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Research article

The impact of green technology innovation on carbon dioxide emissions: The role of local environmental regulations

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ABSTRACT

Environmental pollution has become a global issue attracting ever-increasing attention. Green technology innovation (GTI) is considered an effective strategy in countering this problem and helping achieve sustainability goals. However, the market failure suggests that intervention from the government is necessary to promote the effectiveness of technological innovation and hence, its positive social impacts on emissions reduction. This study investigates how the environmental regulation (ER) influences the relationship between green innovation and CO_2 emissions reduction in China. Employing data from 30 provinces from the period 2003 to 2019, the Panel Fixed-effect model, the Spatial Durbin Model (SDM), the System Generalised Method of Moments (SYS-GMM) and the Difference-In-Difference (DID) models are applied to take issues relating to endogeneity and spatial impact into consideration. The results indicate that environmental regulations positively moderate the impact of green knowledge innovation (GKI) on CO_2 emissions reduction but have a much weaker moderation effect when green process innovation (GPI) is considered. Among different types of regulatory instruments, investment-based regulation (IER) is the most effective in promoting the relationship between green innovation and emissions reduction, followed by command-and-control-based regulation (CER). Expenditure-based regulation (EER) is less effective and can encourage short-termism and opportunistic behaviour among firms, who can accept the paying of fines as a cheaper cost over the short-term than investment in green innovation. Moreover, the spatial spillover effect of green technological innovation on carbon emissions in neighbouring regions is confirmed, in particular when IER and CER are implemented. Lastly, the heterogeneity issue is further examined by considering differences in the economic development and the industrial structure across different regions, and the conclusions reached remain robust. This study identifies that the market-based regulatory instrument, IER, works best in promoting green innovation and emissions reduction among Chinese firms. It also encourages GKI which may assist firms in achieving long-term sustained growth. The study recommends further development of the green finance system to maximise the positive impact of this policy instrument.

1. Introduction

It has been a global effort to counter climate change and achieve air quality improvements by reducing greenhouse gas emissions. The adoption of the Paris Agreement provides a durable framework guiding the global effort, under which the governments are being pressured to submit their intended Nationally determined contributions (NDCs). Demographic, institutional and economic factors have long been seen as major attributes related to worldwide environmental degradation. As the world's second-largest economic entity holding one-fifth of the world's total population, China is also among the countries affected most severely by environmental degradation. In 2005, China's CO_2 emissions exceeded those of the US for the first time, making it the world's largest CO_2 emitter (Wang et al., 2017a). With the country's continued economic expansion, the cost of such high-pollution growth is increasing at an alarming pace. Therefore, the transition to a low-carbon economic development model is crucial for the country's sustained growth and CO_2 emissions reduction (Balsalobre-Lorente et al., 2018;

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Zhou et al., 2019).

This study is motivated by a growing body of literature on drivers of carbon emissions reduction (Mongo et al., 2021). Green technology innovation (GTI) has been recognised as an important driver of environmental quality improvement via reduced energy intensity, improved production process efficiency, and increased sustainable and environmentally friendly products and services (Cheng et al., 2021). The green process innovation (GPI) and green knowledge innovation (GKI) are commonly adopted by firms in achieving emissions reduction targets over different time horizons (Zhang et al., 2017b; Wang et al., 2021). However, as suggested by the resource-based view, firms would only conduct GTI if it enables them to gain competitive advantages (Hart and Dowell, 2011). This has therefore called for effective and enforceable mechanisms, like government regulations, to direct firms' behaviour. Despite the potential compliance costs incurred by firms, Porter (1991) argues that the flexible environmental regulations can, in fact, promote the environmental benefits of innovation effectively. It helps firms save high discharge fees or additional tax payments in case of noncompliance and assists them to gain government green subsidies (Peng, 2020).

In line with this belief, the Chinese government also initiated a series of environmental policies, including the command-and-control environmental regulation (CER) (e.g. Atmospheric Pollution Prevention and Control Law (2015 Revision)) and the market-based environmental regulation (MER) (e.g. Emission Trading Markets Pilots Policy (2007), Guidelines for Green Credit issued by the China Banking Regulatory Commission (2012), and Guiding Opinions on Further Promoting Compensable Use and Pilot Tests of Emissions Trading (2014)). Meanwhile, the government also increased its environmental pollution treatment investments by over 600 billion yuan over the ten-year period to 2017.[1] As a result, compared with polluters, cleaner firms with successful GTI tend to be more sustainable.

Furthermore, several scholars emphasise the potential impact of foreign direct investment (FDI) on green technology adoption and carbon emissions (Yu et al., 2021). They argue that FDI can enhance green innovation capabilities through knowledge spillover and the transfer of low-emissions technologies (Yu et al., 2021). However, as the primary target for foreign firms is rent seeking but not green development, the expected green benefits are hardly achievable, not to say that firms from developed countries may use this opportunity to transfer their highly polluted operations to bypass regulatory control (Luo et al., 2021; Shahbaz et al., 2018). Additionally, studies also suggest that firms could be pressurised to become greener through educating the society (Chen et al., 2021). With increased public awareness towards environmental protection, firms would be forced to invest more in green innovation to demonstrate their determination (Lee and Lee, 2022). However, such a strategy can be time-consuming, and the result is hard to be predicted. Last but not least, industrialisation is also identified to impact green technologies and CO_2 emissions but the rapid industrialisation in China has always been criticised for its lack of environmental considerations and limited green innovation (Wu et al., 2020; Lin and Ma, 2022). It has therefore been argued that unlike the environmental regulations which impose hard orders on firms' CO_2 emissions targets, the effects of FDI, public education, and industrialisation are largely contingent upon their effective interaction with environmental regulations (Tang et al., 2020). In other words, environmental regulations may create constraints as well as incentives that may shape the path of green technological development (Kleer, 2010). This has therefore made a thorough understanding of the transmission channel among environmental regulations, green innovation and emissions reduction more prominent.

As a result, this study provides empirical evidence for the Porter Hypothesis (PH) based on the sample of the world's biggest developing economy. In particular, the paper aims to investigate how local environmental regulations moderate the relationship between green innovation and CO_2 emissions reduction in China. It is aware that firms react to different types of governmental regulations differently. Consequently, two types of environmental regulations are used, CER, the commend-based environmental regulations (e.g. programmatic guidance on environmental regulatory objectives), and MER, the market-based environmental regulations. The latter can be further categorised into expenditure- (EER) and investment-type environmental regulation (IER) based on their different impacts on firms' R&D capacity (Böhringer et al., 2012). EER may induce costs for firms to meet emissions targets, such as purchasing emissions permits or paying pollution discharge fees while IER may stimulate firms to make long-term investments to build up long-term competence in green innovation (Yuan, 2019; Tian and Feng, 2022). These different types of regulations would work together to shape firms' behaviours.

Therefore, it seems that the transition to a green economy cannot be achieved without innovation and the enforcement/motivation of appropriate policies. To test the above relationship empirically, this study employs a panel data of 30 Chinese provinces from 2003 to 2019 and applied a series of models including the fixed effect regression models, the system Generalised Method of Moments (SYS-GMM), and the difference-in-difference (DID) model. In particular, the following research questions are investigated: firstly, how are the three factors including environmental regulations, green innovation and CO_2 emissions reduction, acting on each other? Or in other word, what is the transmission mechanism among these three factors? Does tougher regulation guarantee additional green investments and whether these additional investments will lead to further CO_2 emissions reductions? Secondly, do different types of environmental regulations and green innovation have different impacts on the transmission mechanism? Thirdly, given different levels of economic development and environmental governance in different regions, are there regional heterogeneities?

The novelty of this paper is reflected in the following three aspects. First, the results provide empirical evidence for the validation of the PH. More specifically, as the concepts of environmental protection, technology innovation, and CO_2 emissions reduction were initiated in Western countries, most discussions about the PH are based on the sample of developed economies. However, developing countries are the biggest contributors to newly generated emissions today. As the world's biggest developing country, China's development model has always been criticised and the country has tried hard to balance its economic growth and the resulting pollution over the past decade. The Chinese government has initiated policies to regulate firms' behaviours, on the one hand, while stimulating the innovation of greener technologies, on the other hand. Then, an interesting question is how the country is performing now after the implementation of all these policy initiates. If China's reform has been indeed successful, these 'best practices' can then be generalised to other emerging economies. This will help improve energy efficiency at the global level and assist more economies to achieve sustainable development.

Secondly, this research investigates how environmental regulations moderate the influence of GTI on CO_2 emissions. While most of the studies focusing on the relationship between environmental regulations and technology innovation or green innovation and emissions reduction, few research has linked all three together to investigate the transmission mechanisms in between. It is proved empirically that the market-based regulatory tools work better and this should be pleased by the government as China is trying hard to transform into a market-based economy. To maximise the benefits of the market, the country should continue relying more on such market-based mechanisms in guiding and enforcing corporate behaviours. Such an experience could also be shared with other developing countries to reduce red tapes and unnecessary resource wastes.

Last but not least, this study provides diverse explanations for the relationship between GTI and carbon emissions and also takes regional heterogeneity into consideration. Both the short-term (GPI) and long-

[1] Data is collected from China Statistical Yearbook 2019).

term (GKI) environmental impacts of GTI are explored respectively to capture firms' different innovation incentives. It is confirmed that different regulatory tools (CER, EER and IER) have different levels of enforcement power in shaping the path of green technological development. Meanwhile, the diversified economic development stage and demographical characteristics of different regions are also confirmed of capable of impacting the tested results. This research has therefore contributed to research on the heterogeneity effect of environmental regulations.

The rest of this study is organised as the following. Section 2 undertakes the literature review and develops the hypotheses. Section 3 describes the variables and methodology. Section 4 discusses the empirical results. Finally, Section 5 presents the conclusions of this study.

