Global NEST Journal, Vol 27, No 6, 07317

Does Air pollution affect the green innovation of industrial enterprises? Insights from Urban Sewage Control Policies in China

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Received: 31/01/2025, Accepted: 23/04/2025, Available online: 29/04/2025
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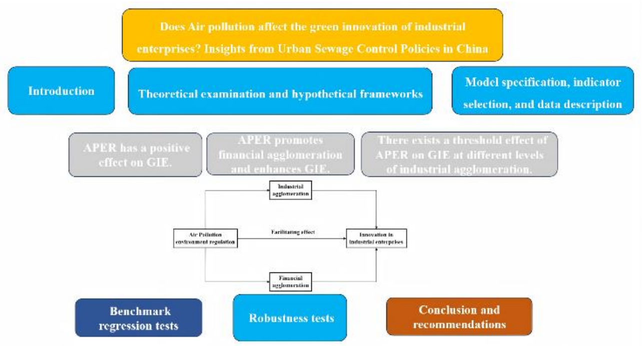
https://doi.org/10.30955/gnj.07317

Graphical abstract



Abstract

Environmental protection and technological innovation are key strategies for transforming economic development and have long been a focus of research. Environmental regulation plays a vital role in addressing the externalities of environmental governance and fostering corporate innovation. This study analyzes panel data from 28 manufacturing sectors in Shandong Province over the period from 2012 to 2023. It assesses the changes in environmental regulation levels that industrial firms face, focusing on pollution reduction initiatives under China's emission control policies from *the 12th to the 14th Five-Year Plans*. Using the System GMM method, the study investigates the impact and mechanisms of air pollution environmental regulation (APER) on the efficiency of green innovation (GIE) in industrial enterprises, while also considering the spatial and temporal dynamics of air pollution. The results show that WPER significantly enhances GIE at the 1% significance level. Threshold analysis reveals a notable double-threshold effect of industrial agglomeration on the influence of APER on green innovation efficiency. Specifically, when industrial agglomeration is below a certain threshold, APER promotes industrial innovation. However, when the industrial agglomeration surpasses another threshold, the positive effect of APER on GIE diminishes. This study provides valuable insights into the effectiveness of APER in tackling environmental pollution and offers policy recommendations for promoting corporate innovation and balanced environmental development.

Keywords: Air pollution, environmental regulation, technological innovation, manufacturing industry, pollution reduction

1. Introduction

Environmental pollution and ecological imbalance have become critical threats to human existence (Wang & Ma, 2024). With the advancement of economy, industrialization, and urbanization in China, severe degradation of the ecological environment has occurred (Wang *et al*., 2024). The perception of sustainable development has emerged as a pivotal pillar for achieving high-quality economic development in the country. Environmental regulation theory posits that governments can productively address the "market failure" due to green technological innovations through environmental guidelines (Kriecher *et al*., 2009; Ma *et al*., 2024). This is because the uncertainty of environmental policy's impact on technological innovation institutional factors can give rise to the redesign of enterprise innovation elements and changes in innovation directions, priorities, and scales (Wen *et al*., 2024b). Therefore, government implementation of environmental regulatory policies aims to restrain and contain the negative consequences of exploiting environmental resources through public means, while supporting policies for enterprises aim to maximize the positive impacts generated by green technological innovations and stimulate their investments in green R&D (Li & Gao, 2022; Zou *et al*.,2024). On the other hand, environmental regulation involves substantial government expenditure on subsidies for enterprises, supporting environmental R&D expenses to achieve energy conservation and emission reduction goals (Tong *et al*.,2024). Environmental regulation effectively internalizes the negative externalities of innovation subjects, optimizes innovation division of labor and collaboration, and constructs collaborative spaces for green innovation utilizing complementary resources and hierarchical labor division, thereby enhancing regional green innovation (Wu *et al*.,2024; Wen *et al*.,2024b).

