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Innovation-driven industrial green development: the moderating role of regional factors

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Abstract

Industrial green development (IGD) is a critical response to the over-consumption of natural resources and pollution caused by modern industry. Innovation-driven IGD has generated great interest in recent years. However, relatively less attention has been paid to the various aspects of IGD and the moderating role of regional factors, including the developmental stage of IGD, government-scale, and enterprise-scale. The present study was conducted to fill these research gaps using panel data across 30 provinces in China from 2005 to 2015. The empirical results show that 1) innovation does promote IGD and is most effective in low-carbon production, followed by resource reduction, economic operation, and pollution abatement; 2) there is an inverted U-shaped relationship between the regional IGD level and the role of innovation in IGD; and 3) both government-scale and enterprise-scale contribute to the innovation-driven IGD. These findings provide new insights into the impact of innovation on IGD and may shed light on future decisions related to green development.

Keywords

Innovation; Industrial green development; Developmental stage; Government-scale; Enterprise-scale

1. Introduction

China has emerged as the world's largest manufacturer. Its industry value-added reached US\$4.95 trillion in 2017, ranking the highest among all countries and contributing to nearly a quarter of the world total ([World Bank, 2018](#)). However, the achievement of industrial growth is accompanied by severe environmental cost; it consumed approximately 70% of energy sources and emitted 80% of sulfur dioxide (SO₂) and dust. In order to mitigate the detrimental effect on natural resources and the environment, industrial green development (IGD) has been proposed as a goal in the national innovation strategy.

The role of innovation in IGD has been discussed extensively in the literature (details are provided in Section 2). Most previous studies pointed to the positive effects of innovation, showing that research and development (R&D) and technology improvement lead to green development ([Jaffe et al., 2002](#); [Lin and Nelson, 2017](#); [Shao et al., 2016](#)). But on the other hand, innovation has also been found to increase production capacity which leads to a higher consumption of natural resource as well as pollution ([Wang et al., 2014](#); [Zhao et al., 2010](#)). Our study joins the debate and presents evidence from a different perspective. We expect that the role of innovation in IGD varies with the contextual factors for each region, such as the developmental stage of IGD, the role of government and industry. These factors interact with the level of innovation and jointly affect IGD. The relationships are tested using system generalized method of moments (GMM), panel quantile regression, and fixed-effects panel threshold methods.

The remainder of the study is structured as follows: Section 2 provides a literature review and discusses the relationship between relevant factors. Section 3 describes the variables, data, and models used for empirical tests. Section 4 presents the results, and Section 5 contains a brief summary, conclusions, and recommendations.

2. Literature review and theoretical analysis

This section discusses the relationship between innovation and IGD and evaluates the moderating role of three factors (developmental stage of IGD, government-scale, and enterprise-scale) in innovation-driven IGD.

2.1 Innovation and IGD

Innovation contributes to IGD in several ways. It increases resource productivity (Dangelico and Pujari, 2010), reduces carbon emission intensity (Zhou et al., 2010), improves water-saving and wastewater treatment efficiency, reduces air pollution (Levinson, 2009) and other environmental risks (Dangelico and Pujari, 2010), enhances waste treatment, and allows for more efficient resource recycling (De Marchi, 2012).

In 1996, the American Society of Manufacturing Engineers proposed the concept of green manufacturing, wherein enterprises can minimize the negative environmental impacts via environmental design, production, and treatment. Walker and Preuss (2008) divided green technological innovation into green product innovation, cleaner process innovation, end-technology innovation, and other categories; green technology can also be classified as cleaner production technology, waste recycling technology, as well as pollution treatment and prevention technology. In the present study, we analyzed the effect of innovation on IGD in three stages of the industrial process: upstream design, midstream production, and downstream disposal.

In the upstream design stage, innovation can strengthen the utilization of clean energy sources (e.g., natural gas, solar power, and electricity) instead of high-carbon energy sources (e.g., coal and petroleum), and enhance the application of environmentally friendly and renewable materials. Moreover, innovation is indispensable in designing eco-friendly products which are sufficiently lightweight, energy-efficient, easy to recycle, and high-quality. The Organization for Economic Co-

operation and Development has stressed that enterprises should prevent pollution in their product and process designs (Koomey, 2007).

In the midstream production stage, energy consumption and waste gas emissions can be reduced by adopting advanced technologies in clean coal utilization system along with combined heat and power system. Besides, technological innovation is also the primary driving force in improving the energy efficiency of conventional equipment such as boilers, motors, and transformers. Fernando et al. (2016) suggested using environmental technologies and equipment to reduce environmental impacts. Innovation also contributes to intelligent production, which enhances the full use of idle resources, dynamic management of energy utilization, and the operation of the pollution control system.

In the downstream disposal stage, innovation contributes to the recycling of wastes, remanufacturing of waste products, and reuse of waste heat. These contributions can improve resource productivity. Technological progress can also have a positive impact on treating industrial wastes, including wastewater, waste gas, and solid waste.

While innovation has shown various positive effects on IGD, it may also bring negative ones. Fisher-Vanden and Wing (2008), for example, noted that technological innovation can give rise to excess energy consumption and carbon emissions in a phenomenon called the Jevons paradox (Gunderson and Yun, 2017). This paradox occurs because innovative technologies can significantly increase production capacity, which leads to an increase in energy consumption and pollution. In addition, some new products are benefit-oriented rather than green-oriented; the materials used in these new products may also cause high energy consumption and pollution. Acemoglu et al. (2012) found that new technologies can be divided into clean and pollution-based categories and there is path-dependence in the environmental impacts of technologies. A newly developed technology often

exacerbates pollution if the original technology is not environmentally friendly. Moreover, there may also be an inverted U-shaped relationship between innovation and environmental impacts (Feng and Yuan, 2016; Mensah et al., 2018). Technological progress may start with a detrimental effect before it begins to exert a positive effect on the environment, similar to the mechanism of the environmental Kuznets curve (Grossman and Krueger, 1991).