2. Literature review and hypothesis development

2.1. Green technological innovation and carbon emissions

In recent decades, a growing body of literature has examined the drivers of carbon emissions reduction. The natural resource-based view suggests that GTI can be a valuable firm resource for establishing the competitive advantage and beneficial for the natural environment (Hart and Dowell, 2011). This is verified by recent studies on the role of green innovation in facilitating the relationship between high-quality economic development and environmental sustainability across different countries and regions (Ganda, 2019; Shao et al., 2021). Ganda (2019) shows that expenditure on R&D negatively affects CO_2 emissions, while the number of patents is positively related to carbon emissions in the OECD countries. Shao et al. (2021) find GTI and renewable energy can help mitigate the consumption base CO_2 emissions in N-11 countries in the long rather than the short run.

However, evidence on the impact of green technological innovation and carbon emissions is mixed and even contradictory. As suggested by Rennings and Rammer (2011), the market itself may not be able to effectively promote GTI. Firms may need sufficient incentives or penalties to increase their willingness to engage in green innovation. This reiterates the important role played by government regulations. Further, Mongo et al. (2021) find that there is an indirect 'rebound effect' of green technological innovation: as the green innovation improves, both the output and energy consumption levels increase.

2.2. Green technological innovation, environmental regulations, and carbon emissions

The seminal works of Porter (1991) and Porter and Van Der Linde (1995) suggest that stringent but properly designed environmental regulations may stimulate green innovation that could offset compliance costs and enhance firms' productivity. This can create a win-win situation that enables the firm to increase profitability and simultaneously achieve emissions reduction targets.[2] The PH provides a new dynamic perspective to understand the impact of environmental regulations on firms' innovation behaviour and its subsequent impacts on emissions reduction. Since then, a number of studies were conducted to test the hypothesis empirically. Specifically, Studies based on neoclassical economics hold that environmental regulations induce higher costs such as pollution charges, and divert valuable capital from promising innovative projects to ones that concentrate on emissions reduction only (Xie et al., 2017; Wei et al., 2022). The "compensation effect" view suggests that under a well-functioning environmental regulation system, the benefits from the environmental efficiency of resource utilisation can exceed the offset effect caused by the internalisation of environmental costs (Luo et al., 2021). Using data on manufacturing sectors of 17 European countries, Rubashkina et al. (2015) find a positive relationship between the environmental regulation and innovation outputs. Others show that such technological progress can improve green competitiveness in the long run and strengthen the innovation performance of enterprises (Wen et al., 2021). Shao et al. (2021) show the importance of implementing environmental regulations, such as carbon pricing or taxation policies, for countries that highly rely on imported non-renewable energy sources for consumption demand.

As aforementioned, GTI may have an indirect and uncertain impact on carbon emissions (Lin and Ma, 2022). Environmental regulations are designed to deal with the negative externalities of environmental degradation, which can justify regulatory intervention and promote the effectiveness of technological innovation. Given the uncertain nature of innovation activities and the substantial capital investments required, it is argued that appropriate regulations are needed to incentivise or force firms to invest continuously in innovation to reduce CO_2 emissions (Xie et al., 2019). Therefore, this study proposes the following hypothesis:

Hypothesis 1a. Environmental regulation positively moderates the impact of GTI on CO_2 emissions reduction.

As for GPI, previous studies suggest that it could be further divided into two categories: GPI and GKI. The former generally focuses on optimising the production process to reduce energy consumption (Song et al., 2020), while the latter refers to the eco-innovation-related knowledge capital endowment, such as the production of green patents (Zhang et al., 2017b; Wang and Zhu, 2020). The two types of green innovations have their respective focus on prompting sustainable development. With limited supplementary inputs, GPI focuses on transforming the process to reduce emissions and is used as a 'shortcut' by firms to bypass potential punishments (Liu et al., 2020). Meanwhile, GKI is acting as an internal driving force for green innovation activities as it may provide the knowledge and technological foundations for such activities. Therefore, the adoption of GKI could be said of creating a 'dual externality', improving knowledge spillover on one hand, while inspiring other types of green innovation activities on the other (Wang and Li, 2022).

Therefore, compared with GPI, GKI represents an advanced innovation which requires more capital and time inputs but also has the potential to generate more sustained long-term positive impacts related to environmental protection. Under the pressure from environmental regulations, firms are likely to make discretionary decisions based on their own conditions, exhibiting heterogeneous self-selection behaviours of technological innovation modes. To consider the heterogeneity of these two types of innovations, this study proposes the following hypotheses:

Hypothesis 1b. Environmental regulation positively moderates the impact of GPI on CO_2 emissions reduction.

Hypothesis 1c. Environmental regulation positively moderates the impact of GKI on CO2 emissions reduction.

2.3. Green innovation and carbon emissions: different types of environmental policy instruments

Environmental policy instruments can be categorised into different types, such as CER, EER, and IER. Iraldo et al. (2011) show that the type of environmental regulation may be as important as its stringency in determining the nature of its relationship with economic performance. Thus, while evaluating the impact of environmental policy instruments on green innovation, different types of policy tools and the diversified institutional background is considered accordingly (Frondel et al., 2008).

[2] For example, when an enterprise achieves the technological innovation that meets the requirements of environmental regulations, it can apply for patent protection. Under the context of strict environmental regulations, this behaviour can encourage other enterprises to purchase its innovation, which will bring high profits to the enterprise (Porter, 1991).

CER is the government regulation which regulates both the amount and process by which firms should comply with. This regulation affects a wide range of aspects, including market access, product standards, product bans, and technology knowledge dissemination (Tian and Feng, 2022). As environmental protection and emissions reduction are generally long-term oriented, the ultimate goal of CER is to help firms develop effective long-term emissions reduction technologies (Li et al., 2019). Therefore, one may expect that under regulatory requirements, firms are more likely to develop advanced green innovation to achieve both financial benefits and environmental benefits. Therefore, this study proposes the following hypotheses:

Hypothesis 2a. CER does not positively moderate the impact of GPI on CO_2 emissions reduction.

Hypothesis 2b. CER positively moderates the impact of GKI on CO_2 emissions reduction.

In many cases, violating a regulation is punishable by fines. Through the introduction of the emissions trading system, EER seeks to change firms' behaviour by imposing higher charges for non-compliance. When investments in technology innovation exceed the costs of paying the discharge fee, firms will have little incentive to innovate, and vice versa (Sun et al., 2021). In China, this situation has become even more complicated due to the deficiencies of the discharge fee system (Shen et al., 2020). Considering the flaws of EER and investments needed for green innovation, this study proposes the following hypotheses:

Hypothesis 3a. EER does not positively moderate the impact of GPI on CO_2 emissions reduction.

Hypothesis 3b. EER does not positively moderates the impact of GKI on CO_2 emissions reduction.

IER aims to promote green innovation and environmental performance by reallocating financial resources and influencing the firms' financing costs (Zhang, 2021). Unlike EER which may trigger firms to adopt countermeasures to bypass financial punishments, IER is expected to incentivise firms to develop green technologies, such as by reducing credit constraints over the longer term. Therefore, this type of market-based mechanism strengthens the legitimate motives of firms to promote green technologies for more sustained growth, and hence, generate a larger positive impact on the whole society (Sun et al., 2021). To attract more sustainable green investments, compared with GPI, firms are more likely to develop relatively advanced GKI to build a competitive advantage and gain higher market status. Therefore, this study proposes the following hypotheses:

Hypothesis 4a. IER does not positively moderate the impact of GPI on CO_2 emissions reduction.

Hypothesis 4b. IER positively moderates the impact of GKI on CO_2 emissions reduction.

3. Methodology and variables

3.1. Data and variables

This study adopts panel data of 30 Chinese provinces and municipalities (except Tibet and Hong Kong, Macao, and Taiwan due to lack of comparability) over the period 2003–2019 with a total of 510 observations. As described in Table 1, the data used are collected from various sources. For the dependent variable, following Zhao et al. (2022), this study uses CO_2 emissions (CE) as the dependent variable and calculates it as the logarithm of annual CO_2 emissions (LnCE) for each province. Fig. 1 displays the CO_2 emissions of various regions in China. It shows that total carbon emissions have been rising consistently across all regions, with the eastern region exhibiting the highest increase.

Following Böhringer et al. (2012) and Tian and Feng (2022), this study considers two types of regulations: CER and MER, with MER is further divided into EER and IER. In prior studies, CER is mainly measured by the number of environmental protection personnel, enactment of environmental protection regulations, or promulgation of environmental protection legislation. However, these indicators fail to provide a comprehensive measurement of the strength of different types of CERs. Instead, the provincial government work report may be a better proxy (Chen and Chen, 2018). The report is more like a programmatic document, that guides the government's work in all aspects including environmental laws, market access, technology innovation, etc. As a result, the frequency of environment-related words used in such report could be considered as a good proxy to capture the overall picture of the government's attitude towards environmental protection. Hence, following the study of Chen and Chen (2018), this study uses the ratio of environmental-related word frequency to total word frequency in government reports as the measure of CER.

As for EER, a cost measure, it is generally measured by the cost of purchase of pollutant emissions rights or payment for environment-related taxes (Tian and Feng, 2022). Therefore, for a region, it can be calculated as the ratio of pollutant discharge fees to the total GDP of that region (Luo et al., 2021).

IER can be proxied by the green credit level (Böhringer et al., 2012), as it represents the volume of financial resources and investments flowing into non-heavy polluting firms (Zhang et al., 2021). It can also be interpreted as a market signal which guides more investments towards environmentally friendly industries and promotes the rapid advancements of green technologies (Zhang et al., 2021). To estimate the scale of green credit, the level of interest expenses is chosen as a good proxy (Hu et al., 2020). Numerically, IER is calculated as the ratio of interest expense of non-six high energy-consuming industries to the total industrial interest expense of a region.

Regarding the overall intensity of environmental regulation, this study adopts the Entropy-TOPSIS method to estimate the ER variable. A larger value of Entropy-TOPSIS index represents stricter environmental regulation (Lin and Zhou, 2022).

