 and BRICS countries/Traditional panel approach	IV regression	Combination of GTI types significantly reduce CO_2 emissions
Du and Li (2019)	1996–2012	71 economies/Traditional panel approach	Threshold model	GTI improves energy consumption structure and suppresses CO_2 emissions
Bai et al. (2020)	2000 to 2015	China	FE models	GTI in renewable energy plays a positive role in reducing per capita emissions
Du et al. (2017)	2006–2012	China	PDA model	GTI that increases energy use efficiency drive China's carbon intensity decline
Wurlod and Noailly, (2018)	1975 to 2005	17 OECD countries/Traditional panel approach	Structural equation	Green innovation reduces energy intensity
Li et al. (2019)	2005 to 2015	30 Chinese provinces/Traditional panel approach	Two-step system GMM	Innovation improves Industrial green development, thus mitigating carbon production intensity
Liu et al. (2024)	1995 to 2020	750 balanced panel data (consisting of 30 Chinese provinces, cities and autonomous regions)	Feasible generalized least squares (FGLS)	The effects of GTI increase carbon emission via the scale effect, decrease carbon emission via technological effect. Generally, GTI mitigates carbon emission
Yang et al. (2023)	1997 to 2017	30 Chinese provinces/Traditional panel approach	Panel regression and GMM	Impacts of GTI are heterogeneous. GTI in crude coal and crude oil reduces emissions but increases emissions for natural gas
Industrial structure and environmental degradation				
Gao et al. (2022)	2008 to 2020	30 Chinese provinces/Traditional panel approach	FE models	The combination of industrial structure upgrading with GTI significantly reduces CO_2 emissions
Dong et al. (2020)		41 countries/Traditional panel approach	Input and output table	GTI moderates how industrial structure influence emission reduction
Zhang et al. (2018)	2006–2014	China	Dynamic factor decomposition model	Industry restructuring aids emission reduction
Lin & Ma (2022)	2006–2017	China's 264 prefecture-level cities	Linear function-coefficient model	GTI potentially lowers emissions via upgrade of industry structure
Hu et al. (2023)	2000–2019	Chinese Eastern, Central and West regions/Traditional panel approach	Nonlinear ARDL	Carbon emission is expected to lower in China via rationalization of the industrial structure in the long term
Xu et al. (2021b)	2007–2013	China's 218 prefecture-level cities	Two-way fixed effect, instrumental variable, and spatial econometric model	Carbon emissions depend on the interaction between green innovation on the structure of industrial and energy sectors, FDI, and urbanization
Yang et al. (2022)	1997 to 2020	28 Chinese provinces/Traditional panel approach	Spatial Dobbin model	rogress in agricultural technology increases China's agricultural total factor productivity

Table 1 (continued)

Author	Samples	Sample countries/Approach	Empirical methods	Summary of findings
Zhao et al. (2022)	1999 to 2017	30 Chinese provinces/Traditional panel approach	Spatial econometric methods	Energy consumption spurs environmental degradation while financial depth and financial efficiency, respectively, exert negative and positive effect

IV regression: Instrumental variable regression, Nonlinear ARDL: Nonlinear autoregressive lagged distribution model, FE models: Fixed effect models, CS-ARDL: Cross-sectional augmented ARDL, GMM: Generalized Method of Moment

the global push for environmental protection and the formulation of targeted environmental policies from the Chinese economic perspective.

Data and empirical analysis

This study examines the factors affecting carbon emissions for five of the most populous provinces (Guangdong, Henan, Hunan, Shandong, and Sichuan) and 85 cities for the period 2007–2019 using a multidimensional panel model (Baltagi et al. 2001). Meanwhile, the examined model follows the conceptual understanding relating to the drivers of ecological indicator (Holdren & Ehrlich 1974; York, 2003). The multidimensional panel data model consists of a time dimension and two individual dimensions (province and city). Thus, we present a three-dimensional panel data model in which cities.

are nested within provinces as follows:

Model 1:

$$CO2_{\mathrm{ijt}} = \alpha_0 + \alpha_1 \mathrm{gti}_{\mathrm{ijt}} + \alpha_2 \mathrm{ais}_{\mathrm{ijt}} + \alpha_3 \mathrm{gdp}_{\mathrm{ijt}} + \alpha_4 \mathrm{fd}_{\mathrm{ijt}} + \alpha_5 \mathrm{il}_{\mathrm{ijt}} + \mu_i + \eta_j + \lambda_t + u_{\mathrm{ijt}} \tag{1}$$

Model 2:

$$\mathrm{CO2}_{\mathrm{ijt}} = \beta_0 + \beta_1 (\mathrm{gti} * \mathrm{ais})_{\mathrm{ijt}} + \beta_2 \mathrm{gdp}_{\mathrm{ijt}} + \beta_3 \mathrm{fd}_{\mathrm{ijt}} + \beta_4 \mathrm{il}_{\mathrm{ijt}} + \mu_i + \eta_j + \lambda_t + e_{\mathrm{ijt}} \tag{2}$$

Model 3:

$$\mathrm{CO2}_{\mathrm{ijt}} = £_0 + £_1 \mathrm{gti}_{\mathrm{ijt}} + £_2 \mathrm{isr}_{\mathrm{ijt}} + £_3 \mathrm{gdp}_{\mathrm{ijt}} + £_4 \mathrm{fd}_{\mathrm{ijt}} + +£_5 \mathrm{il}_{\mathrm{ijt}} + \mu_i + \eta_j + \lambda_t + \varepsilon_{\mathrm{ijt}} \tag{3}$$