As shown in Fig. 1, we established a theoretical model of the relationship between innovation and IGD, where a positive impact is indicated by a solid line together with a plus sign, while a negative impact is indicated by a dotted line together with a minus sign.

Fig. 1. Impacts of innovation on industrial green development

2.2 Developmental stage of IGD

An increasing developmental stage of IGD may mediate the impact of innovation on IGD both positively and negatively. Regions with a low-IGD-level to start with may benefit more from innovation as they are likely to have higher improvement potential, low technology threshold, and late-mover advantage.

Improvement potential. Regions with a low-IGD-level usually have a large proportion of energy- and pollution-intensive industries, with greater potential in industrial upgrading and green development. By contrast, high-IGD-level regions may have already optimized resource utilization with environmentally friendly technologies, processes, and equipment. Hence, innovation has more room to play its role in low-IGD-level regions.

Technology threshold. High-IGD-level regions are usually closer to the technological forefront than low-IGD-level regions. Due to increasing international competition for green technology, developed countries are likely to restrict the transfer of cutting-edge green technologies, leaving high-IGD-level regions in developing countries less able to further upgrade their (already advanced) technologies.

Late-mover advantage. Late-mover regions can directly absorb technologies from advanced regions and the costs of innovation are much lower than those in regions adopting innovation earlier. Brezis et al. (1993) noted that by directly absorbing high-tech technologies or emerging technologies, late-mover regions can achieve “leapfrogging” in technological advancement. Late-mover regions also have the opportunity to free-ride leading regions by learning from their experiences and lessons (Von Hippel et al., 2006).

On the other hand, low-IGD-level regions may be at a disadvantage due to the lack of technology and public support, as well as the path dependence.

Technology and cost. As one of the cutting-edge technologies, the green technology needs adequate innovative factors such as knowledge, technology, capital, and talent as inputs. Hence, it is difficult for low-IGD-level regions, with limited green innovative factors, to conduct green innovation.

Public support. Compared with their low-IGD-level counterparts, high-IGD-level regions generally receive more support from the government such as green financial subsidies, taxation and credit support, and have higher public awareness of environmental issues. These benefits could effectively strengthen green innovation and thus promote IGD.

Path-dependence. The path-dependence theory suggests later events in a given series of events are closely related to previous events (North, 1991). First-generation technology could form an advantageous self-enhancement cycle due to first-mover advantage (Redding, 2002). Therefore, resources such as technology, capital, and talents are usually centralized in high-IGD-level regions, leading to scale and spillover effects, which may “lock” these regions into a virtuous cycle.

The role of regional IGD level in innovation-driven IGD is illustrated in Fig. 2.

Fig. 2. Moderating role of regional IGD level in innovation-driven IGD

2.3 Government-scale

Government-scale expansion can strengthen the impact of innovation-driven IGD. According to the externality theory, market failures on environmental issues are caused by inconsistency between private costs and social costs (Stiglitz, 1988). The government can expand its scale to efficiently address such failures (Glemarec and de Oliveira, 2012). For instance, the government can adopt policy instruments to allocate property rights to the natural environment and economy (Bromley, 1991) and internalize the external social costs of detrimental industrial activities, which could encourage enterprises to enhance their green technological innovation.

In terms of administrative functions, government-scale expansion strengthens environmental regulation effects, which are essential in compelling enterprises to adopt environmentally friendly practices (Cumming, 2007). Light environmental penalties are not effective given the high costs of cleaner production practices. The government can also affect environmental practices in manufacturing enterprises by monitoring them closely (Ghosh and Shah, 2012; Koh et al., 2012). Porter and Vanderlinde (1995) found that environmental regulation leads to the increased technological level as well as resource productivity, and brings about “innovation offsets”, which can offset the costs generated by the environmental regulation.

Unlike enterprises, the government usually has a long-term plan for green development. IGD policies are designed to encourage enterprises to perform green innovation (Martinelli and Midttun, 2010), and promote the development of green industries such as new energy, energy conservation, and environmental protection industries. However, the implementation of green innovation is costly in the short term, with uncertain returns; enterprises thus have little incentive to adopt green innovation practices. To address this issue, the government can intervene by increasing green R&D investment, purchasing green products, and strengthening taxation incentives to lower R&D costs. In

addition, the government can encourage enterprises to innovate and reduce pollution and greenhouse gas emissions by allocating emission rights in the market (Coase, 1960) and highlighting the role of emission tax (Villegas-Palacio and Coria, 2010).

On the other hand, government-scale expansion may have undesirable results, such as excessive bureaucracy and low administrative efficiency due to increased administrative units and paperwork. An expanding government-scale may also lead to rent-seeking, thus reducing the incentive for enterprises to adopt green innovation. Even worse, an increase in government-scale can result in unclear responsibilities, inconsistent goals, and conflicts due to the difference in departments' interests. These problems hinder the coordination between departments, thereby reducing organizational efficiency for promoting green development. The role of government-scale in innovation-driven IGD is shown in Fig. 3.

2.4 Enterprise-scale

An increase in enterprise-scale can enhance innovation-driven IGD for reasons such as economies of scale, better financial and human resources, and more corporate social responsibilities. The comparative advantage theory suggests that economies of scale can lead to comparative advantages (Krugman, 1987). Original innovation requires a large number of fixed asset investment; only by expanding the innovation scale can enterprises reduce their unit cost of innovation. The expansion of enterprise-scale improves technological innovation efficiency owing to technology spillover effects, the sharing of innovation resources, and “offset effects” (Pavitt et al., 1987).