Fig. 2 shows the evolution of the environmental regulation intensity over the sample period. Interestingly, the regulations have become stringent on average over time, with the only exception of EER. A higher level of EER indicates more firm expenditures for CO_2 emissions reduction. However, the observed decrease in EER implies a lower cost of operation. Furthermore, as shown in Graph 1, mapping environmental regulation indicators for different provinces reveals the regional variation in environmental regulation intensity. For the eastern and southern regions, they tend to have stronger environmental regulations, showing the role of regional economic development level played in enforcing environmental regulations.

For GTI, this paper also classifies it into two categories, GPI and GKI. The former is measured as the ratio of technical transformation investment to the total industrial output value added of a region (Feng and Chen, 2018). While for GKI, following Zhang et al. (2017b), it is proxied by the logarithm of the total green patent count. For GTI, it is measured by the Entropy-TOPSIS method.

This study also includes the following control variables in the benchmark analysis: (1) Foreign direct investment (FDI) measured by the ratio of FDI to GDP in a province (Chen et al., 2021); (2) Rate of industrialisation (INDR) calculated by the ratio of industrial value-added to regional GDP (Wang et al., 2017b); (3) Education level (EDU) measured by $EDU_i = p_{i1} \times 6 + p_{i2} \times 9 + p_{i3} \times 12 + p_{i4} \times 16$, where p_{i1}, p_{i2}, p_{i3}, and p_{i4} denote the ratio of employees in province i graduated from primary school, junior high school, senior high school, and university or above, respectively, weighted by corresponding schooling years (Xie et al., 2017); and (4) Population (POP) estimated by the logarithmic value of the total regional population at the end of the year (Peng, 2020).

Different economic development levels may also lead to regional heterogeneity in the relationships between environmental regulations, technology innovation, and emissions reduction capacities (Frondel

Table 1
Descriptive statistics of variables.

Type	Variables	Explanation	Obs.	Mean	Std. Dev.	Min	Max	Data Source
Dependent Variable	LnCE	Logarithm of CO_2 Emissions	510	9.96	0.80	7.351	11.448	A, F
Independent Variables	ER	Environmental Regulation	510	0.30	0.06	0.129	0.648	B, C, D, E, K
	CER	Command-and-control Environmental Regulation	510	0.01	0.00	0.000	0.018	K
	EER	Expenditure-type Environmental Regulation	510	0.05	0.04	0.002	0.460	B, D, E, G
	IER	Investment-type Environmental Regulation	510	0.46	0.14	0.094	0.808	C
	GTI	Green Technology Innovation	510	0.26	0.12	0.037	0.891	B, C, G, I
	GPI	Green Process Innovation	510	2.33	1.81	0.111	11.641	B, C
	GKI	Green Knowledge Innovation	510	7.01	1.70	1.386	10.934	I
Control Variables	FDI	Foreign Direct Investment	510	0.42	0.50	0.048	5.705	A, H, J
	INDR	Rate of Industrialisation	510	0.38	0.09	0.111	0.592	A, C
	EDU	Education Level	510	2.16	0.11	1.798	2.548	A, H
	POP	Population	510	8.17	0.75	6.280	9.352	A, H

Note: The data come from different statistical yearbooks and databases; abbreviations are as follows: A: China Statistical Yearbook; B: China Environmental Yearbook; C: China Industry Statistical Yearbook; D: China Taxation Yearbook; E: China City Statistical Yearbook; F: Carbon Emission Accounts & Datasets for emerging economies; G: China Statistical Yearbook of Environment; H: Easy Professional Superior; I: Chinese Research Data Services; J: China Trade and External Economic Statistical Yearbook; and K: Report on the Work of the Government for each region.

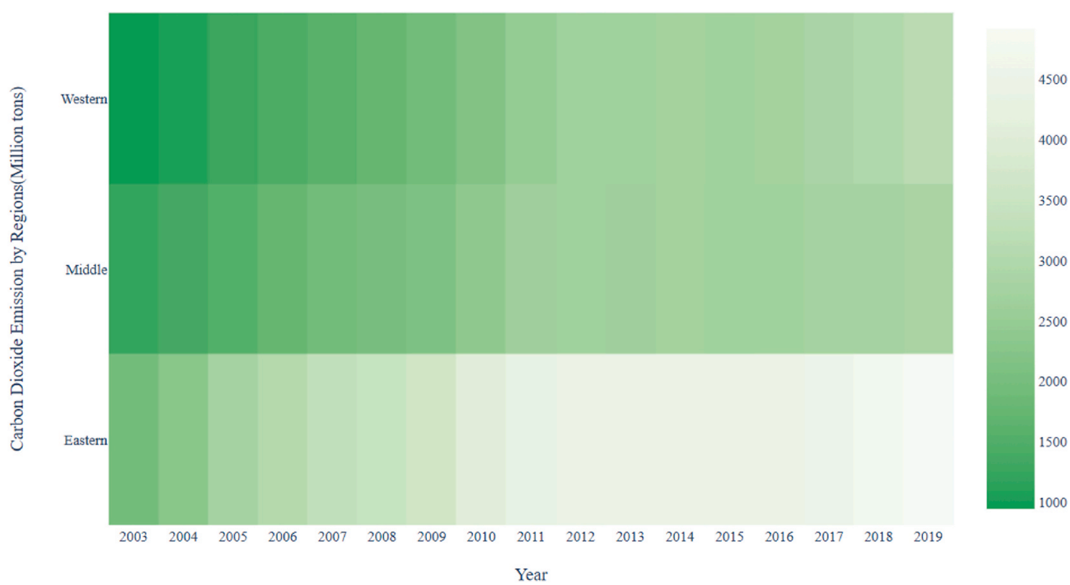

Fig. 1. The CO_2 emissions of different regions in China, by year. Note: This figure shows CO_2 emissions of different regions in China from 2003 to 2019. For each region, the CO_2 emissions of each year is the sum of provinces located in this region.

et al., 2008; Iraldo et al., 2011). To consider this regional heterogeneity in China, this study classifies China's 30 provincial regions into two groups, the Eastern and other less developed regions, according to the classification criteria of the National Bureau of Statistics.[3]

3.2. Regression models

First, the panel fixed-effect model is applied to test the moderating effects of environmental regulations on GTI and CO_2 emissions. Then, considering the spatial impact of CO_2 emissions, Spatial Durbin Model (SDM) is employed for the robustness test. Lastly, to mitigate endogenous problems and investigate the validity of results obtained using alternative measurements, the system generalised method of moments (SYS-GMM) and the Difference-in-Difference (DID) model are applied, respectively.[4]

3.2.1. The panel fixed-effect model

The panel fixed-effect model is applied to estimate the moderating effect of environmental regulations on green innovation and CO_2 emissions reduction. This model is represented by the following equations (1)–(6).

$$LnCE_{i,t} = \beta_0 + \beta_1 ER_{i,t} + \beta_2 GTI_{i,t} + \beta_3 X_{i,t} + u_i + \nu_t + \varepsilon_{i,t} \tag{1}$$

$$LnCE_{i,t} = \beta_0 + \beta_1 ER_{i,t} + \beta_2 GTI_{i,t} + \beta_3 ER_{i,t} \times GTI_{i,t} + \beta_4 X_{i,t} + u_i + \nu_t + \varepsilon_{i,t} \tag{2}$$

$$LnCE_{i,t} = \beta_0 + \beta_1 ER_{i,t} + \beta_2 GPI_{i,t} + \beta_3 GKI_{i,t} + \beta_4 ER_{i,t} \times GPI_{i,t} + \beta_5 ER_{i,t} \times GKI_{i,t} + \beta_6 X_{i,t} + u_i + \nu_t + \varepsilon_{i,t} \tag{3}$$

[3] The economically more advanced eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; and relatively less developed other regions includes the middle (Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan) and western regions (Inner Mongolia, Chongqing, Sichuan, Guizhou, Yunnan, Guangxi, Tibet, Shaanxi, Gansu, Ningxia, Qinghai, and Xinjiang) regions. http://www.stats.gov.cn/tjsj/zxfb/201701/t20170120_1455967.html.

[4] Pearson Correlation is also tested and can be extracted from supplementary material.

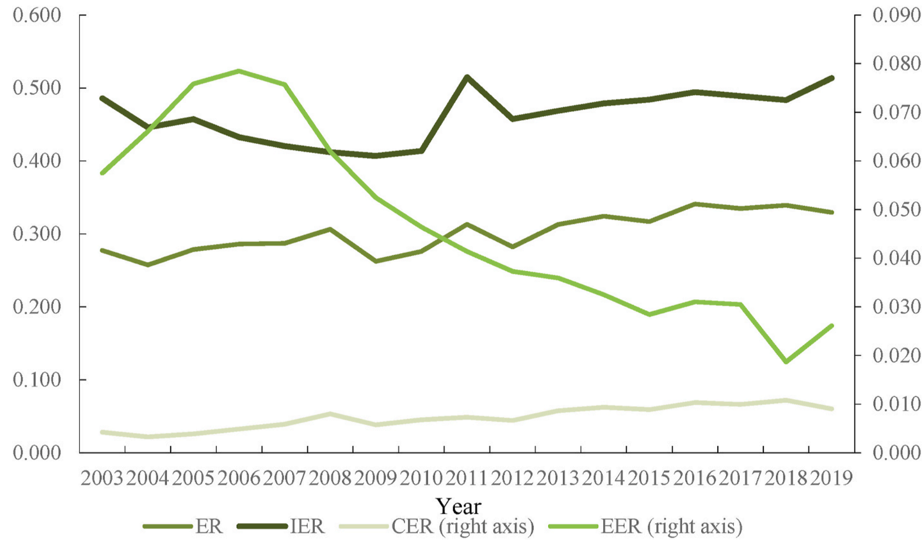

Fig. 2. The average intensity of environmental policy instruments in China, by year. Note: This figure shows the average intensity of the four proxies for environmental regulations (ER, CER, EER and IER) in China from 2003 to 2019. The average intensity of ER and IER is show in the left axis, and the average intensity of CER and EER is show in the right axis.

$$LnCE_{i,t} = \beta_0 + \beta_1 CER_{i,t} + \beta_2 EER_{i,t} + \beta_3 IER_{i,t} + \beta_4 GPI_{i,t} + +\beta_5 GKI_{i,t} + \beta_6 ERs_{i,t} \times GPI_{i,t} + \beta_7 ERs_{i,t} \times GKI_{i,t} + \beta_8 X_{i,t} + u_i + \nu_t + \varepsilon_{i,t} \quad (4\text{–}6)$$

i and t refer to the province and year, respectively. $LnCE_{i,t}$ measures the CO_2 emissions. $ER_{i,t}$ represents ER, $CER_{i,t}$ represents CER, $EER_{i,t}$ represents EER, and $IER_{i,t}$ represents IER. $ERs_{i,t}$ represents CER (equation (4)) or EER (equation (5)) or IER (equation (6)). $GTI_{i,t}$ represents GTI, $GPI_{i,t}$ represents GPI, and $GKI_{i,t}$ represents GKI.