Model 4:

$$\mathrm{CO2}_{\mathrm{ijt}} = \varphi_0 + \varphi_1 (\mathrm{gti} * \mathrm{isr})_{ijt} + \varphi_2 \mathrm{gdp}_{\mathrm{ijt}} + \varphi_3 \mathrm{fd}_{\mathrm{ijt}} + \varphi_4 \mathrm{il}_{\mathrm{ijt}} + \mu_i + \eta_j + \lambda_t + \xi_{\mathrm{ijt}} \tag{4}$$

where i is city dimension ($i = 1, \ldots,$ N (85)) and j is province dimension ($j = 1, \ldots,$ M (5)) while t is time dimension ($t = 1, \ldots,$t (2007–2019). Additionally, μ_i denotes the city effect, while η_j refers to province effect Additionally, λ_t indicates time effect, while u_{ijt}, e_{ijt}, ε_{ijt}, ξ_{ijt} state the error term with three dimensions. The CO2 is the CO_2 emission level (measured by coefficient method constructed by the IPCC), while *GTI* is the green technology innovation (calculated as the number of green patents granted, including the number

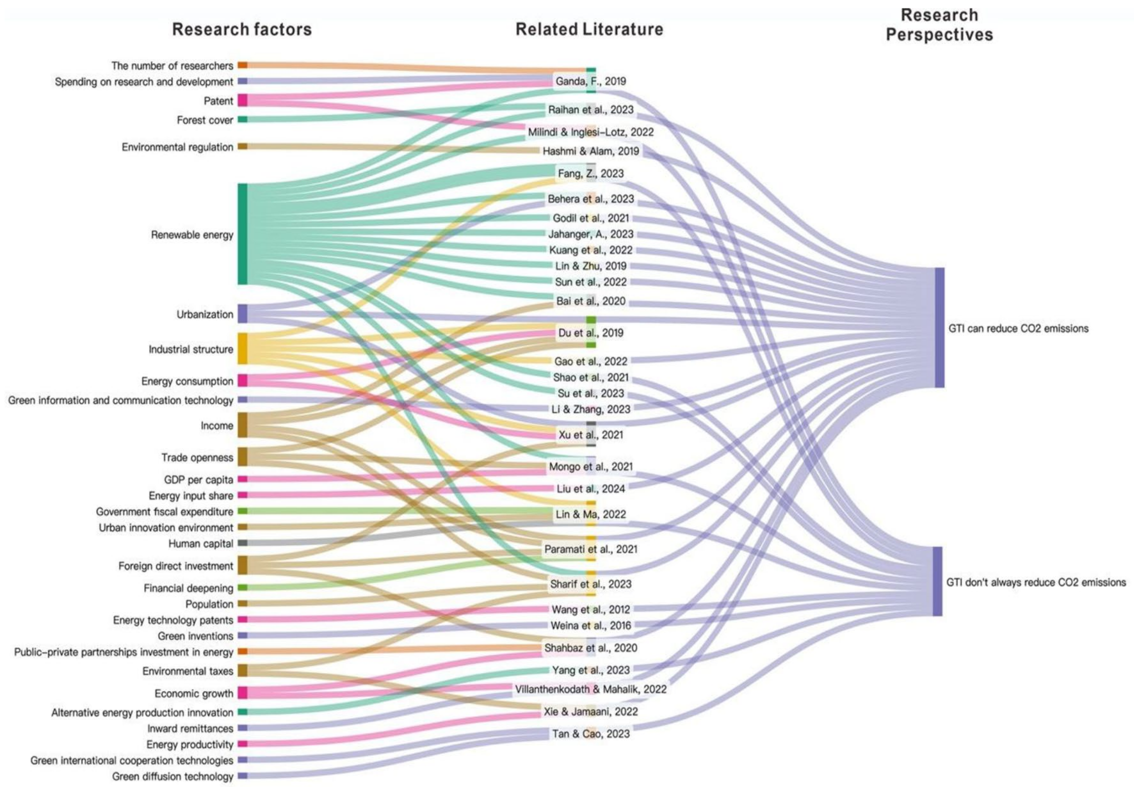


Fig. 1 GTI and CO_2 emissions

Table 2 Summary statistics of the data and correlation analysis results

Panel A. Summary statistics of the data

Variable	Obs	Mean	Std. Dev	Min	Max
lnCO2	1105	8.01	0.27	7.40	8.69
lnGTI	1105	4.92	1.61	0.00	10.18
lnAIS	1105	1.86	0.05	1.73	2.01
lnISR	1105	− 1.27	0.81	− 5.85	0.21
lnGDP	1105	10.46	0.68	4.60	13.06
lnIL	1105	− 0.72	0.21	− 1.91	− 0.27
lnFD	1105	0.56	0.35	− 0.27	1.64
ln(GTI*AIS)	1.105	6.78	1.65	1.73	12.16
ln(GTI*ISR)	1.105	3.65	1.38	− 0.97	7.25

Panel B: Correlation analysis

	lnco	lngti	lnais	lnisr	lngdp	lnil	lngxa
lnCO2	1						
lnGTI	0.47***	1					
lnAIS	0.59***	0.79***	1				
lnISR	− 0.30***	− 0.51***	− 0.68***	1			
lnGDP	0.49***	0.82***	0.78***	− 0.59***	1		
lnIL	− 0.33***	− 0.04	− 0.17***	− 0.13***	0.13***	1	
ln(GTI*AIS)	0.47***	0.99***	0.80***	− 0.52***	0.83***	− 0.05***	1
ln(GTI*ISR)	0.36***	0.86***	0.51***	− 0.01	0.61***	− 0.13***	0.85***
lnFD	0.25***	0.59***	0.57***	− 0.31***	0.42***	− 0.33***	0.60***

***$p < 0.01$; **$p < 0.05$; *$p < 0.10$, respectively of green invention-based patents granted and the number of green utility-based patents granted). Moreover, *AIS* means advanced industrial structure, while *GDP* denotes Per capita gross domestic product (measured as constant in 2005 US dollars). Following that *IL* displays the industrialization level (measured as industrial value added/total output value), while *ISR* means industrial structure rationalization, and *FD* states the level of financial development. *(GTI*AIS)* stands for the interaction between green technology innovation and advanced industrial structure, while *(GTI*ISR)* stands for the interaction between green technology innovation and industrial structure rationalization.