Schumpeter (1942) proposed that large enterprises are more suitable for technological innovation due to their advantage in financial and risk-taking capabilities. Green technologies are characterized by massive R&D investment, strong externalities, unclear prospects in applications, and uncertainty in returns (Comanor, 1967). Implementing a new green technological practice

requires reinvestment for new production devices, which is costly for small enterprises.

Small enterprises are also less likely to have adequate capital for green R&D, which can be detrimental to continuous innovation. By contrast, large enterprises have a large pool of scientific and technological talents that are essential in reaching the technological forefront of green innovation. Large enterprises are also more likely to be supported by sufficient capital and preferential policies from financial institutions and government, which propels green innovation ([Beck et al., 2005](#); [Schumpeter, 1942](#)).

In addition, large enterprises, especially state-owned enterprises, often have high corporate social responsibilities in exchange for political resources. They are also more focused on their brand value and may prioritize environmental practices such as green innovation to improve customer perception.

Despite all the advantages, an increase in enterprise-scale may have some undesirable effects as well. Scholars have observed an inverted U-shaped relationship between enterprise-scale and innovation capability ([Mei and Shao, 2016](#); [Zhu et al., 2018](#)). Too large a scale may result in over-complicated organizational rules and structures, leading to rigidity in management. Small enterprises are more efficient in innovation due to organizational flexibility, direct internal communication, and quick responses to market demands. Furthermore, a market full of large-scale enterprises or monopolistic enterprises may lack competition that is necessary to stimulate innovation.

The impact of enterprise-scale on innovation-driven IGD is shown in Fig. 4.

Fig. 3. Moderating role of government-scale in innovation-driven IGD

Fig. 4. Moderating role of enterprise-scale in innovation-driven IGD

3. Data and methodology

3.1 The dependent variable: IGD performance

The dependent variable IGD is a composite indicator. Based on previous literature (OECD, 2017; UNEP, 2011; UNIDO, 2011), the core objective of IGD is to reduce the industrial resource consumption and undesirable environmental impacts (pollution and CO₂ emissions) while promoting industrial economic growth. Hence, we established an index system with four themes: economic operation, resource reduction, pollution abatement, and low-carbon production based on previous practices (Hara et al., 2009; Hashim et al., 2014; Song et al., 2016).

Similar to Zhen et al. (2009), the weights of themes are equal whereas the weights of indices are different. We gave an equal weight of 0.25 to each of the four themes because: (1) the goal of green development is multiple and each theme is equally essential; and (2) themes with equal weight are widely adopted in environmental research (Allevi et al., 2018; Hu et al., 2018).

We then selected 20 indices based on the literature and data availability. The index systems are presented in Table 1. For performance evaluation, specific indices are usually of different importance to an overall goal. We thus chose the global factor analysis method to determine the weights of the 20 indices. This method reveals dynamic information from panel data and potential relevance between indices as well as reducing the information overlap between multiple indices (Jia and Lu, 2010). Based on the determined weights, we carried out a weighted-TOPSIS to measure the performance of IGD. The weighted-TOPSIS allows for full use of the original data, minimal information loss, and no strict control over data (e.g., sample size and number of indices) (Kaur et al., 2018).

Table 1. Index system for IGD performance evaluation

Theme	Index	Weight	Attribute	References
Economic operation	Industrial added value per worker (ten thousand yuan/per capita)	0.35	Positive	(Chen et al., 2016; Jiang et al., 2018; Wang et al., 2018)
	Ratio of profits, taxes, and interests to industrial average assets (%)	0.08	Positive	
	Ratio of profits to total industrial costs (%)	0.10	Positive	
	Share of sales revenue from high-tech industries in total industries (%)	0.47	Positive	
Resource reduction	Energy consumption per unit of industrial added value (ton/ten thousand yuan)	0.20	Negative	(Chen et al., 2016; Huang et al., 2018; Tan and Lu, 2015; Wang et al., 2018)
	Water consumption per unit of industrial added value (ton/yuan)	0.18	Negative	
	Solid wastes generated per unit of industrial added value (ton/ten thousand yuan)	0.19	Negative	
	Land used area per unit of industrial added value (square meters/one hundred yuan)	0.18	Negative	
	Ratio of industrial water reused (%)	0.06	Positive	
	Ratio of industrial solid wastes utilized (%)	0.19	Positive	
Pollution abatement	Wastewater discharged per unit of industrial added value (ton/ten thousand yuan)	0.10	Negative	(Chen et al., 2016; Cheng et al., 2016; Tan and Lu, 2017; Yin et al., 2014)
	Waste gas emissions per unit of industrial added value (ton/ten thousand yuan)	0.10	Negative	
	COD discharged per unit of industrial added value (ton/ten thousand yuan)	0.12	Negative	
	Ammonia nitrogen discharged per unit of industrial added value (ton/ten thousand yuan)	0.12	Negative	
	Sulfur dioxide emissions per unit of industrial added value (ton/ten thousand yuan)	0.12	Negative	
	Nitrogen oxides emissions per unit of industrial added value (ton/ten thousand yuan)	0.13	Negative	
	Soot (dust) emissions per unit of industrial added value (ton/ten thousand yuan)	0.13	Negative	
	Ratio of industrial water reused (%)	0.10	Positive	
	Ratio of industrial solid wastes disposed and utilized (%)	0.08	Positive	
Low-carbon production	Carbon dioxide emissions per unit of industrial added value (ton/ten thousand yuan)	1.00	Negative	(Dong et al., 2018)

3.2 Independent and control variables

The independent variable, innovation (*Inn*) is measured by the share of industrial R&D expenditure in overall industrial expenditure, which captures the intensity of industrial innovation in the region. Government-scale (*GS*) is measured by the proportion of public expenditure to GDP (Aidt and Jensen, 2009; Persson, 2002) and enterprise-scale (*LnES*) is measured as the log transform of the average sales revenue per industrial enterprise, both used as threshold variables.