To investigate the moderating effect, a series of mean-centred interaction terms of environmental regulations and green innovation are constructed (Hasan et al., 2018). A negative coefficient of the interaction term represents a positive moderating effect of environmental regulations on the relationship between green innovation and CO_2 emissions reduction, and vice versa (Wu et al., 2020). Here, $ER\times GTI_{i,t}$ represents the interaction term of environmental regulation and GTI of province i in year t. $ERs \times GPI_{i,t}$ ($CER \times GPI_{i,t}$ or $EER\times GPI_{i,t}$ or $IER \times GPI_{i,t}$) and $ERs \times GKI_{i,t}$ ($CER \times GKI_{i,t}$ or $EER \times GKI_{i,t}$ or $IER \times GKI_{i,t}$) represents the cross-terms between the respective types of environmental regulations and green innovation. $X_{i,t}$ is the vector for control variables, including FDI, INDR, EDU, and POP. u_i and ν_t refer to the individual and time fixed-effects, respectively, and $\varepsilon_{i,t}$ represents the random error.

3.2.2. Spatial Durbin Model

Besides the direct influence of environmental regulations, Wang and Zhu (2020) argue that the emissions reduction of one region can be affected by policies applied in its neighbouring regions as well. A closer geographical location tends to be associated with a stronger relationship. To verify the potential spatial impact of adjacent geographical regions, the Moran's I index is calculated for the following application of the spatial autocorrelation test (Peng, 2020).[5]

Then this study adopts the spatial econometric model, which incorporates the spatially autoregressive process in the regression equation, to investigate the relationship between environmental regulations, GTI, and CO_2 emissions (Jia et al., 2021). Among the three types of commonly used spatial models, the Spatial Autoregressive Model (SAR), the Spatial Error Model (SEM), and SDM, the last one is considered to be a more general form as it can be transformed into SAR and SEM under certain conditions (Jia et al., 2021). Therefore, SDM is employed in the study and can be illustrated by the following equations (7)–(12):

$$LnCE_{i,t} = \rho \sum_{j=1}^{N} W_{i,j} LnCE_{j,t} + \beta_1 ER_{i,t} + \varphi_1 \sum_{j=1}^{N} W_{i,j} ER_{j,t} + \beta_2 GTI_{i,t} + \varphi_2 \sum_{j=1}^{N} W_{i,j} GTI_{j,t} + \beta_3 X_{i,t} + \varphi_3 \sum_{j=1}^{N} W_{i,j} X_{j,t} + u_i + \nu_t + \varepsilon_{i,t} \quad (7)$$

$$LnCE_{i,t} = \rho \sum_{j=1}^{N} W_{i,j} LnCE_{j,t} + \beta_1 ER_{i,t} + \varphi_1 \sum_{j=1}^{N} W_{i,j} ER_{j,t} + \beta_2 GTI_{i,t} + \varphi_2 \sum_{j=1}^{N} W_{i,j} GTI_{j,t} + \beta_3 ER_{i,t} \times GTI_{i,t} + \varphi_3 \sum_{j=1}^{N} W_{i,j} ER_{i,t} \times GTI_{i,t} + \beta_4 X_{i,t} + \varphi_4 \sum_{j=1}^{N} W_{i,j} X_{j,t} + u_i + \nu_t + \varepsilon_{i,t} \quad (8)$$

$$LnCE_{i,t} = \rho \sum_{j=1}^{N} W_{i,j} LnCE_{j,t} + \beta_1 ER_{i,t} + \varphi_1 \sum_{j=1}^{N} W_{i,j} ER_{j,t} + \beta_2 GPI_{i,t} + \varphi_2 \sum_{j=1}^{N} W_{i,j} GPI_{j,t} + \beta_3 GKI_{i,t} + \varphi_3 \sum_{j=1}^{N} W_{i,j} GKI_{j,t} + \beta_4 ER_{i,t} \times GPI_{i,t} + \varphi_4 \sum_{j=1}^{N} W_{i,j} ER_{i,t} \times GPI_{i,t} + \beta_5 ER_{i,t} \times GKI_{i,t} + \varphi_5 \sum_{j=1}^{N} W_{i,j} ER_{i,t} \times GKI_{i,t} + \beta_6 X_{i,t} + \varphi_6 \sum_{j=1}^{N} W_{i,j} X_{j,t} + u_i + \nu_t + \varepsilon_{i,t} \quad (9)$$

[5] Moran's I index is calculated based on the following function: $Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(X_i-\overline{X})(X_j-\overline{X})}{(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij})\sum_{i}^{n}(X_i-\overline{X})^2}$. Where X_i and X_j are the spatial data of region i and j, respectively. W_{ij} is the spatial weight matrix. The Moran's I index generally takes the value of [-1,1].

$$LnCE_{i,t} = \rho \sum_{j=1}^{N} W_{i,j} LnCE_{j,t} + \beta_1 CER_{i,t} + \varphi_1 \sum_{j=1}^{N} W_{i,j} CER_{j,t} + \beta_2 EER_{i,t} + \varphi_2 \sum_{j=1}^{N} W_{i,j} EER_{j,t} + \beta_3 IER_{i,t} + \varphi_3 \sum_{j=1}^{N} W_{i,j} IER_{j,t} + \beta_4 GPI_{i,t} + \varphi_4 \sum_{j=1}^{N} W_{i,j} GPI_{j,t} + \beta_5 GKI_{i,t} + \varphi_5 \sum_{j=1}^{N} W_{i,j} GKI_{j,t} + \beta_6 ERs_{i,t} \times GPI_{i,t} + \varphi_6 \sum_{j=1}^{N} W_{i,j} ERs_{i,t} \times GPI_{i,t} + \beta_7 ERs_{i,t} \times GKI_{i,t} + \varphi_7 \sum_{j=1}^{N} W_{i,j} ERs_{i,t} \times GKI_{i,t} + \beta_8 X_{i,t} + \varphi_8 \sum_{j=1}^{N} W_{i,j} X_{j,t} + u_i + \nu_t + \varepsilon_{i,t} \tag{10–12}$$

Where $W_{i,j}$ represents the spatial weight matrix. Following Zhang et al. (2017a), the adjacent weight matrix for China's 30 provincial administrative regions is constructed as follows:

$$W_{ij} = \begin{cases} 1 \text{ if provinces i and j are adiacent} \\ 0 \text{ if provinces i and j are not adiacent} \end{cases} \tag{13}$$

3.2.3. The system Generalised Method of moments

Considering the issue of endogeneity, the SYS-GMM model is applied for the robustness test. It overcomes the estimation problem in single-equation and ordinary panel regressions and suits well for the dynamic panel data model as it not only avoids the autocorrelation problem, but also considers the impact of the explained variable lag on the current period. In the estimation process, the different transformation method is employed to eliminate the individual heterogeneity that does not change over time. This combines differential and horizontal GMM estimation methods to improve the efficiency of parameter estimation. The general form of the SYS-GMM model is expressed as follows:

$$LnCE_{i,t} = \beta_0 + \beta_1 LnCE_{i,t-1} + \beta_2 ER_{i,t} + \beta_3 GTI_{i,t} + \beta_4 X_{i,t} + u_i + \nu_t + \varepsilon_{i,t} \tag{14}$$

$$LnCE_{i,t} = \beta_0 + \beta_1 LnCE_{i,t-1} + \beta_2 ER_{i,t} + \beta_3 GTI_{i,t} + \beta_4 ER_{i,t} \times GTI_{i,t} + \beta_5 X_{i,t} + u_i + \nu_t + \varepsilon_{i,t} \tag{15}$$

$$LnCE_{i,t} = \beta_0 + \beta_1 LnCE_{i,t-1} + \beta_2 ER_{i,t} + \beta_3 GPI_{i,t} + \beta_4 GKI_{i,t} + \beta_5 ER_{i,t} \times GPI_{i,t} + \beta_6 ER_{i,t} \times GKI_{i,t} + \beta_7 X_{i,t} + u_i + \nu_t + \varepsilon_{i,t} \tag{16}$$

$$LnCE_{i,t} = \beta_0 + \beta_1 LnCE_{i,t-1} + \beta_2 CER_{i,t} + \beta_3 EER_{i,t} + \beta_4 IER_{i,t} + \beta_5 GPI_{i,t} + +\beta_6 GKI_{i,t} + \beta_7 ERs_{i,t} \times GPI_{i,t} + \beta_8 ERs_{i,t} \times GKI_{i,t} + \beta_9 X_{i,t} + u_i + \nu_t + \varepsilon_{i,t} \tag{17–19}$$

Where β_1 is a hysteresis multiplier capturing the effect of the previous period's CO_2 emissions reduction, $LnCE_{i,t-1}$, which is the lagged variable of $LnCE_{i,t}$. The meaning of other parameters is the same as those in equations (1)–(6).