A detailed information for the data is in Appendix 1. Here, the summary statistics of the data and the results of the correlation analysis are computed (see Table 2). Accordingly, a multidimensional panel analysis was carried out with 1105 observations with the highest deviation from mean observed in GTI followed by ISR, and GDP. After checking the raw data, it was decided taking the natural logarithm of the variables will be useful to specificqally reduce the variances of the data and to calculate the elasticity values. Additionally, correlation analysis results in the lower part of Table 1 reveal that there is a positive relationship between CO_2 and GTI, AIS, GDP, GXA, GxI, and FD, whereas there is a negative relationship between CO_2 and ISR and IL.

Empirical analysis

Subsequently, two indivual effects and one time effect were estimated by performing within-group transformations under the assumption that they were correlated with the independent variables. As a result of the within-group transformation, the effects were removed from the model. Additionally, in line with the test results, within-group transformation was made in accordance with the two-dimensional model. The transformed models were then tested using the method of pooled least squares. In this way, a three-dimensional within-group estimator with fixed effects is obtained as follows (Baltagi et al. 2001; Tatoğlu 2016; Tatoğlu & İçel, 2019):

$$\hat{\beta}_{\mathrm{WE}} = \mathrm{WE}_{X'X}^{-1}\mathrm{WE}_{X'Y} \tag{5}$$

Another test is the Hausman test. This test is used to determine whether the effects mentioned are correlated with independent variables. The null hypothesis of Hausman test is as follows (Baltagi, 2001; Tatoglu, 2020):

$$H_0 = E(\mu_i X_{\mathrm{ijt}}) = E(\eta_j X_{\mathrm{ijt}}) = E(\lambda_t X_{\mathrm{ijt}}) = 0 \tag{6}$$

In Eq. (6), X_{ijt} states the independent variables. The null hypothesis of the Hausmann test implies that the random effects model is appropriate, while the alternative hypothesis implies that the fixed effects model is appropriate (Tatoğlu 2016). We first tested the existence of the effects (the city, province, and time) for the four models using thelikelihoodratio (LR) test. The hypotheses tested for the LR test and the test results are shown in Table 3. In the next part of the analysis, the test results were compared with the system GMM approach.

The null hypothesis of the LR test proves that the classical model, in which there is no effect, is valid. It can be seen that the null hypothesis is rejected for four models. Therefore, it has been established that the classical model is not valid. In this context, the results of the LR tests reported in Table 3 indicate the existence of three effects in Model 1, namely the city, the province, and the time effect. In addition, there are two effects in Model 2, namely the city effect and the province effect. Model 3 is a three-dimensional model with province, city, and time effects. Finally, Model 4 is a two-dimensional model with city and province effects. Besides, the Hausman test results reported in Table 3 imply that the fixed effects model is suitable for the estimation process. Therefore, the fixed effects (within) with Driscoll–Kraay standard errors were performed for the entire panel and

Table 3 Results of LR test

Null hypothesis	Model 1 LR test statistic	Model 2 LR test statistic	Model 3 LR test statistic	Model 4 LR test statistic
$H_0 : \sigma_\mu = \sigma_\eta = \sigma_\lambda = 0$	2158.37*** (0.000)	2236.04*** (0.000)	2229.10*** (0.000)	2242.21*** (0.000)
$H_0 : \sigma_\mu = \sigma_\eta = 0$	1895.68*** (0.000)	1975.55*** (0.000)	1985.07*** (0.000)	1995.89*** (0.000)
$H_0 : \sigma_\mu = \sigma_\lambda = 0$	1908.91*** (0.000)	1989.21*** (0.000)	1982.92*** (0.000)	1995.90*** (0.000)
$H_0 : \sigma_\eta = \sigma_\lambda = 0$	1975.34*** (0.000)	2046.94*** (0.000)	2049.44*** (0.000)	2051.16*** (0.000)
$H_0 : \sigma_\mu = 0$	1808.09*** (0.000)	1887.91*** (0.000)	1884.35*** (0.000)	1885.18*** (0.000)
$H_0 : \sigma_\eta = 0$	1415.09*** (0.000)	1467.64*** (0.000)	1596.15*** (0.000)	1556.69*** (0.000)
$H_0 : \sigma_\lambda = 0$	14.72*** (0.000)	1.00 (0.1585)	4.85** (0.013)	0.59 (0.220)
Hausman test	22.07*** (0.000)	18.82*** (0.000)	21.92*** (0.000)	16.51 *** (0.002)

$^{***}p < 0.01$

Table 4 Fixed effects (within) estimation results for four models

Variables	Model 1	Model 2	Model 3	Model 4
GTI_{ijt}	0.053***	–	0.103***	–
$(GTI * AIS)_{ijt}$	–	0.019*	–	–
$(GTI * ISR)_{ijt}$	–	–	–	−0.069***
AIS_{ijt}	4.955***	–	–	–
GDP_{ijt}	0.107***	0.312***	0.277***	0.453***
FD_{ijt}	0.050**	−0.145***	0.092***	−0.089***
IL_{ijt}	−0.711**	−0.832***	−1.116***	−0.920***
ISR_{ijt}	–	–	−0.113***	–
F test statistic	645.11***	390.82***	488.85***	437.40***
R^2	0.74	0.58	0.68	0.61
Adj.R^2	0.74	0.58	0.68	0.61
No of observations	1105	1105	1105	1105

***$p<0.01$; **$p<0.05$; *$p<0.10$, respectively

for each of the five provincial cases (Guangdong, Henan, Hunan, Shandong, and Sichuan).