The control variables are as follows:

(1) Industrial cleaner structure (*ICS*). The ICS represents the industries' dependence on natural resource and environment, which affects the region's IGD performance.

(2) Unemployment (*Une*). The Institute of Industrial Economics of the Chinese Academy of Social Sciences noted that 3.96 million jobs would be lost if China achieves the goal of saving 9.1 billion tons of standard coal from 2011 to 2020 (CASS, 2011). Therefore, the government may be refrained from promoting IGD at the expense of a high unemployment rate.

(3) Public environmental awareness (*LnPEA*). A large number of industrial projects have been rebuilt or even suspended due to public protests, so the level of public awareness is an indispensable factor in promoting IGD.

(4) Environmental regulation (*LnER*). On the one hand, environmental regulation may urge industrial enterprises to implement green production. On the other hand, environmental regulations from the supply side can enable energy owners to accelerate energy exploitation due to rising energy prices in the future, thereby resulting in the "green paradox" (Gerlagh, 2011; Smulders et al., 2012).

(5) Foreign direct investment (*FDI*). FDI can bring advanced cleaner production technologies and technological spillover effects, thus improving the environment in the host country and creating

a “pollution halo” (Levinson, 2009). But on the other hand, foreign enterprises are likely to transfer polluting industries to less developed regions with lower environmental standards; FDI may thus deteriorate the local environment and cause a “pollution haven” (Tiwari et al., 2013).

3.3 Data

The unit of analysis in this study is the province in China. The data were drawn from the 2006-2015 *China Statistical Yearbook*, *China Industry Statistical Yearbook*, *China Statistical Yearbook on Environment*, *China Statistical Yearbook on Science and Technology*, *China Energy Statistical Yearbook*, *China Environment Yearbook*, *China Statistical Abstract*, and the statistical yearbook of each province. All monetary variables were converted to real values (in 2005 prices) as per the producer price indices of industrial products. A logarithm was applied to eliminate heteroskedasticity in the non-proportional and non-standardized variables. The linear interpolation technique was used when required to fill in missing data. Table 2 presents the descriptions of the variables and the sources of data.

Table 2. Variable descriptions

	Variable	Description	Source
Dependent variable	<i>IGD</i>	Performance of IGD	Index variable; see Table 1
Independent variable	<i>Inn</i>	Ratio of industrial expenditures on R&D to sales revenue	China Statistical Yearbook on Science and Technology
Threshold variable	<i>GS</i>	Ratio of public expenditure to GDP	China Statistical Yearbook
	<i>LnES</i>	The log of average sales of industrial enterprises	China Industry Statistical Yearbook
Control variable	<i>ICS</i>	Share of sales revenue from energy- and pollution-intensive industries in total industries	China Energy Statistical Yearbook China Statistical Yearbook on Environment
	<i>Une</i>	Unemployment rate	China Statistical Yearbook
	<i>LnPEA</i>	The log of petitioner cases for	China Environment Yearbook

	environmental issues		
<i>LnER</i>	The log of environmental administrative punishment cases	China Environment Yearbook	
<i>FDI</i>	FDI as % of GDP	China Statistical Yearbook	

Table 3 shows the correlation coefficient matrix and descriptive statistics of the dependent variable and independent/control variables. The dependent variable *IGD* is significantly correlated with the independent/control variables. The variance inflation factor (VIF) test shows that there is no severe multi-collinearity among the selected independent/control variables (VIF <10).

Table 3. Correlation coefficient matrix and descriptive statistics

Variable	<i>IGD</i>	<i>Inn</i>	<i>ICS</i>	<i>Une</i>	<i>LnPEA</i>	<i>LnER</i>	<i>FDI</i>
<i>IGD</i>	1.000						
<i>Inn</i>	0.580	1.000					
<i>ICS</i>	-0.636	-0.479	1.000				
<i>Une</i>	-0.431	-0.289	0.195	1.000			
<i>LnPEA</i>	0.136	0.015	-0.223	0.200	1.000		
<i>LnER</i>	0.363	0.382	-0.361	-0.177	0.176	1.000	
<i>FDI</i>	0.490	0.415	-0.342	-0.118	0.155	0.148	1.000
Obs	300	300	300	300	300	300	300
Mean	0.642	0.006	0.290	3.540	-1.325	7.404	0.026
Std. Dev	0.090	0.002	0.074	0.643	0.989	1.330	0.019
Min	0.166	0.001	0.159	1.200	-6.954	2.079	0.001
Max	0.793	0.014	0.508	5.100	0.684	10.557	0.089
VIF	1.62	1.48	1.28	1.18	1.17	1.27	1.62

3.4 Regression models

We first set up a classical static panel model to test the effect of innovation on *IGD*, as shown in Eq. (1):

$$IGD_{i,t} = \beta_0 + \beta_1 Inn_{i,t} + \beta_2 ICS_{i,t} + \beta_3 Une_{i,t} + \beta_4 LnPEA_{i,t} + \beta_5 LnER_{i,t} + \beta_6 FDI_{i,t} + \delta_i + \varepsilon_{i,t}, \quad (1)$$

where *i* stands for the province, *t* represents the year, β_0 is the coefficient of the constant term, β_1 — β_6 are the coefficients of independent and control variables, δ_i denotes the individual effect,

and $\varepsilon_{i,t}$ is the error term.