4. Empirical results

4.1. Benchmark model regression results

This study reports the benchmark regression results in Table 2. Columns (1) and (2) report the moderating effect of environmental regulation and its interaction term, respectively, on GTI and CO_2 emissions. Meanwhile, columns (3)–(6) report the results for different types of environmental regulations and GTI

Column 1 shows that neither ER, GTI, nor their interaction term have significant effects on carbon emissions. Thus, hypothesis 1a is not supported. Meanwhile, when this paper considers the heterogeneity of green innovation, the interaction terms of environmental regulations with both GKI and GPI significantly negatively affect carbon emissions. Thus, hypotheses 1 b and 1c are supported. Notably, the interaction term for GKI is much stronger than that for GPI. This indicates that firms may be more willing to invest their limited capital into more advanced and sustainable innovation (GKI) to reduce CO_2 emissions. Similarly, Yuan (2019) finds that different types of environmental regulations may have

Table 2
Regression results for the benchmark model.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE
ER	−0.219 (−0.84)	−0.119 (−0.44)	−0.605** (−2.39)			
CER				0.875 (0.19)	1.442 (0.45)	2.087 (0.63)
EER				−0.199 (−0.77)	1.430 (1.54)	−0.171 (−0.54)
IER				−0.332** (−2.60)	−0.460*** (−3.15)	−0.408** (−2.72)
GTI	0.010 (0.09)	−0.016 (−0.15)				
GPI			−0.006 (−1.06)	−0.005 (−0.98)	−0.000 (−0.05)	−0.004 (−0.86)
GKI			0.130*** (3.30)	0.117*** (2.92)	0.119*** (2.85)	0.114*** (2.93)
ER*GTI		−1.985 (−1.52)				
ER*GPI			−0.130* (−1.73)			
ER*GKI			−0.428*** (−2.84)			
CER*GPI				−0.273 (−0.12)		
CER*GKI				−8.887** (−2.68)		
EER*GPI					0.184 (1.35)	
EER*GKI					1.202*** (2.90)	
IER*GPI						−0.066 (−1.64)
IER*GKI						−0.193** (−2.68)
FDI	−0.037* (−1.72)	−0.038* (−1.72)	−0.028* (−1.97)	−0.045*** (−3.07)	−0.034* (−1.88)	−0.017 (−1.02)
INDR	0.815*** (3.81)	0.827*** (3.86)	0.592** (2.46)	0.534** (2.19)	0.605** (2.14)	0.606** (2.32)
EDU	0.060 (0.10)	0.041 (0.07)	−0.271 (−0.52)	−0.176 (−0.35)	−0.258 (−0.49)	−0.355 (−0.65)
POP	−0.503 (−0.96)	−0.525 (−1.00)	−0.289 (−0.63)	−0.275 (−0.61)	−0.264 (−0.58)	−0.209 (−0.44)
R-squared	0.857	0.858	0.879	0.884	0.887	0.880
Province F.E.	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES

Note: Robust t statistics are enclosed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

a synergistic effect on innovation and emissions reduction. For instance, the two types of regulations considered by Yuan (2019)–CER and MER–can be complementary to each other, enabling companies to respond flexibly and cost-efficiently to promote advanced green innovation and achieve emissions reduction targets. This paper also observes this synergistic effect in the benchmark model, as ER positively moderates the impact of GPI and GKI on CO_2 emissions reduction. However, this result is contrary to Du et al.'s (2019) finding that green innovation can only help firms in developed economies to reduce CO_2 emissions. Thus, the experience of China offers valuable insights for less developed economies, especially in terms of environmental regulation design and green technology advancement.

Regarding different types of environmental regulations, CER has no (a significant positive) moderating effect on the relationship between GPI (GKI) and CO_2 emissions reduction. These results support hypotheses 2a and 2 b. This may be because although GPI may assist firms in meeting government environmental regulations over the short term, tougher regulations may have forced firms to undertake more advanced green investments in the form of GKI to build up emissions reduction capacity over the longer term. This finding aligns with prior literature, which highlights that firms are more inclined to foster more efficient and advanced green innovation to secure a sustained competitive advantage (Shen et al., 2020). Although earlier studies also find a negative impact of CER on technology development and pollution mitigation (Li et al., 2019), this may be primarily due to the proxy chosen to measure CER. As environmental fine is selected by most of the earlier studies, it is not surprising that it impairs firms' innovation capacity as only the punitive aspect of the government regulation is considered.

Similar to CER, EER has no significant moderating effect on the relationship between GPI and CO_2 emissions reduction. Meanwhile, when EER is combined with GKI, this can lead to increased carbon emissions. As firms are trying hard to minimise costs, when the cost of pollution penalties is less than the cost of developing GKI, firms may choose not to invest in GKI, and thus, CO_2 emissions reduction. This is especially true in China, as the country has low environmental standards, narrow scope of levies, and weak enforcement strength (Shen et al., 2020). As GKI is relatively costly, paying the pollution fees is more economical for firms. Meanwhile, as GPI is not as expensive, some firms may choose to refine the production process for potential emissions reductions. However, the number of such firms is limited. In general, EER might encourage the opportunism behaviour of firms, damaging the long-term emissions reduction capacity of firms, and these results are consistent with prior research (Shen et al., 2020; Luo et al., 2021) and support hypotheses 3a and 3 b.

Finally, IER has a significant positive (no significant) moderating effect on the relationship between GKI (GPI) and carbon emissions reduction. These results are consistent with hypotheses 4a and 4 b. IER is designed to stimulate firms' long-term investments in green technologies. Therefore, when combined with more advanced green innovation, GKI, its moderating effect on carbon emissions reduction is positive. However, for GPI, as it only involves some adjustments/alterations in the existing process but does not require significant investments (Shen et al., 2020; Wang et al., 2021), the tested moderation effect is insignificant. Therefore, under IER, firms are stimulated to invest heavily in more advanced green technologies for emissions reduction, represented by GKI, rather than GPI. These findings are consistent with earlier research, suggesting that firms are more inclined to foster advanced and superior green innovation to attract greater capital investment (Wang et al., 2022). This can help firms build up a long-term competitive advantage and gain the first-mover advantage in future development. Furthermore, when firms perform well in green innovation, they are more likely to be granted additional investments and this can further strengthen their innovation capacity (Wang et al., 2022). This reinforces the positive moderating effect of IER on GKI for emissions reduction.

Regarding control variables, only FDI has a significant negative impact on CO_2 emissions in most cases. This is consistent with Xie et al.'s (2017) finding that FDI generally involves the transfer of advanced technologies and managerial experiences to investee firms, which can directly promote emissions reductions. The rate of industrialisation has a significant positive impact on CO_2 emissions, suggesting that regions with a higher level of industrialisation are more polluted. This is consistent with research showing that the extravagant growth model adopted by the Chinese government in the early days has led to severe pollution (Wu et al., 2020). While several policies have been adopted to restructure the economy over the past decade, the impact of the earlier production model remains (Zhang et al., 2017b).

Meanwhile, both educational level and population size have no significant impact on CO_2 emissions. This finding is consistent with the literature (Lee and Lee, 2022). Theoretically, these two factors are important in influencing CO_2 emissions levels. However, empirical results are mixed (Lee and Lee, 2022). This may be because a higher level of educational level does not necessarily lead to more green innovation or a higher level of environmental awareness. Similarly, a higher level of population agglomeration may not lead to higher CO_2 emissions.

4.2. Robustness test – Spatial Durbin Model results

To further examine this spatial correlation, this study applies the SDM and reports the results in Tables 3a and 3b.This study reruns the six regressions of the baseline model by incorporating spatial factors. The results are reported in columns (1) to (6).[6]

First, the test models are validated. The spatial rho, representing the existence of the spatial effect, is significant in almost all models except for regressions (1) and (2), suggesting that the SDM fits well for regressions (3) to (6). Hence, this study focuses on these four regressions. This study also applies the likelihood ratio (LR), calculated by the maximum likelihood estimation (MLE), to decide the best fit model from SAR, SEM, and SDM (Wang and Zhu, 2020). All statistical values of the LR tests are significant, implying that the SDM model is the best fit for the sample. Moreover, to address the potential endogeneity problem caused by the inclusion of lag terms of the dependent variables in SDM, this study applies the MLE method based on the conditional log-likelihood function. This method is regarded as an appropriate estimation approach for the SDM and has been widely used in the literature (Jia et al., 2021). Lastly, referring to the literature, when interpreting the results generated by the SDM, this study divides them into direct and indirect effects (Jia et al., 2021). The former refers to the impact of independent variables in one province on the CO_2 emissions of the same province, while the latter is the influence of independent variables in one province on the CO_2 emissions of its neighbouring provinces. The total effect is the sum of the direct and indirect effects (Wang and Zhu, 2020).

This study finds significant direct and indirect moderating effects of ER on the impact of GKI on CO_2 emissions reductions in local and neighbouring regions. This is consistent with Hypothesis 1b. In China, each local government has certain powers in setting up local policies, and local businesses are responsive to local authorities and follow these policies. Hence, in line with Peng (2020), the environmental regulations set up by the local government are more likely to be followed by the local business due to enforcement power at the local level, resulting in a significant direct effect. Meanwhile, good local practices could also be diffused and adopted by other regions. This positive spillover effect on neighbouring regions may explain the significant indirect effects (Wu et al., 2020).

Moreover, this study finds significant positive moderating effects of ER on GPI and carbon emissions reduction as well. However, this effect is relatively smaller compared with GKI, as observed in the benchmark regression results. This is as expected as more advanced GKI is preferred

[6] This paper also conducts Global Moran's I test. Due to the limit of space, the Global Moran's I Result is presented in the supplementary material.

Table 3a
Regression results for SDM.