However, China remains a developing country and must strengthen environmental protection while transforming its economic growth model (Shen *et al*.,2024). Technological innovation serves as a crucial element in attaining the mutual benefit objective of safeguarding the environment and fostering economic growth (Li *et al*., 2024). The influence of environmental regulations on technological innovation has been a key area of investigation (Duan *et al*.,2025). Whether this impact manifests as a positive "compensation effect" or a negative "offset effect" is debated among scholars. Furthermore, both environmental regulation and green technological innovation are long-term, continuous processes. Analyzing them from a dynamic perspective can more accurately reflect their connection (Xia *et al*.,2024). As a consequence, this article aims to analyze the mechanism of how air pollution environmental regulation influences technological innovation from my point of view of direct effects. It employs the dynamic GMM method for empirical research, which carries great theoretical and practical significance for China in addressing the challenges of technological progress and environmental protection within the context of global value chain division and facilitating the transition of its economic growth model.

The significance of this study is to deeply explore the impact of air pollution environmental regulation (APER) on green innovation efficiency (GIE) of industrial enterprises and its mechanism of action. Currently, with the increasingly severe global environmental problems, governments have strengthened environmental regulation in order to promote enterprises to realize green transformation through policy guidance. However, there are still many controversies about the impact of environmental regulation on firms' innovative behavior, especially in the specific economic context of developing countries, and how to balance the relationship between environmental protection and economic growth is an urgent issue to be solved. By analyzing panel data from 28 manufacturing sectors in Shandong Province, China, for the period 2012 - 2023, this study aims to provide new empirical evidence for research in this area, reveal the complex relationship between environmental regulation and firms' green innovation, and provide scientifically sound policy recommendations for policy makers.

The main objectives of this study include: first, to test whether air pollution environmental regulation has a significant contribution to green innovation efficiency and to explore its mechanism of action. Second, to reveal the transmission mechanism by which air pollution environmental regulation affects green innovation efficiency, and to analyze the mediating role of financial agglomeration between air pollution environmental regulation and green innovation efficiency, in order to reveal through which pathway environmental regulation affects the green innovation behavior of enterprises. Again, industrial agglomeration is introduced as a threshold variable to analyze its moderating role in the relationship between environmental regulation of air pollution and green innovation efficiency, in order to reveal whether there is a difference in the impact of environmental regulation on green innovation efficiency under different levels of industrial agglomeration. Finally, based on the results of the study, specific suggestions are provided for policymakers to optimize environmental regulation policies, promote green innovation of enterprises and achieve sustainable development of the regional economy.

The innovations of this paper compared to previous literature are as follows: first, this paper reveals the relationship between APER and the GIE from a macro to micro perspective, and explains the mechanism of the impact. Second, previous researches have primarily concentrated on air pollution, while the already scarce studies on air pollution are more inclined to the environmental benefits of regulation. Therefore, this article analyzes the economic losses of APER for GIE from the perspective of firm-level data. Finally, by examining the adverse effects of air regulation in an institutional context where regulation implementation depends on local governments, it helps to enrich research on the political economy of centralized governance and environmental regulation.

2. Theoretical examination and hypothetical frameworks

2.1. Impact of APER on GIE

Environmental regulation theory posits that environmental regulatory policies represent effective tools to tackle market failures related to green technological innovation (Zhang *et al*.,2024). The existing body of literature exploring the influence of environmental regulation on green innovation efficiency has progressively developed two contrasting perspectives: the hypothesis of the pollution haven and the Porter hypothesis.

From a static viewpoint, the neoclassical economic school argues that stringent environmental regulations lead to an increase in production costs for enterprises, leading to the formation of pollution havens in areas where lower environmental regulation (Wen *et al*.,2024d). Thus, stringent environmental regulations may not effectively promote the enhancement of industrial enterprise innovation. Research has shown that in the context of decentralized governance and performance assessment systems, governments tend to prioritize short-term economic development over long-term green economic growth. This phenomenon, known as "race to the bottom" among regional administrations, results in spatial spillover of environmental pollution. Supporting this view, local governments often weaken environmental regulation intensity to reduce compliance costs for local enterprises, thereby promoting economic growth. Even in regions with strict environmental regulation policies, the potential advantages of investments in environmental governance might be restricted (Cheng & Kong, 2022). Studies by

Mahmood *et al*. (2022) discussed that the extent of environmental protection taxes, particularly in environmental regulatory tools, is insufficient to incentivize corporate investments in green ecological innovation. These perspectives collectively suggest a "cost effect" of environmental regulation on GIE. Zou & Zhang (2022) further noticed that strengthened environmental regulation increases environmental protection and pollution control costs for governments and enterprises, thereby inhibiting output performance and economic development. Strong environmental regulation may also divert financial resources away from the secondary industry, thereby hindering the efficiency improvement of green growth.