Endogeneity needs to be addressed as it causes bias in the coefficient estimation. Endogenous biases usually come from two sources: missing variables and two-way causality (simultaneous). The fixed-effects model eliminates heterogeneity between individuals and minimizes the endogenous biases caused by missing variables. The two-way causality caused by the correlation between the current independent variable and the current error term can be addressed by using first-order lag terms of the independent variable or using generalized method of moments (GMM) or two-stage least squares model. Here, we used a two-step system GMM to conduct a robust estimation for the following reasons: (1) considering the heteroskedasticity, GMM is more efficient than the two-stage least squares; (2) compared to the one-step GMM, the two-step GMM better handles autocorrelation and heteroskedasticity; and (3) our data meets the requirements of GMM, i.e., the cross-section number of the panel data ($N=30$) is greater than the period number ($T=10$). The system GMM model is as shown in Eq. (2):

$$IGD_{i,t} = \beta_0 + \beta_1 Inn_{i,t} + \beta_2 ICS_{i,t} + \beta_3 Une_{i,t} + \beta_4 LnPEA_{i,t} + \beta_5 LnER_{i,t} + \beta_6 FDI_{i,t} + IGD_{i,t-1} + \delta_i + \varepsilon_{i,t}, \quad (2)$$

where $IGD_{i,t-1}$ is the first-order lag term of the dependent variable.

We also applied a panel quantile regression model to test the impact of innovation on IGD under different developmental stages of IGD, as shown in Eq. (3):

$$IGD_{i,t}^{\varphi} = \beta_0^{\varphi} + \beta_1^{\varphi} Inn_{i,t} + \beta_2^{\varphi} ICS_{i,t} + \beta_3^{\varphi} Une_{i,t} + \beta_4^{\varphi} LnPEA_{i,t} + \beta_5^{\varphi} LnER_{i,t} + \beta_6^{\varphi} FDI_{i,t} + \delta_i^{\varphi} + \varepsilon_{i,t}^{\varphi}, \quad (3)$$

where the superscript φ denotes the conditional quantile and $0 < \varphi < 1$.

In addition, we used the panel fixed-effects threshold model designed by Wang (2015) to test the scale threshold effect of government and enterprise, as shown in Eq. (4):

$$IGD_{i,t} = \beta_0 + \beta_1' x_{i,t} \theta(q_{i,t} < \gamma) + \beta_2' x_{i,t} \theta(q_{i,t} \geq \gamma) + \delta_i + \varepsilon_{i,t}, \quad (4)$$

where $\theta(q_{i,t} \leq \gamma)$ is the indicator function. If the expression is true, the value of θ is equal to 1 or otherwise 0; $q_{i,t}$ refers to the threshold variable, γ represents the threshold parameter in two regimes with coefficients β_1' and β_2' , and x denotes the vector of independent variables.

4. Results

4.1 Impact of innovation on IGD

Table 4 reports the results of static panel regression. Column (1) indicates that the regression coefficient of innovation is positive and significant at the level of 1%. In other words, innovation does contribute to IGD, and the “green effect” of innovation is greater than its “growth effect”. Industrial innovation makes energy, materials, equipment, production processes, pollution treatment, and products more environmentally friendly.

Innovation is further divided into two types: (a) basic and applied innovation, and (b) experimental development innovation. Column (2) shows that the coefficient of basic and applied innovation is insignificant. Basic and applied innovation, which centers on expanding scientific and technological knowledge, has no substantial impact on IGD; this type of innovation cannot be directly translated into green productivity. Column (3) shows that the coefficient of experimental development innovation is positive and significant at the level of 1%, indicating that experimental development effectively promotes IGD. Experimental development is necessary for developing cleaner production practices.

Table 4. Impact of innovation on IGD

Variable	(1) IGD	(2) IGD	(3) IGD	(4) EO	(5) RR	(6) PA	(7) LP
<i>Inn</i>	7.262*** (4.03)			8.771*** (3.36)	10.076*** (3.70)	6.305** (2.04)	10.778*** (3.85)

<i>Inn-a</i>		-1.609					
		(-0.23)					
<i>Inn-b</i>			6.799***				
			(3.83)				
<i>ICS</i>	-0.723***	-0.714***	-0.736***	-0.639***	-0.824***	-1.004***	-1.151***
	(-9.11)	(-8.72)	(-9.22)	(-5.55)	(-6.87)	(-7.36)	(-9.32)
<i>Une</i>	-0.057***	-0.068***	-0.057***	-0.094***	-0.089***	-0.092***	-0.066***
	(-7.76)	(-9.66)	(-7.83)	(-8.85)	(-8.08)	(-7.33)	(-5.85)
<i>LnPEA</i>	0.008***	0.008***	0.008***	0.013***	0.011***	0.001	0.008*
	(3.09)	(2.85)	(3.27)	(3.43)	(2.88)	(0.15)	(1.92)
<i>LnER</i>	0.003	0.002	0.002	0.008*	0.000	-0.006	0.002
	(0.84)	(0.68)	(0.75)	(1.72)	(0.08)	(-0.99)	(0.44)
<i>FDI</i>	-0.105	-0.410	-0.173	-0.094	-0.488	-0.632	-0.023
	(-0.34)	(-1.31)	(-0.56)	(-0.21)	(-1.04)	(-1.18)	(-0.05)
<i>C</i>	0.999***	1.094***	1.014***	0.674***	1.238***	1.477***	1.332***
	(20.24)	(24.44)	(20.98)	(9.41)	(16.60)	(17.40)	(17.34)
<i>N</i>	300	300	300	300	300	300	300
<i>Adj. R2</i>	0.454	0.420	0.450	0.409	0.396	0.316	0.383
<i>F</i>	47.216	41.939	46.686	40.346	38.518	28.880	36.767

Notes: EO: economic operation, RR: resource reduction, PA: pollution abatement, LP: low-carbon production.