Variables	(1)			(2)			(3)		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE
ER	−0.072 (−0.29)	0.291 (0.41)	0.219 (0.27)	0.027 (0.10)	0.305 (0.42)	0.332 (0.40)	−0.335 (−1.58)	0.105 (0.31)	−0.230 (−0.72)
GTI	0.034 (0.30)	0.648 (1.60)	0.682 (1.58)	−0.006 (−0.05)	0.548* (1.83)	0.542* (1.68)			
GPI							−0.005 (−0.86)	0.034** (2.22)	0.029* (1.87)
GKI							0.156*** (4.62)	0.023 (0.28)	0.180** (2.19)
ER*GTI				−2.139 (−1.43)	−3.949 (−0.56)	−6.089 (−0.78)			
ER*GPI							−0.149* (−1.79)	−0.424** (−2.02)	−0.573** (−2.34)
ER*GKI							−0.320*** (−2.66)	−0.504** (−2.13)	−0.824*** (−3.48)
rho	0.012 (0.09)			0.002 (0.02)			−0.196** (−2.23)		
sigma2_e	0.014*** (4.76)			0.014*** (4.99)			0.010*** (5.90)		
LR-lag	34.07***			36.27***			82.73***		
LR-sem	34.30***			36.71***			77.76***		
Control Variables	YES			YES			YES		
Province F.E.	YES			YES			YES		
Year F.E.	YES			YES			YES		
Log likelihood	370			373.9			436.7		

Note: Robust z statistics are enclosed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3b
Regression results for SDM.

Variables	(4)			(5)			(6)		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE
CER	3.798 (0.91)	0.311 (0.04)	4.108 (0.45)	5.697* (1.89)	−4.455 (−0.54)	1.242 (0.14)	4.921 (1.56)	−3.502 (−0.55)	1.419 (0.20)
EER	−0.139 (−0.63)	1.050 (1.38)	0.911 (1.29)	0.961 (1.23)	2.808*** (3.11)	3.769*** (3.94)	−0.084 (−0.31)	1.557** (1.98)	1.473** (1.97)
IER	−0.256** (−2.21)	−0.393 (−1.36)	−0.649*** (−2.63)	−0.372*** (−2.95)	−0.479 (−1.57)	−0.850*** (−3.23)	−0.330*** (−2.70)	−0.125 (−0.57)	−0.455** (−2.08)
GPI	−0.004 (−0.81)	0.040** (2.38)	0.036** (2.22)	−0.001 (−0.17)	0.035** (2.16)	0.034** (2.15)	−0.002 (−0.40)	0.042*** (2.85)	0.041*** (2.75)
GKI	0.140*** (4.46)	0.003 (0.03)	0.143* (1.72)	0.146*** (4.94)	0.086 (1.06)	0.232*** (3.08)	0.140*** (4.45)	0.045 (0.57)	0.186** (2.40)
CER*GPI	−0.539 (−0.26)	0.802 (0.20)	0.264 (0.07)						
CER*GKI	−6.745*** (−2.75)	−6.264* (−1.75)	−13.009*** (−3.00)						
EER*GPI				0.209* (1.94)	0.104(0.38)	0.313 (1.02)			
EER*GKI				0.910*** (2.79)	1.119* (1.84)	2.030*** (3.25)			
IER*GPI							−0.077* (−1.88)	−0.163 (−1.62)	−0.239* (−1.96)
IER*GKI							−0.136** (−2.54)	−0.261 (−1.51)	−0.396** (−2.45)
rho	−0.174** (−2.12)			−0.260*** (−3.01)			−0.234*** (−3.09)		
sigma2_e	0.010*** (5.38)			0.010*** (5.49)			0.010*** (6.14)		
LR-lag	71.89***			88.08***			97.24***		
LR-sem	68.21***			76.06***			92.33***		
Control Variables	YES			YES			YES		
Province F.E.	YES			YES			YES		
Year F.E.	YES			YES			YES		
Log likelihood	441.7			456.9			447.4		

Note: Robust z statistics are enclosed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

by the government as it may lead to long-term sustained environmental protection. For firms, GKI is also preferred over GPI as it may assist firms in earning additional profits. For example, firms can apply for green patent protection for those that have CO_2 emissions reduction effect. Then, other firms may buy its green innovation, which can benefit the innovating firm (Porter, 1991). Through GPI, the transformation of technology and equipment in the production process can help CO_2 emissions reductions in the short-term; however, the upgraded equipment will be depreciated over time. Then, the capital input in this process cannot generate more profits for firms over the long-term period. Therefore, under strict environmental regulations, firms are more likely to promote GKI to achieve long-term sustained economic growth.

Regarding the different combinations of regulatory policies and green innovation, the results are similar to those for the benchmark model (regressions 4–6). For CER, its positive moderation effect on GKI and CO_2 emissions reduction is significant for the direct effect and the indirect effect. When firms are required to reach certain emissions reduction targets, they may weigh the costs and benefits of different types of green innovation. The more advanced GKIs are preferred by firms for the creation of long-term competitive advantages (Zhang et al., 2017b; Wang and Li, 2022). Then, these moderating effects of CER appear in local and neighbouring regions due to the demonstration and spillover effects in different regions.

Meanwhile, EER has significant negative moderating effects on the impact of GKI on carbon emissions reductions for direct, indirect, and total effects. Significant negative direct, but not indirect and total effects, are observed for GPI. Overall, these results are in line with the benchmark regression results that EER rather promotes carbon emissions. These findings are unsurprising, as deficiencies have been documented in the Chinese EER system. The implementation of EER is not strong enough to promote green innovation for carbon emissions reductions as firms can easily settle the punishment by paying an insignificant amount of fine. Meanwhile, some firms may purposely choose to invest in R&D, which can be more costly (Shen et al., 2020).

Lastly, for IER, its moderation effects on GKI and CO_2 emissions reduction remain significantly positive in direct and total effect models. To seek for more sustained investments, firms are more willing to advance superior green innovation, thereby meeting the emissions reduction targets. However, these effects only exist in the local province. Even though the coefficient *IER*GPI* is significantly negative, the smaller coefficient and less significant level indicate that firms prefer investments in GKI, especially cash-strapped ones which need to use their capital effectively.

4.3. Additional robustness test – SYS-GMM results

Next, this study applies the SYS-GMM to address endogeneity concerns. This paper performs the SYS-GMM estimation of dynamic panel data in China including the eastern, central, and western areas. During the SYS-GMM estimation, it is necessary to test the adequacy of the model and the validity of instrument variables. The test includes two aspects: First, the difference method is used to test the suitability of the model, and the null hypothesis that there is no sequence related and subjected to asymptotic distribution (Zhou and Xu, 2022). Second, the Sargan estimation is used to test whether the instrumental variables are over-identified. If this is not true, the asymptotic chi-square distribution will be obeyed. The difference between the number of instrumental variables and parameters is the degree of freedom (Yuan, 2019). The results of the dynamic SYS-GMM estimation are summarised in Table 4.

To ensure the validity of the model, the p-values of AR (1) and AR (2) are tested and they indicate no serious second-order sequence correlation, confirming the appropriateness of the GMM approach (Zhou and Xu, 2022). Moreover, the Sargan tests indicate that the null hypothesis that all instrumental variables used in the GMM estimations are effective could not be rejected (Yuan, 2019). This indicates that the dynamic panel model is set properly. Again, the statistical results obtained are in general consistent with previous findings. Notably, the *ER*GKI* still outperforms the *ER*GPI* combination in reducing CO_2 emissions (Column 3), but the interaction term of environmental regulation and GPI becomes insignificant (columns 3 and 6).

This paper also considers the regional heterogeneity, and the results are reported in Tables 5 and 6. For the eastern region, the findings for ER with different types of green innovation are consistent with findings at the national level. However, CER does not promote carbon emissions reductions. This may be because the eastern region has more firms with foreign investments, who may possess relatively advanced technologies (Su et al., 2022). Therefore, they are not that sensitive to CER and EER as the firms may have already met the emissions reduction targets. Instead,

Table 4
Regression results for SYS-GMM.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE
L.LnCE	0.918*** (19.62)	0.908*** (19.19)	0.884*** (14.32)	0.863*** (15.54)	0.850*** (20.18)	0.867*** (15.69)
ER	−0.095 (−0.82)	−0.009 (−0.08)	−0.199 (−1.19)			
CER				−3.540 (−0.98)	−1.670 (−0.68)	−2.480 (−0.78)
EER				−0.042 (−0.28)	0.835*** (2.90)	−0.032 (−0.28)
IER				−0.106 (−1.28)	−0.116 (−1.53)	−0.052 (−0.65)
GTI	−0.058 (−0.64)	−0.064 (−0.82)				
GPI			−0.005 (−1.16)	0.003 (0.65)	0.003 (0.69)	−0.001 (−0.18)
GKI			−0.005 (−0.25)	0.007 (0.29)	0.004 (0.22)	0.008 (0.47)
ER*GTI		−0.204 (−0.23)				
ER*GPI			0.000 (0.01)			
ER*GKI			−0.091* (−1.72)			
CER*GPI				1.701 (0.79)		
CER*GKI				−2.995* (−1.88)		
EER*GPI					−0.022 (−0.29)	
EER*GKI					0.437** (2.64)	
IER*GPI						0.024 (0.70)
IER*GKI						−0.036* (−1.88)
Control Variables	YES	YES	YES	YES	YES	YES
Province F.E.	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES
AR (1) p-value	0.00494	0.00573	0.00390	0.00447	0.00678	0.00368
AR (2) p-value	0.165	0.106	0.0858	0.226	0.136	0.180
Sargan p-value	0.425	0.621	0.296	0.627	0.802	0.296