From a dynamic perspective, the Porter hypothesis contends that stringent environmental regulatory policies can indeed net positively influence the innovation capabilities of regulated enterprises (Wen *et al*.,2024c). By promoting cost reduction and efficiency improvement, such policies can mitigate or utterly offset the expenses of environmental regulation, thereby facilitating the implementation of innovations in new technologies and helping enterprises attain international technological leadership positions. Lv *et al*. (2021) discovered that both environmental regulatory measures and governmental subsidies positively impact green technological innovation, with their combined effect being particularly strong. Empirical research by Bao and Chai (2022) corroborated this viewpoint, demonstrating a positive connection between environmental regulation and regional GIE, where improved fiscal resource allocation by governments enhances green innovation efficiency.

However, a substantial body of literature analyzing panel data from various regions in China suggested a "U"-shaped relationship between environmental regulation and enterprise technological innovation (Zhang *et al*., 2022; Shen *et al*.,2025). Scholars have also calculated optimal environmental regulation for many industries from a productivity standpoint, finding that moderate environmental regulation intensities for heavily polluting enterprises are reasonable and can promote industrial technological innovation and efficiency improvement. In contrast, environmental regulation intensities for moderate and light industries exhibited a weaker, "U"-shaped relationship with technological innovation (Ouyang *et al*., 2020).

Objectively, existing literature offers varied perspectives regarding the impact of environmental rules on technological advancements, providing valuable insights for the present study. However, technological innovation is a multifactor interactive process influenced by factors such as innovation inputs, R&D infrastructure, institutions, and culture. Facing environmental regulatory limitations, these factors may change the direction and degree of their impact on technological innovation, indirectly reflecting the influence of environmental regulation on technological innovation.

In short, the impact of environmental regulation on enterprise innovation efficiency remains controversial. Broadly speaking, environmental regulation influences enterprise innovation activities primarily through two mechanisms: the detrimental "compliance cost effect" and the beneficial "innovation compensation effect." Some academics assert that the positive innovative impacts of environmental regulation can adequately counteract the costs associated with environmental governance, thereby fostering green innovation. On the contrary, others maintain that the "compliance cost effect" of environmental regulation surpasses the "innovation incentive effect," thereby hindering urban green development. Based on this analysis, the subsequent hypothesis is formulated:

H1: APER has a positive effect on GIE.

2.2. The mediating role of financial agglomeration

Environmental regulation not only directly impacts green technological innovation efficiency but also exerts indirect effects through various factors. The analysis of how financial agglomeration mediates the impact of APER on GIE focuses on two main aspects: the influence of APER on financial agglomeration and the impact of financial agglomeration on GIE.

2.2.1. Theoretical impact of APER on financial agglomeration

Pursuing green development requires financial institutions to allocate resources in a way that reduces or limits flows to highly polluting industries and enterprises. Environmental regulation, as an external regulatory tool, guides the sensible allocation of financial resources, effectively balancing the interdependent relationship between environmental conservation and economic growth. Appropriate environmental regulation facilitates the rational allocation of financial resources, thereby promoting economic green transformation. Supporting this view, Qiu (2020) suggests that stringent environmental regulation helps drive enterprise innovation activities, while the development of green finance alleviates financial constraints faced during innovation and R&D processes.