Results and discussion

Table 4 presents the fixed effects estimation results of the entire panel of provinces for the four models. Accordingly, the F test statistic values for the four established models prove that the models are statistically significant and can be interpreted. The parameter results of Model 1 demonstrate that a 1% increase in GTI rises CO_2 by 0.053%, while a 1% increase in AIS rises CO_2 by 4.95%. Besides, a 1% increase in GDP rises CO_2 by 0.107%, while a 1% increase in FD rises CO_2 by 0.05%. Additionally, a 1% increase in IL reduces CO_2 by 0.71%. Again, the R-squared (R^2) result illustrates that the independent variables can explain 0.74 of the changes in the dependent variable. The results of Model 2 indicate that a 1% increase in (GTI*AIS) leads to a 0.019% rise in CO_2, while a 1% increase in GDP leads to a 0.312% rise in CO_2. However, a 1% increase in FD reduces CO_2 by 0.145%, while a 1% increase in IL decreases CO_2 by 0.83%. For the third model, the result of the R-squared indicates that the independent variables can explain the dependent variable by 0.58. This results show that a 1% increase in GTI increases CO_2 by 0.103%, while a 1% increase in GDP lead to rise in CO_2 by 0.277%. A 1% increase in FD increases CO_2 by 0.09%, while a 1% increase in IL decreases CO_2 by 1.116%. Meanwhile, a 1% increase in ISR reduces CO_2 by 0.113%. Lastly, for the entire panel scenario, the R-squared result reveals that the independent variables can explain the dependent variable at a rate of 0.68. The results of Model 4 illustrate that a 1% increase in (GTI*ISR) leads to a 0.069% decrease in CO_2, while a 1% increase in GDP leads to a 0.453% rise in CO_2. Following that a 1% increase in FD and IL, respectively, reduces CO_2 by 0.089% and 0.920%. The R-squared test result demonstrates that the independent variables can explain the dependent variable by 0.61.

Provincial results

Table 5 presents fixed effects results for Guangdong province for two-dimension model. Here, it is presented that the F test statistic values for the four established models are statistically significant. Accordingly, Model 1 indicates that a 1% increase in GTIrises CO_2 by 0.048% and a 1%

Table 5 Guangdong province for two-dimension model

Variables	Model 1	Model 2	Model 3	Model 4
GTI_{it}	0.048***	–	0.050**	–
$(GTI * AIS)_{it}$	–	0.050***	–	–
$(GTI * ISR)_{it}$	–	–	–	0.029***
AIS_{it}	0.440	–	–	–
GDP_{it}	0.118**	0.124**	0.125***	0.152***
FD_{it}	0.114**	0.118**	0.117**	0.146
IL_{it}	-0.009	-0.038	-0.041	-0.074
ISR_{it}	–	–	0.002	–
F test statistic	1338.09***	390.82***	393.84***	235.93***
Within R-squared	0.78	0.78	0.78	0.76
No of observations	273	273	273	273
Hausman test	50.80*** (0.000)	54.45*** (0.000)	56.21*** (0.000)	36.35*** (0.000)

***$p<0.01$; **$p<0.05$; *$p<0.10$, respectively. Additionally, Guangdong province has 21 cities (Guangzhou, Shaoguan, Shenzhen, Zhuhai, Shantou, Foshan, Jiangmen, Zhanjiang, Maoming, Zhaoqing, Huizhou, Meizhou, Shanwei, Heyuan, Yangjiang, Qingyuan, Dongguan, Zhongshan, Chaozhou, Jieyang, Yunfu) increase in GDP rises CO_2 by 0.118%. Also, a 1% increase in FD increases CO_2 by 0.114%. Finally, these explanatory variables can explain the statistical properties of CO_2 by 78% (i.e., R-squared value). The results of Model 2 show that a 1% increase in (GTI*AIS) leads to a 0.05% rise in CO_2. Similarly, a 1% increase in GDP and FD, respectively, leads to a 0.124% and 0.118% rise in CO_2. The results of the R-squared indicate that the independent variables can explain the dependent variable by 0.78. Furthermore, the results of Model 3 indicate that a 1% increase in GTI, GDP, and FD, respectively, increases CO_2 by 0.050%, 0.117%, and 0.117%. In this case, R-squared results also reveal that the independent variables can explain the dependent variable by 0.78. Lastly, Model 4 results illustrate that a 1% increase in (GTI*ISR) leads to a 0.029% rise in CO_2. Additionally, CO2 is also triggered by 0.152% when there is a 1% increase in GDP. Following that the R^2 result demonstrates that the independent variables can explain the dependent variable by 0.76.

Table 5 presents fixed effects (with Driscoll–Kraay standard errors) results for Henan province for two-dimension models. By implication, the F test statistic (362.58) shows that our established models are statistically significant. According to the results of the parameter in Model 1, a 1% increase in GDP rises CO_2 by 0.185%, while a 1% increase in FD rises CO_2 by 0.262%. Also, the R-squared results illustrate that the independent variables (especially GDP and FD) can explain 0.67 of the changes in the dependent variable. The results of Model 2 indicate that a 1% increase in GDP and FD leads to a rise

Table 6 Henan province for two-dimension model

Variables	Model 1	Model 2	Model 3	Model 4
GTI_{it}	0.066	–	0.006	–
$(GTI * AIS)_{it}$	–	0.006	–	–
$(GTI * ISR)_{it}$	–	–	–	0.019*
AIS_{it}	−0.009	–	–	–
GDP_{it}	0.185***	0.185***	0.187***	0.163***
FD_{it}	0.262***	0.262**	0.255***	0.250***
IL_{it}	−0.009	−0.007	−0.032	−0.005
ISR_{it}	–	–	0.046*	–
F test statistic	362.58***	392.61***	393.84***	285.78***
Within R-squared	0.67	0.67	0.68	0.67
No of observations	221	221	221	221
Hausman test	56.96*** (0.000)	65.15*** (0.000)	30.13*** (0.000)	59.81*** (0.000)

***$p<0.01$; **$p<0.05$; *$p<0.10$, respectively. Additionally, Henan province has 17 cities (Zhengzhou, Kaifeng, Luoyang, Pingdingshan, Anyang, Hebi, Xinxiang, Jiaozuo, Puyang, Xuchang, Luohe, Sanmenxia, Nanyang, Shangqiu, Xinyang, Zhoukou, Zhumadian)