Note: Robust t statistics are enclosed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5
SYS-GMM regression results for the eastern region.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE
L.LnCE	0.943*** (34.00)	0.944*** (35.29)	0.933*** (36.74)	0.945*** (64.26)	0.927*** (55.09)	0.949*** (65.87)
ER	−0.145 (−1.42)	−0.116 (−1.03)	−0.015 (−0.15)			
CER				1.276 (0.58)	−3.165 (−1.31)	−1.257 (−0.54)
EER				0.483 (1.56)	0.297 (1.21)	0.458 (1.54)
IER				−0.048 (−1.26)	−0.068** (−2.25)	0.002 (0.07)
GTI	0.073 (0.74)	0.063 (0.59)				
GPI			−0.000 (−0.09)	0.003 (0.85)	0.004 (0.90)	−0.001 (−0.34)
GKI			−0.010 (−1.43)	−0.003 (−0.26)	0.007 (0.65)	0.001 (0.06)
ER*GTI		−0.425 (−0.26)				
ER*GPI			0.031 (0.65)			
ER*GKI			−0.104* (−2.09)			
CER*GPI				2.532** (2.53)		
CER*GKI				−1.117 (−0.99)		
EER*GPI					−0.151 (−1.31)	
EER*GKI					0.318** (2.88)	
IER*GPI						0.009 (0.29)
IER*GKI						−0.037* (−2.19)
Control Variables	YES	YES	YES	YES	YES	YES
Province F.E.	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES
AR (1) p-value	0.0123	0.0102	0.0113	0.0111	0.0147	0.0137
AR (2) p-value	0.133	0.0956	0.130	0.127	0.190	0.166
Sargan p-value	0.243	0.332	0.312	0.268	0.373	0.338

Note: Robust t statistics are enclosed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6
SYS-GMM regression results for the middle and western regions.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	LnCE	LnCE	LnCE	LnCE	LnCE	LnCE
L.LnCE	0.853*** (9.65)	0.858*** (9.69)	0.883*** (10.45)	0.831*** (11.14)	0.853*** (18.21)	0.883*** (13.04)
ER	−0.023 (−0.23)	0.007 (0.04)	−0.014 (−0.06)			
CER				1.965 (0.39)	1.471 (0.38)	−1.085 (−0.33)
EER				0.125 (0.83)	1.287** (2.54)	0.038 (0.25)
IER				0.005 (0.02)	−0.008 (−0.06)	0.008 (0.06)
GTI	−0.045 (−0.83)	−0.040 (−0.56)				
GPI			−0.000 (−0.10)	−0.001 (−0.18)	−0.000 (−0.03)	−0.004 (−0.79)
GKI			0.024 (0.92)	−0.002 (−0.08)	−0.016 (−0.63)	0.026 (1.21)
ER*GTI		−0.134 (−0.19)				
ER*GPI			0.002 (0.04)			
ER*GKI			0.004 (0.06)			
CER*GPI				2.502 (0.81)		
CER*GKI				−2.891 (−1.39)		
EER*GPI					0.055 (0.59)	
EER*GKI					0.689** (2.56)	
IER*GPI						0.010 (0.39)
IER*GKI						−0.033 (−0.83)
Control Variables	YES	YES	YES	YES	YES	YES
Province F.E.	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES
AR (1) p-value	0.0181	0.0216	0.0268	0.0274	0.0411	0.0247
AR (2) p-value	0.0315	0.0242	0.0163	0.144	0.0842	0.0233
Sargan p-value	0.417	0.667	0.485	0.781	0.935	0.693

Note: Robust t statistics are enclosed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

some may even expand their production, thereby generating more pollution up to their emissions allowance. Nevertheless, when the investment-based regulation is considered, it is found to be able to play a positive moderation effect on the impact of GKI on CO_2 emissions reduction (Column 6). This is as expected as the investment-type regulations tend to be long-term focused and could assist firms to build up their sustained competitive advantages, which is in line with the findings of Zhou and Xu (2022). Thus, the synergistic effect of advanced regulation and green innovation on CO_2 emissions reduction is clear in the eastern region, as evidenced by the robust results for *IER*GKI*.

This paper observes a different picture for the middle and western regions. Almost all tested moderating effects are insignificant or negative, suggesting that regulations in these regions may not effectively influence the impact of green innovation on emissions reduction. This does not come as a surprise. Compared with the more economically developed eastern region, firms in the western and middle regions tend to be less developed and are governed by local authorities with weaker enforcement power. This can reduce the effectiveness of CER. The findings for EER remain consistent with those observed before: it does not reduce carbon emissions. When the cost of environmental penalties is less than the cost of developing green innovation, firms may choose not to invest in green innovation and CO_2 emissions reductions (Wang et al., 2019). Moreover, with limited capital available, firms in the middle and western regions tend to accept green innovation passively,

Table 7
Regression and placebo results for the DID model.

Variables	(1)	(2)	(3)
	LnCE	LnCE	LnCE
IER2*GPI	−0.012 (−0.93)	−0.015 (−0.70)	−0.024 (−0.89)
IER2*GKI	−0.088*** (−3.25)	−0.009 (−0.51)	−0.025 (−1.15)
R-squared	0.891	0.907	0.909
Control Variables	YES	YES	YES
Province F.E.	YES	YES	YES
Year F.E.	YES	YES	YES

Note: Robust t statistics are enclosed in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Only interaction terms are presented here due to space limit, full table can be requested from authors.

and the results are in line with Tang et al. (2020). This could be evidenced by the insignificant moderation effect of IER on the relationship between green innovation and emissions reduction.

4.4. Robustness test – alternative measures and DID analysis results

To measure the impact of different types of regulations, this paper uses green credit as the alternative measure of IER (IER2). To apply for green credit, firms need to increase clean investments. This can enhance the emissions reduction effect of green innovation. That is, the green credit represents the government's intention of fund allocation and can directly affect firms' behaviour. Following Nunn and Qian (2011) and Kim and Valentine (2021), this paper uses GCG2012 as an alternative proxy for IER and employs the DID model with continuous grouping variables to test the fundamental hypotheses.[7] Since this paper focuses on IER, the key is to validate hypotheses 4a and 4 b. Also, as time is fixed, IER2 is not added alone in the equations because of the perfect collinearity. The paper also undertakes time trend analysis and the placebo test to ensure the validation of the model constructed (Li et al., 2022).

The results are summarised in Table 7. Column (1) shows the results of DID model, whereas columns (2) and (3) present the placebo test results for the years 2010 and 2011, respectively. The coefficient of *IER2*GKI* is negative and statistically significant, indicating that IER together with GKI can reduce CO_2 emissions. This finding is consistent with conclusions reached in earlier sections. Also, as shown in Fig. 3, the parallel trends assumption is supported because all the interactions before 2012 are insignificant. The results of placebo tests show that when the study;assumes 2010 or 2011 as the implementation year of the IER policy GCG2012, all coefficients of *IER2*GKI* are insignificant. This provides convincing evidence that the positive moderating effect identified in this paper is indeed caused by the IER, thereby further supporting hypothesis 4b (see Fig. 4).

5. Conclusion, policy implications and future research orientation

5.1. Conclusion

Resource scarcity and climate change have been the core of the economic and political debate during the last decades. Environment-related technical progress brings about opportunities to create a more sustainable low-carbon future. However, green innovation is a complicated and dynamic process. Firms' willingness and ability to conduct green innovation are conditioned by the financial rewards from doing so and the resource available. Interventions from the government are considered useful in correcting market failure to maximise the environmental and economic benefits brought about by green innovation.

This study contributes to growing concerns about the effectiveness of environmental regulations in promoting green innovation and the achievement of emissions reduction. Based on panel data of 30 Chinese provinces from 2003 to 2019, a series of carefully chosen models were applied for this analysis. First of all, the Panel Fixed-effect model is applied for the benchmark analysis. Through controlling for individual and time fixed effects, it reduces omitted variable bias, enhances estimation accuracy and leads to the high R-squared values estimated across all models (Hasan et al., 2018). Then the SDM is adopted to capture the spatial factors to verify the robustness of the empirical findings (Jia et al., 2021). The validation tests all confirm the presence of spatial effects, e.g. coefficients of LR-lag and LR-sem are 34.07 and 34.30, respectively, and are both significant at the 1% level. Thirdly, to mitigate the endogeneity problem and improve parameter estimation efficiency, the SYS-GMM model is conducted (Zhou and Xu, 2022). The instrumental variables are strictly selected according to the Sargan tests estimation to ensure the effectiveness of tested results (all Sargan-p values are larger than 0.1) (Yuan, 2019). Lastly, the DID model is applied to further verify the robustness of the results. Further, the key values of placebo tests confirm that the positive moderation effect found in this paper is indeed caused by the IER.

The paper concludes with the following main findings. First, the environmental outcomes of GKI can be efficiently promoted by environmental regulations, as evidenced by the change of sign, from 0.130 to −0.428, of the coefficient of GKI in the benchmark model. However, the effect of GPI is unstable. GKI is typically more advanced than GPI and has the potential to bring sustained competitive advantages to firms. Therefore, the results suggest that in China, the synergistic effect of environmental regulations performs well but is only stable in promoting the emissions reduction effect of more advanced green innovation. Second, regarding the effectiveness of different types of environmental regulations, both CER and IER promote the CO_2 emissions reduction effect of GKI significantly (e.g. in benchmark results, both coefficients of CER*GKI (−8.887) and IER*GKI (−0.193) are significant at 5% level). In particular, stimulated by IER, firms are more likely to invest heavily in more advanced GKI, enabling them to achieve a higher emissions reduction target. However, a different picture emerges for EER. It has a significant negative moderating effect on the relationship between GKI and emissions reduction. As firms are profit-oriented, when paying pollution penalties becomes more economical, they may reduce efforts in green innovation and CO_2 emissions control. Although this may bring short-term benefits to firms, it may damage their reputation and growth potential over the long run.

All these findings remain robust when considering spatial factors and regional heterogeneity. ER is confirmed to be effective in moderating the relationship between green knowledge innovation and CO_2 emissions reduction among both local and neighbouring regions, as suggested by the estimated coefficients of ER*GKI (direct effect: 0.320, significant at 1% level and indirect effect: 0.504, significant at 5% in Table3a). This is consistent with the spillover and positive demonstration effects. GKI remains the most effective type of green innovation chosen by firms for carbon emissions reduction as it may benefit firms over the long-term period. Meanwhile, regarding regional heterogeneity, the ER is found to be effective in promoting the impact of GKI on CO_2 emissions reduction for the relatively well-developed eastern region only (e.g. the coefficients of ER*GKI (−0.104) and IER*GKI (−0.037) are both significant at 10% level for the eastern region but insignificant when middle and western regions are under investigation). This is as expected. With large amounts of FDI and a well-developed economic infrastructure, it is unsurprising that investment-led policies will further stimulate firms' innovation capacity, leading to the development of more advanced green technologies, and hence, carbon emissions reduction. However, in other regions, environmental regulations fail to positively moderate the impact of green innovation on CO_2 emissions reduction.