2.2.2. Theoretical impact of financial agglomeration on GIE

Studying the patterns of financial agglomeration and its impact on the efficiency of enterprise green innovation is crucial for promoting high-quality coordinated regional development. Financial agglomeration centers stimulate the development of financial services and related industries in surrounding areas through modern networks, facilitating resource flows and optimizing resource allocation to reduce transaction costs and enhance regional green innovation efficiency. Research by Mentes (2023) indicates that the progress of the financial sector advocates green economic efficiency by fostering innovation in related green technologies and enhancing public awareness of green development. Similarly, Habiba *et al*. (2022) find that financial agglomeration stimulates innovation effects and corresponding green efficiency improvements, demonstrating fluctuating growth trends. However, some studies caution that enterprises, upon obtaining financial resources, may continue to produce highly polluting and energy-intensive products, leading to increased emissions of pollutants like carbon dioxide and sulfur dioxide. This could potentially trigger environmental pollution or a "herd effect," thereby impacting the efficiency of regional green technological innovation.

In conclusion, financial agglomeration plays a mediating role in the mechanism through which APER impacts GIE. Following the analysis, a hypothesis is proposed:

H2: APER promotes financial agglomeration and enhances GIE

2.3. Threshold effect

The consequences of industrial agglomeration on the connection between APER and GIE can be analyzed from two perspectives: "industrial synergy effect" and "pollution transfer effect."

2.3.1. Industrial synergy effect

Geographical clustering facilitates the transmission of information. As the cooperation and division of labor among enterprises intensify, comprehensive industrial chains begin to take shape progressively (Li *et al*., 2025). Firms located within agglomerated regions can jointly utilize information, infrastructure, labor markets, and specialized services, thereby efficiently managing production expenses. Consequently, when industrial concentration reaches a certain threshold, environmental regulations can facilitate the sharing and dissemination of green knowledge, spurring advancements in green technology (Wu *et al*.,2025).

2.3.2. Pollution transfer effect

When industrial agglomeration attains a specific scale, challenges such as environmental deterioration, resource scarcity, high population density, and traffic congestion start to surface. The benefits associated with agglomeration diminish, and the scale economies in these clustered areas weaken. As a result, industries characterized by lower green technology incorporation and higher pollution levels may relocate to adjacent regions due to the erosion of their competitive edges (Zeng *et al*.,2024). This relocation exacerbates adverse environmental consequences in neighboring territories, impeding the progress of green development in those areas.

Based on this analysis, the following conjecture is put forth:

H3: There exists a threshold effect of APER on GIE at different levels of industrial agglomeration.

In conclusion, through comprehensive theoretical analysis focusing on how APER affects GIE and the contributing factors involved in this process, a proposed research framework, as depicted in **Figure 1**, is presented.

3. Model specification, indicator selection, and data description

3.1. System GMM model specification

The most frequently utilized estimation techniques in panel data models are fixed effects models and random effects models. However, when the lagged dependent variable is introduced as an explanatory variable in the regression model to enhance its dynamic explanatory power, endogeneity issues arise. Therefore, Arellano (1995) and others proposed the Generalized Method of Moments (GMM), specifically for dynamic panel data models, which includes both DIF-GMM and SYS-GMM methods. While difference GMM methods reduce The implications of endogeneity for the accuracy of model estimation, they suffer from a severe "weak instrument" problem under limited sample circumstances, resulting in imprecise coefficient estimates. Consequently, Blundell (1998) proposed the System GMM estimation method, capable of addressing autocorrelation, heteroscedasticity, endogeneity, and weak instrument issues. Hence, to ensure robust results, we opted for the two-step System GMM method to estimate panel data.