Table 7 Hunan province for two-dimension model

Variables	Model 1	Model 2	Model 3	Model 4
GTI_{it}	0.004	–	-0.008	–
$(GTI * AIS)_{it}$	–	−0.007	–	–
$(GTI * ISR)_{it}$	–	–	–	-0.006
AIS_{it}	−0.023	–	–	–
GDP_{it}	0.238***	0.234***	0.235***	0.233***
FD_{it}	0.189***	0.175***	0.170**	0.168***
IL_{it}	−0.023	−0.011	−0.032	−0.010
ISR_{it}	–	–	−0.005	–
F test statistic	351.71***	546.10***	472.27***	605.63***
Within R-squared	0.83	0.83	0.83	0.83
No of observations	169	169	169	169
Hausman test	104.70*** (0.000)	108.19*** (0.000)	103.51*** (0.000)	104.09*** (0.000)

***$p<0.01$; **$p<0.05$; *$p<0.10$, respectively. Additionally, Hunan province has 13 cities (Changsha, Zhuzhou, Xiangtan, Hengyang, Shaoyang, Yueyang, Changde, Zhangjiajie, Yiyang, Chenzhou, Yongzhou, Huaihua, Loudi) in CO_2 by 0.185% and 0.262% repectively. The results of the R-squared indicate that the independent variables can explain the dependent variable by 0.67. Additionally, the results of Model 3 demonstrate that a 1% increase in GDP leads to rise in CO_2 by 0.187%, while a 1% increase in FD leads to a rise in CO_2 by 0.255%. R-squared test results reveal that the independent variables can explain the dependent variable by 0.68. Finally, Model 4 results illustrate that a 1% increase in (GTI*ISR) leads to rise in CO_2 by 0.019%. Additionally, there are 0.163% and 0.250% increase in CO_2 in response to a respective 1% increase in GDP and FD. Also, the R^2 result demonstrates that the independent variables can explain the dependent variable by 0.67. The other explanatory variables lack statistically significant effect on CO_2 in Henan province (Table 6).

The fixed effect results of two-dimension models for Hunan province are presented in Table 7. The test results in Model 1 reveal that a 1% increase in GDP rises in CO_2 by 0.238%, while a 1% increase in FD rises in CO_2 by 0.189%. However, the R-squared test results illustrate that the independent variables can explain 0.83 of the changes in the dependent variable. Additionally, Model 2 represents that a 1% increase in GDP leads to rise in CO_2 by 0.234%, whereas a 1% increase in FD rises in CO_2 by 0.175%. The results of the *R*-squared indicate that the independent variables can explain the dependent variable by 0.83. Additionally, the results of Model 3 demonstrate that a 1% increase in GDP and FD, respectively, leads to rise in CO_2 by 0.235% and 0.170%. R-squared test results reveal that the independent variables can explain the dependent variable by 0.83. Lastly, Model 4 results indicate that a 1% increase in GDP leads to rise in CO_2 by 0.233%, while a 1% increase leads toFDrise in CO_2 by 0.168%. Also, the R^2 result demonstrates that the independent variables can explain the dependent variable by 0.83.

In Table 8, the fixed effect for Shandong province is presented. The test results in Model 1 reveal that a 1% increase in GDP and FD increases the CO_2 by 0.162% and 0.178%, respectively. Also, a 1% increase in IL decreases the CO_2 by 0.386%. However, the R-squared test results illustrate that the independent variables can explain 0.84 of the changes in the dependent variable. Also, Model 2 indicates that a 1% increase in GDP leads to rise in CO_2 by 0.161% and a 1% increase in FD increases the CO_2 by 0.178%. And, a 1% increase in IL decreases CO_2 by 0.385%. The R-squared test result indicates that the independent variables can explain the dependent variable by 0.84. Additionally, Model 3 shows that a 1% increase in GDP leads to rise in CO_2 by 0.163% and a 1% increase in FD increases CO_2 by 0.173%. Meanwhile, a 1% increase in ISR leads to rise in CO_2 by 0.038%, whereas a 1% increase in IL decreases CO_2 by 0.301%. The R-squared test results reveal that the independent variables can explain the dependent variable by 0.85. Finally, Model 4 indicates that a 1% increase in (GTI*ISR) leads to rise in CO_2 by 0.024%. In addition, a 1% increase in GDP and FD leads to rise in CO_2 by 0.143% and 0.163%, respectively. In contrary, a 1% increase in IL leads to decrease CO_2 by 0.301. The R^2 result demonstrates that the independent variables can explain the dependent variable by 0.85.

In Table 9, the fixed effects results for Sichuan province are presented. The test results in Model 1 reveal that a 1% increase in GTI leads to rise in CO_2 by 0.043%. Similarly, a 1% increase in GDP and FD causes a surge in CO_2 by 0.052% and 0.129%, respectively. For this model, the R-squared illustrates that the independent variables can explain 0.84 of the changes in the dependent variable. Also, Model 2 indicates that a 1% increase in (GTI*AIS) leads to

Table 8 Shandong province for two-dimension model

Variables	Model 1	Model 2	Model 3	Model 4
GTI_{it}	0.010	–	0.013	–
$(GTI * AIS)_{it}$	–	0.010	–	–
$(GTI * ISR)_{it}$	–	–	–	0.024**
AIS_{it}	−0.026	–	–	–
GDP_{it}	0.162***	0.161***	0.163***	0.143***
FD_{it}	0.178***	0.178***	0.173***	0.163***
IL_{it}	−0.386***	−0.385***	−0.309***	−0.301**
ISR_{it}	–	–	0.038**	–
F test statistic	501.77***	366.99***	395.48***	437.89***
Within R-squared	0.84	0.84	0.85	0.85
No of observations	208	208	208	208
Hausman test	131.73*** (0.000)	142.99*** (0.000)	124.06*** (0.000)	133.19*** (0.000)

***$p<0.01$; **$p<0.05$; *$p<0.10$, respectively. Additionally, Shandong province has 16 cities (Jinan, Qingdao, Zibo, Zaozhuang, Dongying, Yantai, Weifang, Jining, Tai'an, Weihai, Rizhao, Linyi, Dezhou, liaocheng, Binzhou, Heze)