[7] That is, IER2 is a policy year dummy variable measuring the impact of GCG2012, which equals one if the year is after 2012, and zero otherwise.

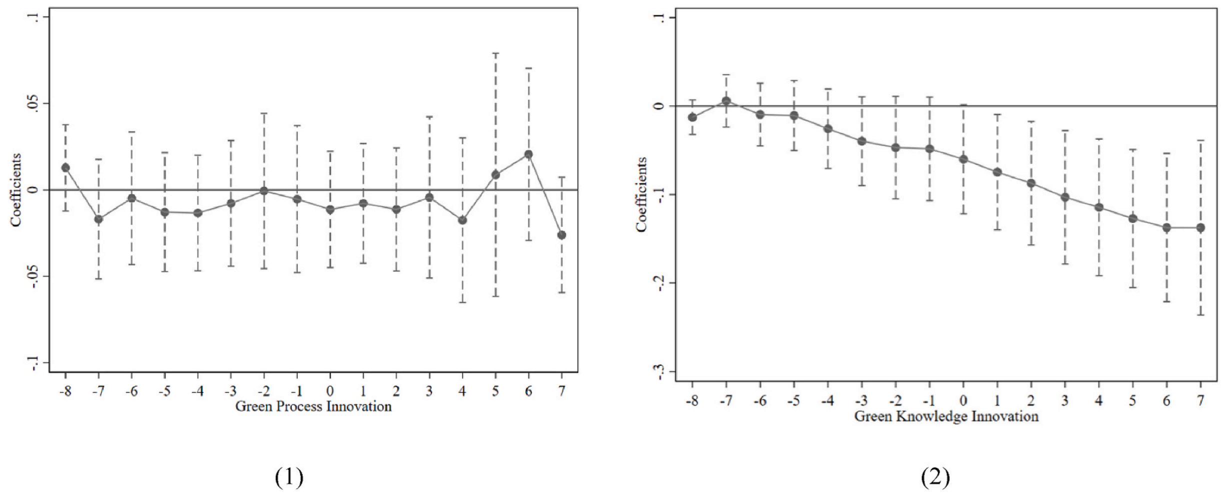

Fig. 3. Parallel Trends Assumption Results for the DID model (GPI and GKI).

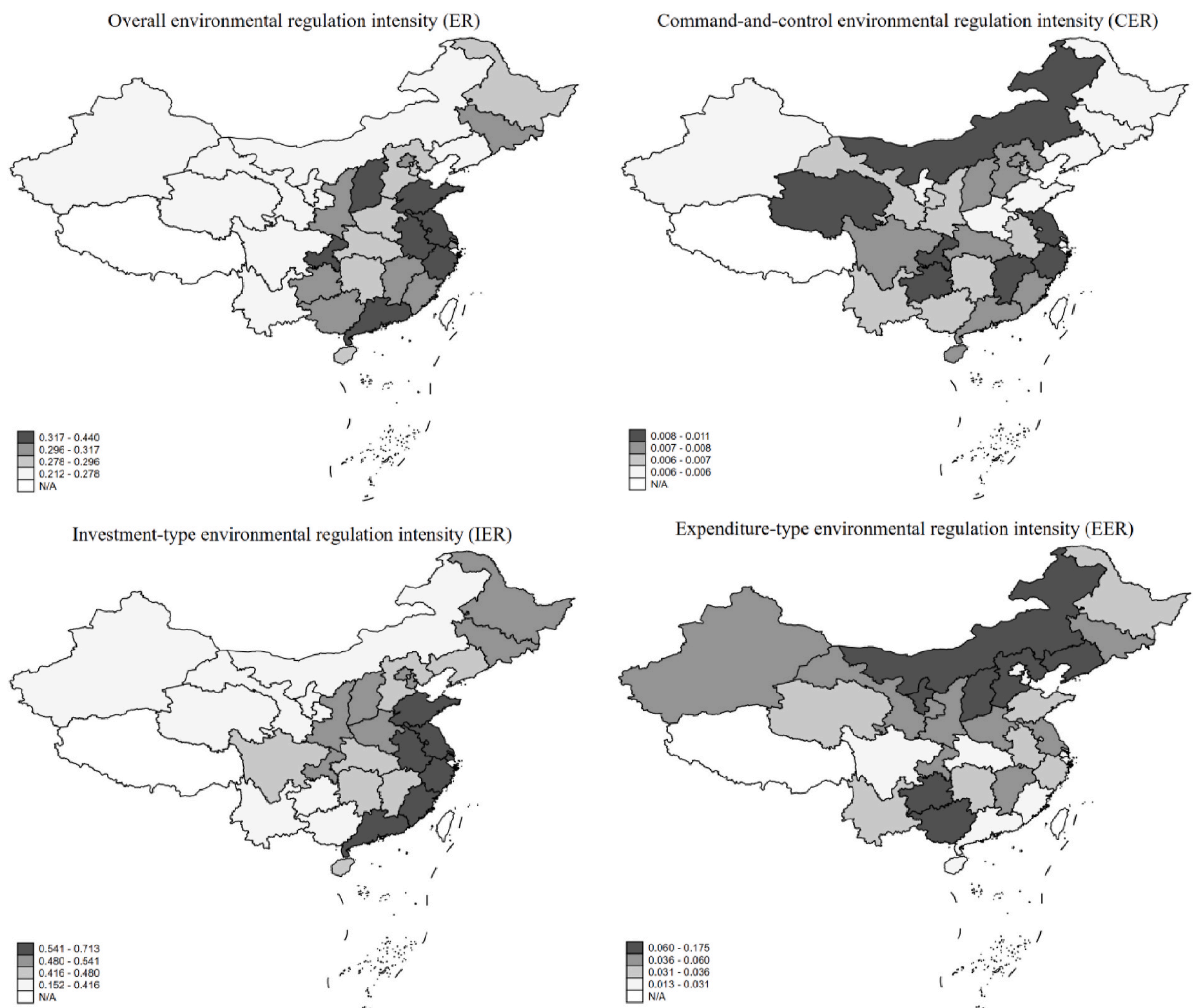

Fig. 4. Graph 1. The average intensity of environmental policy instruments in China, by province
Note: This graph depicts the average intensity of the four proxies for environmental regulations (ER, CER, EER and IER) for different provinces in China. For each province, the average intensity of each proxy is calculated as its simple average value across the sample period.

The main contribution of this paper lies in the following aspects. First, the paper provides empirical evidence in support of the PH in an emerging market. Through comprehensive analysis of the relationship between environmental regulations, green innovation, and CO_2 emissions in the Chinese market, it identifies the importance of environmental regulation in shaping more advanced and long-term green innovation. Moreover, the paper analyses the heterogeneity of environmental regulations, green innovation and regions, which will be helpful for better understanding the efficiency of different policy instruments in the Chinese context and supplementing the PH under different scenarios. Consequently, successful practices can be generalised to other developing countries, accelerating the process of carbon neutrality globally.

5.2. Policy implications

Overall, the empirical analysis suggests that current environmental regulations are effective in moderating the emissions reduction effect of green innovation to some extent, especially for more advanced innovation. The Chinese government should effectively use different environmental policy tools in combination to stimulate their synergistic effects. As the country is moving towards the market economy, the government should make the market-based regulatory instrument play a more dominant role in directing firm behaviours. In this case, IER should be more widely adopted as the main regulatory tool for CO_2 emissions reduction. The further development of the Chinese green finance system is necessary to complement the effectiveness of such policy instruments. Meanwhile, the government should limit the use of expenditure-type environmental regulations, especially for less developed regions, as it may encourage short-termism and opportunistic behaviours of firms.

Further, knowledge-based green innovation may assist firms in achieving long-term sustained growth, while process innovation may be only temporary or window dressing. Effective mechanisms can be designed to facilitate the collaboration of green innovation among big firms, and/or research institutions. This can facilitate information dissemination, and reduce costs and risks faced by all participants. Simultaneously, more stringent laws and regulations on intellectual property protection should be implemented by the Chinese government to protect the legitimate rights of innovators and increase market confidence. As the environmental regulation system matures and improves gradually, the positive effects of green innovation in reducing CO_2 emissions are more likely to strengthen in the future. Therefore, reform efforts and innovation incentives should be continuously initiated. The green sustainable and corporate development goals should also be coordinated to further leverage the positive effect of environmental regulations and green innovation on CO_2 emissions reduction.

5.3. Limitations and possible future work

Although CO_2 is a key component of greenhouse gas (GHG), achieving carbon neutrality requires considering other GHGs, such as nitrous oxides, as well. Therefore, when data becomes accessible, a more comprehensive measurement of GHG emissions should be constructed for future research to testify to the effectiveness of different policy instruments. Furthermore, finance is a key variable to influence sustainable outcomes. Along with the evolution of China's green finance market, more comprehensive and reliable data could be available for further research. In particular, a broader range of financial instruments, such as green bonds and green insurance can be evaluated, to understand their impact on firms' emission reduction and innovation behaviours. This would facilitate the drawing of useful experiences to assist the green transformation process among other developing economies.

Credit author statement

Kaiwen CHANG: Methodology, Formal analysis, Software, Writing–Original Draft Preparation, **Lanlan LIU**: Formal analysis, Writing–Reviewing and Editing, **Dan LUO**: Conceptualization, Methodology, Writing–Reviewing and Editing, **Kai XING**: Resources; Software.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2023.117990.

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