* Significant at 0.1, ** Significant at 0.5, *** Significant at 0.01.

We also explored the effects of innovation on all four IGD themes. Columns (4)-(7) show that the coefficients of innovation are all positive and significant at the level of 1%. low-carbon production and resource reduction have the largest coefficient, followed by economic operation and pollution abatement. The result shows that innovation plays an active role in all four IGD themes, but is more effective in energy-savings than that in pollution treatment. Improving the level of resource reduction not only reduces the environmental impact, but also obtains considerable benefits by saving energy, water, and material resources. For example, electricity has become the major cost of most industrial enterprises, so it is preferable to focus on technical progress in reducing resource consumption such as electricity rather than pollution abatement.

Table 5 reports the regression results of different estimation techniques. Columns (8)-(14) show that in all models, the coefficients of innovation are positive and significant at the 1% level, and thus the empirical results are robust. Model in columns (11) deals with the possible heteroskedasticity

in short panel data ($N \gg T$) by the use of generalized least squares model. Columns (12)-(14) address the possible endogenous biases by respectively using the first-order lag term of the independent variable, the dynamic difference GMM, and the dynamic panel-system GMM. Furthermore, by the use of robust standard errors, the Hansen test shows the selected instrumental variables are statistically valid in difference GMM and system GMM models ($p=0.184$, $p=0.144$). The AR(2) test results ($p=0.548$, $p=0.380$) show that there is no autocorrelation, indicating that the difference GMM and system GMM models used in this study are statistically valid. The results remain consistent across different models.

Table 5. Results of different models

Variable	(8) OLS	(9) MLE	(10) RE	(11) GLS	(12) L.FE	(13) Dif- GMM	(14) Sys- GMM
<i>Inn</i>	7.441*** (4.42)	7.650*** (4.70)	7.660*** (4.66)	8.187*** (8.31)	7.638*** (4.05)	2.812*** (2.96)	3.917*** (2.70)
<i>ICS</i>	-0.451*** (-8.44)	-0.660*** (-9.29)	-0.658*** (-9.38)	-0.425*** (-9.05)	-0.727*** (-9.16)	-0.023 (-0.10)	-0.153 (-0.87)
<i>Une</i>	-0.038*** (-6.97)	-0.054*** (-8.18)	-0.054*** (-8.12)	-0.028*** (-7.05)	-0.060*** (-8.49)	-0.014 (-1.51)	-0.006 (-0.74)
<i>LnPEA</i>	0.005 (1.51)	0.008*** (3.17)	0.008*** (3.13)	-0.002 (-1.35)	0.008*** (3.03)	0.000 (0.13)	0.006* (1.90)
<i>LnER</i>	0.004 (1.42)	0.003 (0.96)	0.003 (0.96)	0.001 (0.70)	0.001 (0.32)	-0.003 (-1.20)	0.000 (0.07)
<i>FDI</i>	1.052*** (5.55)	0.155 (0.58)	0.163 (0.61)	0.567*** (4.05)	-0.099 (-0.32)	-0.389 (-0.85)	-0.020 (-0.04)
<i>L.IGD</i>						0.751*** (7.53)	0.705*** (9.14)
<i>C</i>	0.813*** (21.40)	0.961*** (20.81)	0.960*** (20.97)		1.023*** (21.85)		0.246** (2.10)
<i>N</i>	300	300	300	300	300	240	270
<i>Adj. R2</i>	0.606	/	/	/	0.454	/	/
<i>F</i>	77.774	/	/	/	47.254	/	/

Notes: OLS: ordinary least squares, MLE: maximum likelihood estimation, RE: random effect, GLS: generalized least squares, L.FE: fixed-effects with first-order lag term of the independent variable, Dif-GMM: difference generalized method of moments, Sys-GMM: system generalized method of moments.

* Significant at 0.1, ** Significant at 0.5, *** Significant at 0.01.

4.2 Moderating effects of regional factors

Table 6 reports the empirical results after considering the developmental stage of IGD, government-scale, and enterprise-scale. Columns (15)-(19) show the regression results incorporating regional IGD level. The results demonstrate that innovation coefficients are positive and significant at the 1% level on the main quantile points ($q=0.1$, $q=0.3$, $q=0.5$, $q=0.7$, and $q=0.9$). Coefficients are higher in the middle quantile point and lower in the two end quantiles, forming a non-monotonous trend. This trend is visualized in Fig. 5 with 95% confidence intervals.