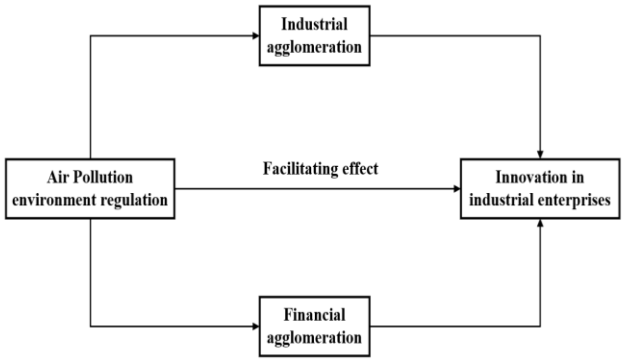


Figure 1. Diagram of the theoretical model

3.2. Indicator selection

3.2.1. GMM model specification

In this article, industrial enterprise green innovation efficiency (*GIE*) serves as the dependent variable. We include the first-order lag of green innovation efficiency and air pollution environmental regulation (Env_regu) as the explanatory variables. This setup satisfies the condition where the dependent variable is dynamic, and not all explanatory variables are entirely exogenous. We control for individual and time fixed effects to meet the requirements of the System GMM model. Additionally, considering the multitude of factors influencing green innovation efficiency, we introduce other variables as control factors. These include economic development level (*AGDP*), urbanization level (*UR*), energy consumption structure (*ECS*), and human capital level (*HCL*). Here, i denotes industry entity, t denotes year, and ε represents the error term. The model also incorporates individual fixed effects δ, time fixed effects μ, εi as the random error term; β_0 as the constant, and βi as the regression coefficients corresponding to each variable. Given the time required for the transformation of industrial enterprise green innovation efficiency outcomes, current-year green innovation efficiency depends not only on its current performance but also on the stock of green innovation efficiency from previous years. Therefore, we incorporate the previous period's green innovation efficiency, denoted as GIE_{it-1}, into the model to account for its intrinsic influence. This establishes a dynamic panel regression model as follows:

$$\ln GIE_{i,t} = \beta_0 + \beta_1 \ln GIE_{i,t-1} + \beta_2 \ln^{\mathrm{Env}_{\mathrm{regu}_{i,t}}} + \beta_3 lncontrol_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \tag{1}$$

3.2.2. Mediation model

In considering the impact of the independent variable X on the dependent variable Y, if X affects variable M, which in turn affects Y, then M is considered a mediator. The connection among the variables can be described using the following regression equations (**Figure 2** illustrates the corresponding path diagram).

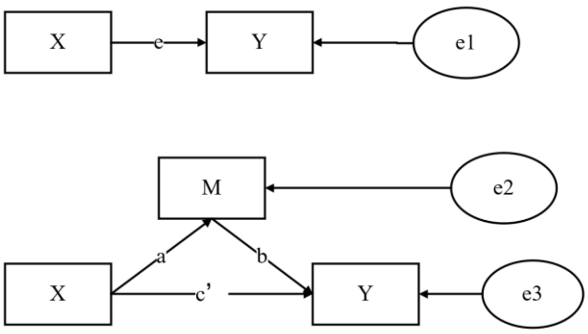


Figure 2. Intermediary inspection diagram

$$Y = cX + e1 \tag{2}$$

$$Y = aX + e2 \tag{3}$$

$$Y = c'X + bM + e3 \tag{4}$$

Where c in Equation (5) stands for the total effect of X on Y. a in Equation (3) stands for the effect of X on mediator M. b in Equation (4) represents the effect of M on Y, controlling for X. c' in Equation (5) represents the direct effect of X on Y after controlling for mediator M. e1, e2, e3 are the regression residuals.

In a straightforward mediation framework, the indirect impact is equivalent to the mediation effect, which is the product of coefficients ab. It relates to the total effect and direct effect as shown in Equation (5).

$$c = c' + ab \tag{5}$$

This article employs the Baron and Kenny's (1986) step-by-step way to test the mediation effect, commonly known as the sequential method: ①Test the coefficient c in Equation (2) i.e., test (H_0: c = 0). ②Sequentially test coefficients a in Equation (3) i.e., test (H_0: a = 0) and b in Equation (4) i.e., test (H_0: b = 0). ③If c in Equation (7) is not significant, it indicates complete mediation.

Thus, this approach systematically assesses how X influences Y through M, providing insights into the mediation effect in the context of the study.