Table 9 Sichuan province for two-dimension model

Variables	Model 1	Model 2	Model 3	Model 4
GTI_{it}	0.043**	–	0.049***	–
$(GTI * AIS)_{it}$	–	0.050***	–	–
$(GTI * ISR)_{it}$	–	–	–	0.041**
AIS_{it}	0.062	–	–	–
GDP_{it}	0.052**	0.059***	0.060***	0.072***
FD_{it}	0.129***	0.164***	0.169***	0.195***
IL_{it}	−0.041	−0.069***	−0.073***	−0.074***
ISR_{it}	–	–	−0.011	–
F test statistic	203.79***	143.03***	318.63***	115.36***
Within R-squared	0.61	0.61	0.61	0.85
No of observations	234	234	234	234
Hausman test	88.58*** (0.000)	143.03*** (0.000)	75.58*** (0.000)	81.84*** (0.000)

***$p<0.01$; **$p<0.05$; *$p<0.10$, respectively. Additionally, Sichuan province has 18 cities (Chengdu, Zigong, Panzhihua, Luzhou, Deyang, Mianyang, Guangyuan, Suining, Neijiang, Leshan, Nanchong, Meishan, Yibin, Guang'an, Dazhou, Ya'an, Bazhong, Ziyang)

Table 10 Results of two-step system GMM estimation for Guangdong province

Variables	Model 1	Model 2	Model 3	Model 4
$CO2_{i(t-1)}$	−0.38***	−0.36***	−0.38***	−0.41***
GTI_{it}	0.02	–	0.03**	–
$(GTI * AIS)_{it}$	–	0.03**	–	–
$(GTI * ISR)_{it}$	–	–	–	0.01
AIS_{it}	0.38**	–	–	–
GDP_{it}	0.07***	0.06**	0.06**	0.11***
FD_{it}	0.00	−0.01	−0.01	0.02
IL_{it}	−0.35***	−0.32***	−0.31***	−0.32***
ISR_{it}	–	–	0.00	–
Constant	9.50***	10.14***	10.41***	10.13***
Arellano–Bond test for AR(1)	0.00	0.01	0.00	0.02
Arellano–Bond test for AR(2)	0.18	0.31	0.28	0.40
Sargan	0.80	0.35	0.10	0.03
Hansen	0.59	0.15	0.14	0.02
Difference-in-Hansen tests				
Hansen test excluding group:	0.40	0.10	0.05	0.00
Difference (null H = exogenous)	0.55	0.29	0.70	0.66

***$p<0.01$; **$p<0.05$; *$p<0.10$, respectively. In addition, Windmeijer (2005) correction is employed for two-step system GMM estimation. The numbers reported for the results of the Arellano–Bond test for AR, the Sargan–Hansen test and the GMM instruments for level tests are probability values. These values are assessed at the 1% significance level. Accordingly, the two-step system GMM is statistically suitable for interpreting the estimation results

rise in CO_2 by 0.050%, while a 1% increase in GDP and FD leads to rise in CO_2 by 0.059% and 0.164%, respectively. Contrarily, a 1% increase in IL leads to decrease in CO_2 by 0.164% and the R-squared test result is 61%. Following that Model 3 demonstrates that a 1% increase in GTI, GDP, and FD leads to rise in CO_2 by 0.049%, 0.060%, and 0.169%, respectively. Contrarily, a 1% increase in IL leads to decrease in CO_2 by 0.073%. The R-squared test result proves that the independent variables can explain the dependent variable by 0.61. Lastly, Model 4 indicates that a 1% increase in

Table 11 Results of two-step system GMM estimation for Henan province

Variables	Model 1	Model 2	Model 3	Model 4
$CO2_{i(t-1)}$	0.40***	0.43***	0.41***	0.45***
GTI_{it}	−0.02	–	−0.02	–
$(GTI * AIS)_{it}$	–	−0.02**	–	–
$(GTI * ISR)_{it}$	–	–	–	-0.01
AIS_{it}	−0.42	–	–	–
GDP_{it}	0.13**	0.10***	0.13***	0.08***
FD_{it}	0.14**	0.12**	0.12**	0.09***
IL_{it}	−0.07	−0.09	−0.02	−0.08
ISR_{it}	–	–	0.06***	–
Constant	4.11***	3.42***	3.25***	3.41***
Arellano–Bond test for AR(1)	0.00	0.00	0.00	0.00
Arellano–Bond test for AR(2)	0.20	0.26	0.22	0.46
Sargan	0.00	0.00	0.02	0.00
Hansen	0.05	0.06	0.07	0.03
Difference-in-Hansen tests				
Hansen test excluding group:	0.03	0.03	0.02	0.03
Difference (null H = exogenous)	0.22	0.27	0.72	0.19

***$p<0.01$; **$p<0.05$; *$p<0.10$, respectively. In addition, Windmeijer (2005) correction is employed for two-step system GMM estimation. The numbers reported for the results of the Arellano–Bond test for AR, the Sargan–Hansen test and the GMM instruments for level tests are probability values. These values are assessed at the 1% significance level. Accordingly, the two-step system GMM is statistically suitable for interpreting the estimation results

Table 12 Results oftwo-step system GMM estimation forhunan province

Variables	Model 1	Model 2	Model 3	Model 4
$CO2_{i(t-1)}$	0.32**	0.30**	0.31**	0.29**
GTI_{it}	0.00	–	0.008	–
$(GTI * AIS)_{it}$	–	0.008	–	–
$(GTI * ISR)_{it}$	–	–	–	0.006
AIS_{it}	−0.59	–	–	–
GDP_{it}	0.13***	0.06**	0.07***	0.07**
FD_{it}	0.17***	0.14**	0.14**	0.14**
IL_{it}	−0.05	−0.003	−0.006	−0.006
ISR_{it}	–	–	0.005	–
Constant	5.29***	4.90***	4.89***	4.95***
Arellano–Bond test for AR(1)	0.00	0.00	0.00	0.00
Arellano–Bond test for AR(2)	0.96	0.85	0.96	0.98
Sargan	0.00	0.00	0.00	0.00
Hansen	0.01	0.01	0.01	0.01
Difference-in-Hansen tests				
Hansen test excluding group:	0.19	0.33	0.19	0.61
Difference (null H = exogenous)	0.00	0.00	0.00	0.00

***$p<0.01$; **$p<0.05$; *$p<0.10$, respectively. In addition, Windmeijer (2005) correction is employed for two-step system GMM estimation. The numbers reported for the results of the Arellano–Bond test for AR, the Sargan–Hansen test and the GMM instruments for level tests are probability values. These values are assessed at the 1% significance level. Accordingly, the two-step system GMM is statistically suitable for interpreting the estimation results

(GTI*ISR) leads to rise in CO_2 by 0.041%. Similarly, a 1% increase in GDP and FD leads to rise in CO_2 by 0.072% and 0.195%, respectively. Furthermore, a 1% increase in IL leads to decrease in CO_2 by 0.074, and the model has a maximum value of R^2 as 0.85.