Table 6. Effects considering the regional factors

Variable	(15) IGD ($q=0.1$)	(16) IGD ($q=0.3$)	(17) IGD ($q=0.5$)	(18) IGD ($q=0.7$)	(19) IGD ($q=0.9$)	(20) IGD	(21) IGD
<i>Inn</i>	9.659*** (3.51)	11.600*** (5.67)	10.666*** (7.65)	9.160*** (8.62)	6.581*** (3.72)		
<i>Inn</i> ($q_{i,t} < \gamma$)						5.371*** (3.31)	-0.883 (-0.39)
<i>Inn</i> ($q_{i,t} \geq \gamma$)						22.316*** (9.21)	3.679** (2.02)
<i>ICS</i>	-0.786*** (-6.78)	-0.426*** (-4.26)	-0.327*** (-5.80)	-0.280*** (-7.03)	-0.347*** (-6.78)	-0.878*** (-11.99)	-0.569*** (-7.10)
<i>Une</i>	-0.046*** (-6.54)	-0.035*** (-7.20)	-0.027*** (-8.09)	-0.024*** (-6.82)	-0.027*** (-5.52)	-0.037*** (-5.28)	-0.043*** (-5.95)
<i>LnPEA</i>	0.000 (0.03)	0.006 (1.48)	0.008* (2.11)	0.012*** (4.84)	0.0152** (2.55)	0.006*** (2.60)	0.007*** (2.73)
<i>LnER</i>	0.000 (0.07)	-0.000 (-0.09)	0.002 (0.57)	0.000 (0.22)	-0.003 (-1.00)	0.003 (0.97)	0.006* (1.78)
<i>FDI</i>	1.406*** (6.64)	1.044*** (4.07)	0.999*** (4.75)	0.921*** (6.12)	0.638*** (3.84)	0.029 (0.10)	-0.029 (-0.10)
<i>C</i>	0.865*** (16.20)	0.782*** (15.64)	0.749*** (18.70)	0.771*** (23.82)	0.876*** (21.93)	0.966*** (21.84)	0.918*** (18.73)
<i>N</i>	300	300	300	300	300	300	300
<i>Adj. R2</i>	/	/	/	/	/	0.565	0.509
<i>F</i>	/	/	/	/	/	60.735	49.495

Note: * Significant at 0.1, ** Significant at 0.5, *** Significant at 0.01.

Fig. 5. Quantile regression coefficient of innovation

As shown in Fig. 5, the impact of innovation increases along with the developmental stage of IGD and then decreases. Innovation makes the greatest contribution in the provinces with a medium range (30%-50%) of IGD level; this contribution gradually declines in both high and low ends of IGD level. In other words, there is an inverted U-shaped relationship between regional IGD level and the impact of innovation on IGD.

In terms of scale thresholds, Figs. 6 and 7 show the likelihood ratio and non-rejection region corresponding to the government-scale and enterprise-scale thresholds, respectively. The horizontal line in the figure shows the 95% confidence level, while the lowest point of the likelihood ratio (LR) represents the real threshold. Table 7 reports the statistical test of the panel fixed-effects threshold model. The results confirm that there are scale threshold effects caused by government and enterprise in the relationship between innovation and IGD. According to the scale thresholds, provinces were classified as being large-government-scale ($GS \geq 0.272$) and small-government-scale ($GS < 0.272$), as well as large-enterprise-scale ($LnES \geq 0.474$) and small-enterprise-scale ($LnES < 0.474$).

Fig. 6. Estimated threshold value and confidence intervals of government-scale

Fig. 7. Estimated threshold value and confidence intervals of enterprise-scale

Table 7. Threshold effect test

Variable	F value	P value	Critical value			Estimate value of the threshold	95% confidence level
			10%	5%	1%		
<i>GS</i>	76.02	0.000	29.28	34.91	44.71	0.272	[0.272, 0.282]
<i>LnES</i>	34.17	0.036	22.92	27.50	57.56	0.474	[0.423, 0.475]

Column (20) in Table 6 shows the regression results considering the government-scale

threshold. The coefficients of innovation are significant regardless of where government-scale falls in respect to the threshold value; however, the coefficient is significantly higher in provinces with large-government-scale ($GS \geq 0.272$). Innovation-driven IGD is more effective in provinces with higher government expenditure.

Column (21) in Table 6 shows the regression result after incorporating the enterprise-scale threshold. The coefficient of innovation is significant in provinces with large-enterprise-scale ($LnES \geq 0.474$), but insignificant in those with small-enterprise-scale ($LnES < 0.474$), where the impact of innovation-driven IGD is limited as the “green effect” of innovation does not significantly exceed the “growth effect”.

4.3 Robustness checks

The results are consistent across various regression estimation techniques as shown in Table 5. We would like to further test whether they are subject to changes in the choice of variables. In order to examine the effect of the inclusion of control variables, we added them one after another (Table 8). The innovation coefficients are still positive and significant at 1% level.

Table 8. Robustness check of the model structure

Variable	(22) IGD	(23) IGD	(24) IGD	(25) IGD	(26) IGD	(27) IGD
<i>Inn</i>	13.199*** (6.18)	12.937*** (7.12)	7.102*** (4.02)	7.428*** (4.26)	7.410*** (4.25)	7.262*** (4.03)
<i>ICS</i>		-0.883*** (-10.18)	-0.740*** (-9.32)	-0.717*** (-9.14)	-0.720*** (-9.16)	-0.723*** (-9.11)
<i>Une</i>			-0.059*** (-8.31)	-0.058*** (-8.18)	-0.056*** (-7.77)	-0.057*** (-7.76)
<i>LnPEA</i>				0.008*** (3.09)	0.008*** (3.08)	0.008*** (3.09)
<i>LnER</i>					0.003 (0.91)	0.003 (0.84)
<i>FDI</i>						-0.105 (-0.34)

<i>C</i>	0.559*** (40.77)	0.817*** (29.30)	1.023*** (29.12)	1.019*** (29.45)	0.993*** (22.16)	0.999*** (20.24)
<i>N</i>	300	300	300	300	300	300
<i>Adj. R2</i>	0.027	0.296	0.438	0.456	0.456	0.454
<i>F</i>	38.238	78.287	88.460	70.868	56.826	47.216

Note: * Significant at 0.1, ** Significant at 0.5, *** Significant at 0.01.