3.2.3. Panel threshold model

The mechanism of how industrial agglomeration affects the GIE is influenced by factors. Drawing on Hansen's (1999) threshold regression approach, this study verifies whether there exists a threshold effect of industrial agglomeration level on the GIE, constructing the threshold model as in Equation (6).

$$\begin{aligned} \ln \mathrm{GIE}_{it} = {} & \beta_1 + \beta_2 \mathrm{Env\_regu} \times \mathrm{I}(\mathrm{AGG}_i \le \gamma_1) + \beta_3 \mathrm{Env\_regu} \times \mathrm{I}(\gamma_2 < \mathrm{AGG}_i \le \gamma_3) \\ & + \beta_4 \mathrm{Env\_regu} \times \mathrm{I}(\mathrm{AGG}_i > \gamma_3) + \beta_3 \mathrm{control} + \varepsilon_i \end{aligned} \tag{6}$$

Where GIE_{it} is the green innovation efficiency of industrial enterprises. AGG_i represents the industrial agglomeration level I(·) is an indicator function, if the condition is true, I( ) = 1, Otherwise I( ) = 0.

3.3. Variable selection

3.3.1. Dependent variable (GIE)

This article employs the non-radial, non-angular Super-SBM model to measure the GIE from 2012 to 2023, which addresses issues of undesirable outputs and non-zero slack. Tone (2001) proposed the Super-SBM model, expressed as Equation (.

$$\min \rho = \frac{1 - \frac{1}{m} \sum_{i=1}^{m} \frac{z_i^-}{x_{ik}}}{1 + \frac{1}{p_1 + p_2} \left(\sum_{r=1}^{p_1} \frac{z_r^+}{y_{rk}} + \sum_{t=1}^{p_2} \frac{z_t^{h-}}{h_{rk}} \right)}$$

$$\text{s.t.} \begin{cases} \sum_{j=1, j \neq k}^{n} x_{rj} \lambda_j - z_i^- \leq x_{ik} \\ \sum_{j=1, j \neq k}^{n} y_{ij} \lambda_j + z_i^- \geq y_{rk} \\ \sum_{j=1, j \neq k}^{n} h_{tj} \lambda_j - z_i^{h-} \leq h_{tk} \\ \lambda, z^-, z^+, z^{h-} \geq 0 \end{cases} \tag{7}$$

$$i = 1,2,\cdots,m; r = 1,2,\cdots,p_1; t = 1,2,\cdots,p_2; \quad j = 1,2,\cdots,n (j \neq k)$$

Where there are *m* inputs, p1 desired outputs, p2 non-desired outputs, with $z = (z_i^-, z_r^+, z_t^{h-})$ denoting the slacks of inputs (xi), desired outputs (yr) and non-desired outputs (hr), and λ denoting the weight vector. The evaluation index system for green innovation efficiency is established based on input and output dimensions, with the selection of specific indicators detailed in **Table 1**.

Table 1. Measurement of indicators

Primary indicator	Secondary indicator	Basic indicator
Input indicators	Labor input	Number of personnel working in information services (10,000 persons)
	Capital input	Output value of information services (100 million yuan)
	Energy input	Provincial electricity consumption share attributed to a specific region (%)
Output indicators	Desirable outputs	Number of patents granted (pieces)
		Technology market transaction volume (100 million yuan)
		Product sales revenue (100 million yuan)
	Undesirable outputs	Industrial wasteair discharge (10,000 tons)
		Industrial sulfur dioxide emissions (10,000 tons)
		Industrial smoke and dust emissions (10,000 tons)

Table 2. Measurement indicators for control variables

Variable name	Measurement indicator	Unit
Economic development level (*AGDP*)	Per capita GDP	Yuan/person
Urbanization level (*UR*)	Proportion of urban population to total population at year end	%
Energy consumption structure (*ECS*)	Provincial electricity consumption / National electricity consumption	%
Human capital level (*HCL*)	Number of higher education students in enterprises / Total population	%

These indicators provide a framework for assessing GIE, covering inputs such as labor, capital, and energy, as well as outputs including desirable and undesirable environmental impacts.