Provincial results: endogeneity robustness

The next part of the analysis uses the system GMM estimator, which is specifically designed to address issues of endogeneity. The specification test results reported in the tables below therefore demonstrate that the parameters can be interpreted (Table 10, Table 11, Table 12, Table 13, and Table 14). Therefore, the findings are consistent with those obtained from the multidimensional tests. One distinctive finding is that industrialization in Guangdongprovince leads to a decrease in environmental degradation (see the consistency in the correspondingtables, i.e., Table 5 and Table 10). Another important and interesting result, which differs from the other estimation results, reveals that integrating green technology innovation and an advanced industrial structure contributes to reducing environmental degradation for Henan province (see the comparison between Table 6 and Table 11). In general, the outcome of the estimationsis largely reliable.

Overview of result

As depicted in the entire panel result (see Table 5), green technology innovation happens to cause a surge in carbon emission in the examined pronvinces and for all examined models. Although this result is unexpected given that development of green technological aspects should promote environmental sustainability, there are possible justifications for this outcome. Specifically, the overall development of green technology through innovative activities might yet be below a desirable threshold and not as much to yield environmental benefit. Given that innovative activities in green technologies are not likely to exhibit proportionate growth in terms of types of technology and industry, hence the overal effect might underscore the specific performance

Table 13 Results oftwo-step system GMM estimation for Shandong province

Variables	Model 1	Model 2	Model 3	Model 4
$CO2_{i(t-1)}$	0.52***	0.56	0.48***	0.54***
GTI_{it}	0.01	–	0.01	–
$(GTI * AIS)_{it}$	–	0.00	–	–
$(GTI * ISR)_{it}$	–	–	–	0.02***
AIS_{it}	-0.69	–	–	–
GDP_{it}	0.06	0.03	0.05**	0.03**
FD_{it}	0.05	0.05	0.06	0.05
IL_{it}	−0.23	−0.16	−0.05	−0.05
ISR_{it}	–	–	0.04***	–
Constant	4.38**	3.06***	3.64***	3.29***
Arellano–Bond test for AR(1)	0.00	0.00	0.00	0.00
Arellano–Bond test for AR(2)	0.15	0.13	0.27	0.20
Sargan	0.00	0.00	0.00	0.00
Hansen	0.02	0.03	0.03	0.03
Difference-in-Hansen tests				
Hansen test excluding group:	0.05	0.18	0.03	0.14
Difference (null H = exogenous)	0.05	0.02	0.08	0.03

$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.10$, respectively. In addition, Windmeijer (2005) correction is employed for two-step system GMM estimation. The numbers reported for the results of the Arellano–Bond test for AR, the Sargan–Hansen test and the GMM instruments for level tests are probability values. These values are assessed at the 1% significance level. Accordingly, the two-step system GMM is statistically suitable for interpreting the estimation results

of technology- and industry-specific performance. As such, the expected environmental quality desirability of GTI could subject to the industry-specific performance of related innovative activities. This clearly explains role of ISL and AIS in moderating the nexus between GTI and CO_2. While GTI and AIS independently spur carbon emission, ISL shows a mitigating effect on carbon emission. As such, the joint impact of GTI and ISL mitigates carbon emission vis-a-vis a 1% increase in their interaction mitigates carbon emission by 0.069%. In the literature, such as Wang et al. (2019), rationalization of industrial structure through resource dependency is unsuitable for carbon emission mitigation. Meanwhile, according to Jiang and Sun (2023), industrial stucture exhibits no statistically significant impact on carbon emission across the provinces in China.

Additionally, alongside advanced industrial structure, GDP and FD all lead to increase in carbon emission in the overall panel. While the impact of AIS shows severity, this results indicate that economic performance in terms of growth and the development of financial aspects are yet to promote environment sustainability across these provinces. This undesirable outcome is expected considering that economic activities and the instruments that contribute to financial development are yet to be decarbonized. As such, this result validates Xu et al. (2016) where economic growth is found to increase multi-regional level carbon emission in China. Of course, yet for the case of China, several results in the literature are partially in line with the current finding (Du et al. 2012; Wu et al. 2019). On the aspect of financial development, Zhao et al. (2021) found that financial efficiency worsens environmental pollution while financial depth acts contrarily to favor environmental quality. Meanwhile, another opinion suggests that financial development worsens carbon emission in China (Xiong & Qi 2018; Zhao & Yang 2020). Contrarily, according to the outcome of this investigation from both the correlation and regression outputs, the level of industrialization is offering an environmental benefit across the Chinese provinces. Although this outcome could be a subject of debate, the desirable outocme can be associated with the country's improvement in technological innovation and efficiency, modernization and economies of scale, and sector-wide adoption of environmental standards within the china's green and low-carbon goals.

As per specific provinces, the outcome of the entire panel is not exactly different from the observation of each province. Specifically, in each of these provinces, the positive imapct of GDP and FD on carbon emission is statistically significant. However, in Henan, Hunan, and Shandong provinces, the impact of AIS and GTI shows no significant effect on carbon emission. But in Henan, Guangdong, Sichuan, and Shandong provinces, rationalization of industrial structure further aggravates carbon emission indirectly with GTI. This result might not be unrelated with the complexity of these provinces' population given that they are China's most populated provinces. Meanwhile, the level of industrialization in Shandong province also mitigates carbon emission. Moreover, unlike the panel observation, in Guangdong and Sichuan provinces, GTI worsens carbon emission with and without direct impact of AIS and ISR. Although the outcomes of the province-specific investigation generally align with the panel outcome, some of the observed differences are arguably associated with the province- and region-specific socioeconomic characteristics as mentioned in Zheng et al. (2020).