We also confirmed our results using a set of proxy variables. The independent variable *innovation* is measured using four different indicators: per capita patent applications from the industry (Model 28), per capita invention patent applications from the industry (Model 29), the proportion of full-time equivalent of R&D personnel in the industry (Model 30), and average education level in the industry (Model 31) (Table 9). All four innovation indicators remain positive and significant, which further demonstrates the robustness of our study.

Table 9. Robustness check of proxy variables

Variable	(28) IGD	(29) IGD	(30) IGD	(31) IGD
<i>Inn</i>	0.043*** (11.60)	0.040*** (13.39)	0.042*** (5.92)	0.925*** (15.33)
<i>ICS</i>	-0.464*** (-6.63)	-0.457*** (-6.93)	-0.649*** (-8.37)	-0.483*** (-7.88)
<i>Une</i>	-0.020*** (-2.90)	-0.012* (-1.76)	-0.042*** (-5.44)	-0.007 (-1.05)
<i>LnPEA</i>	0.006*** (2.96)	0.008*** (3.73)	0.009*** (3.62)	0.003 (1.61)
<i>LnER</i>	0.005* (1.74)	0.005* (1.91)	0.002 (0.57)	0.005** (2.16)
<i>FDI</i>	0.201 (0.78)	0.444* (1.78)	0.201 (0.65)	0.074 (0.32)
<i>C</i>	1.074*** (29.44)	1.064*** (30.73)	1.148*** (26.67)	0.788*** (20.62)
<i>N</i>	300	300	300	300
<i>Adj. R2</i>	0.616	0.655	0.488	0.693
<i>F</i>	85.710	100.272	53.324	118.460

Note: * Significant at 0.1, ** Significant at 0.5, *** Significant at 0.01.

5. Discussion and conclusions

The study has been among the first to examine the effect of innovation on IGD in the context of regional disparities. The existing literature has an extensive discussion on the impact of innovation, focusing on the benefit of resource efficiency, the growth of green productivity, and the recycling of the waste (Jaffe et al., 2002; Lin and Nelson, 2017; Shao et al., 2016). However, much less attention has been paid to the variation of impact across regions. The study contributes to the literature by bringing in the moderation effect of regional factors such as the developmental stage of IGD, government-scale, and enterprise-scale. Using panel data collected from 30 provinces in China during 2005-2015, we conducted an empirical test with an improved measurement model (i.e., global factor analysis-TOPSIS) and regression models including system generalized method of moments, panel quantile regression, and panel fixed-effects threshold.

The result confirms that innovation does promote IGD. Innovation is most effective on low-carbon production, followed by resource reduction, economic operation, and pollution abatement. The study also reveals an inverted U-shaped relationship between the developmental stage of IGD and the role of innovation in IGD. Regions with a medium level of IGD benefit the most from innovation. A high-IGD-level (top 50%) is accompanied by less potential for further IGD improvement and thereby limits the promoting effect of innovation. Regions with high-IGD-level are close to the technological forefront, and thus technical difficulties and costs of innovation can rise steeply while the benefits are incremental. Meanwhile, provinces with low-IGD-level (bottom 30%) are also at a disadvantage because green innovations have a high technology threshold. Enterprises in regions with low-IGD-level may not have adequate financial, technological and human resources to cross the technology threshold. It is also hard for regions with low-IGD-level to benefit from scale, spillover, and learning effects when their absorptive capacity is insufficient.

Both government-scale and enterprise-scale matter for the innovation-driven IGD. The effect of innovation is significantly higher in large-government-scale provinces ($GS \geq 0.272$) than that in small-government-scale provinces ($GS < 0.272$), which confirms that government expenditure contributes to the innovation-driven IGD. The government can promote green innovation by creating environmental policy instruments such as pollution abatement subsidies, environmental regulation, green credit, emission taxes, and green procurement. The externality caused by polluting industrial activities leads to market failures, which also requires the government to expand its functional scale and strengthen its intervention. Similarly, enterprise-scale is found to have a positive role as well. Regions with large enterprises are more successful in innovation-driven IGD. Green innovation involves high cost and risk, along with a long return period. Small enterprises tend to focus on production capacity and market share, and are generally less motivated to conduct innovation-driven IGD spontaneously. By contrast, large enterprises have an advantage as they are more likely to be supported by government and financial institutions and have adequate financial, technological and human resources for green innovation. Technology spillovers and economies of scale also provide large enterprises with more innovation opportunities. In addition, large enterprises need to maintain their reputation and are obligated with higher corporate social responsibility, so they are more motivated to achieve IGD via green innovation.

Exploring these effects generates new insights into more differentiated and effective decision-making related to innovation-driven IGD. Given the regional disparities, more targeted practices should be in place as a one-size-fits-all approach may not be effective. The innovation-driven practices need to be enhanced to promote IGD via a series of environmental policy instruments including finance, taxation, and credit. Innovation is most effective in regions with a medium-IGD-level, or large government and enterprises scales. More emphasis needs to be placed in these regions

to adopt innovation and promote green development. Other regions with factors mitigating the effectiveness of innovation require additional effort to remove the hindrance. For instance, in regions with small-government-scale, it is advisable to expand public spending and enhance government intervention through financial and regulative measures. Small enterprises call for special attention and should be supported by preferential policies and resources to support them in mitigating the cost and risks associated with green innovation.

Highlights:

- Innovation significantly contributes to industrial green development.
- IGD level shows an inverted U-shaped relation with the role of innovation in IGD.
- Large-government-scale enhances innovation-driven IGD.
- Large enterprises have an advantage in promoting innovation-driven IGD.

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