Conclusion

In this investigation, the drivers of carbon emission were examined (i) across the panel of China's most populous provinces (Guangdong, Henan, Hunan, Shandong, and Sichuan) comprising of 85 cities and (ii) for each of the enlisted provinces over the period 2007–2019. Generally, especially for the panel examination, emission of carbon

Table 14 Results oftwo-step system GMM estimation for Sichuan province

Variables	Model 1	Model 2	Model 3	Model 4
$CO2_{i(t-1)}$	0.01	−0.01	−0.02	−0.01
GTI_{it}	0.00	–	0.01	–
$(GTI * AIS)_{it}$	–	0.01	–	–
$(GTI * ISR)_{it}$	–	–	–	0.01***
AIS_{it}	0.28	–	–	–
GDP_{it}	0.06***	0.07***	0.08**	0.07***
FD_{it}	0.08***	0.11***	0.14***	0.12***
IL_{it}	−0.17**	−0.16***	−0.13***	−0.15**
ISR_{it}	–	–	0.02	–
Constant	6.33***	6.86***	6.89***	6.90***
Arellano–Bond test for AR(1)	0.00	0.00	0.00	0.00
Arellano–Bond test for AR(2)	0.15	0.02	0.02	0.02
Sargan	0.00	0.52	0.49	0.55
Hansen	0.02	0.61	0.50	0.68
Difference-in-Hansen tests				
Hansen test excluding group:	0.05	0.55	0.31	0.42
Difference (null H = exogenous)	0.05	0.42	0.55	0.73

***$p<0.01$; **$p<0.05$; *$p<0.10$, respectively. In addition, Windmeijer (2005) correction is employed for two-step system GMM estimation. The numbers reported for the results of the Arellano–Bond test for AR, the Sargan–Hansen test, and the GMM instruments for level tests are probability values. These values are assessed at the 1% significance level. Accordingly, the two-step system GMM is statistically suitable for interpreting the estimation results

dioxide is specifically made worse by increase in GDP, FD, and AIS. Of course GTI also worsens carbon emission, and by the moderating effect of AIS. However, rationalization of industrial structure plays a significant moderating role, thus providing a environmental benefit. Meanwhile, the level of industrialization offers a desirable relief toward improving environmental quality due to it negative impact of carbon emission. Meanwhile, the province-specific results largely reflect the panel outcome especially for the role of GDP and FD. But, in each province, GTI and AIS have no statistically significant impact on carbon emission. Additionally, only in Shandong and Sichuan, the desirable negative impact of IL on carbon emission replicates the overall panel observation. Also, in these two provinces (Shandong and Sichuan), the indirect effect of GTI through ISR exhibits a desirably negative impact on carbon emission, thus improving environmental quality. Importantly, the indirect impact of GTI through ISR on carbon emission degrades environmental quality in Henan, Guangdong, Sichuan, and Shandong.

Importantly, this study is limited because though the effect of GTI is dependent on the level of industrial structure (a moderation effect), the study does not strictly establish a causal pathway through industrial structure (a mediation mechanism). Additionally, this investigation is limited to a few province-specific analyses and could have covered more scope of potential explanatory indicators. Therefore, it is important that future investi gation explores these possibilities. However, the result of this investigation offers policy rethink toward on the pathway of improving environmental quality of industrial activities. This include scaling up investment in environmental-related technological innovations, and research and development through more private and public initiatives, green entrepreneurial activities, and creating and exploring more climate-related financial mechanisms. Moreover, in terms of social and economic activities, there cannot be a better opportunity to explore material circularity potentials through delibrate approach to refurbishing, reuse, and recycle practices.

Appendix 1

Data description.

Variable name (code)	Description
Carbon emissions (CO_2)	Total carbon emissions = Scope 1 emissions + Scope 2 emissions + Scope 3 emissions Where Scope 1 emissions = emissions from transport and buildings + emissions from industrial processes + emissions from agroforestry and land use change + emissions from waste disposal activities, Scope 2 emissions = emissions from purchased electricity + emissions from heating and cooling, and Scope 3 refers to other indirect emissions arising from activities within the city that are generated outside the jurisdiction but are not included in Scope 2
Green technology innovation (GTI)	The sum of the number of green invention patent applications and green utility model patent applications, application data from the China Research Data Service (CNRDS)
Advanced industrial structure (AIS)	Taking into account the relative weights of each industry, the level of advanced industrial structure of each region in China is measured and calculated as follows: $\mathrm{AS} = \sum_{i=1}^{n} yi \times i = y_1 * 1 + y_2 * 2 + y_3 * 3$ AS indicates the level of advanced industrial structure and yi indicates the share of output value of industry i in GDP. The higher the AS value, the higher the level of advanced industrial structure and vice versa
Industrial structure rationalization (ISR)	Industrial structure rationalization is a measure of the balanced coordination between input and output structures among industries. This paper uses the Thiel index to measure and refine this1 and calculates the formula as follows: $\mathrm{RS} = 1 - \sum_{i=1}^{n} \left(\frac{Y_i}{Y}\right) \ln \left(\frac{Yi}{Li} \Big/ \frac{Y}{L}\right)$ RS denotes the level of industrial structure rationalization, Y denotes total output value, L denotes employment, Yi denotes output value of industry i, Li denotes employment in industry i, and n denotes the number of industrial sectors
Level of financial development (FD)	Financial scale expressed as the ratio of total deposits and loans of banking financial institutions to GDP in each province and city
Per capita gross domestic product (GDP)	Per capita gross domestic product can directly reflect the real level of economic growth, in order to eliminate the influence of the scale, choose to do the logarithm of the per capita GDP
Industrialization level (IL)	Industrial value added / total output value, increased industrialization is likely to increase demand for products and boost the economy

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Data availability No datasets were generated or analyzed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

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