3.3.2. Explanatory variable (Env_regu)

Various indicators are used to measure environmental regulation in existing literature, often including pollution control investments and emission fees. In this study, air pollution environmental regulation during the "12th Five-Year Plan" to "14th Five-Year Plan" period is assessed based on municipal targets for pollutant emission reduction policies. Data was collected from air quality monitoring stations as reported in various environmental yearbooks such as the "China Environmental Statistical Yearbook" and "China Environmental Quality Statistical Yearbook." These reports provide geocoded information on monitored air quality stations. The power of air pollution environmental regulation (Env_regu) is defined as follows in equation (8):

$$nv\_regu\ u_{ct}^{m} = \begin{cases} \sum_k \text{Pollut\_Reduction}_{c,12th\_FYP}^{m}, & \text{if } 2012 \le t \le 2015 \\ \sum_k \text{Pollut\_Reduction}_{c,13th\_FYP}^{m}, & \text{if } 2016 \le t \le 2020 \\ \sum_k \text{Pollut\_Reduction}_{ck,14th\_FYP}^{m}, & \text{if } 2021 \le t \end{cases} \quad (8)$$

3.3.3. Control variables

Drawing from Miao *et al*. (2021) regarding industrial green innovation efficiency, this study incorporates five control variables (see **Table 2**).

3.3.4. Mediating variable (FINAL)

Financial agglomeration reflects the concentration of financial resources in a specific spatial area over time. To comprehensively capture the connection between macro financial agglomeration and provincial economic development, this article employs the concept and calculation of location entropy to measure the agglomeration level of financial activities. The particular formula for calculation (9) is outlined as such:

$$FINAL_i = \frac{AVF_i \,/\, GDP_i}{AVF \,/\, GDP} \quad (9)$$

Where *FINALi* represents the financial agglomeration level of the ith firm, and *AVFi* and *GDPi* represent the financial sector value added and GDP of the ith firm, respectively.

3.3.5. Threshold variable (AGG)

Industrial agglomeration serves as a key indication and approach to achieving industrial configuration, as well as an essential requirement for ensuring regional green progress. This study measures regional industrial agglomeration levels using employment density (number of employees per unit area), where higher employment density indicates higher industrial agglomeration levels in the region.

3.3.6. Instrumental variables (VC)

To mitigate the influence of natural factors on carbon emissions (Zhang *et al*., 2025), this study adopts the Ventilation Coefficient (*VC*) as an instrumental variable, which is exogenous to environmental policies. This decision guarantees that the influence of corporate green innovation efficiency is exclusively channeled through air pollution environmental regulations, effectively addressing endogeneity issues. Following the approach of Chen *et al*. (2021), the Ventilation Coefficient is computed using ArcGIS software at a resolution of 0.125 degrees raster, based on the product of 10-meter wind speed and the atmospheric boundary layer height.

Table 3. VIF test results

Variables	VIF	1/VIFr
ln GIE	8.61	0.116
Env_regu	4.82	0.207
ln AGDP	1.71	0.585
ln UR	3.19	0.313
ln ECS	1.10	0.909
ln GHCL	2.98	0.336
ln AGG	3.29	0.304
Mean VIF	3.671	

3.4. Data sources

Considering data availability, panel data analysis includes 28 industries such as food processing and manufacturing in Shandong Province from 2012 to 2023, comprising 671 enterprises and totaling 7381 observations. Data are sourced from various statistical yearbooks including "China Urban Statistical Yearbook," "China Science and Technology Statistical Yearbook," "China Statistical Yearbook," "China Energy Statistical Yearbook," and local statistical yearbooks of prefecture-level cities. All variables are log-transformed to ensure robustness, and missing values are estimated using linear interpolation techniques.

4. Benchmark regression tests

4.1. Correlation tests

4.1.1. Multicollinearity test

To avoid multicollinearity issues, variance inflation factor (VIF) is employed to assess the correlation between variables. VIF values below 10 indicate no multicollinearity. **Table 3** presents the findings of the multicollinearity test for the model variables, all of which have VIF values below 10, indicating no significant multicollinearity issues among the selected indicators.

4.1.2. Hausman test

For panel data analysis, the Hausman test is performed to decide between adopting a random effects model or a fixed effects model. **Table 4** displays the results of the Hausman test, rejecting the null hypothesis in favor of using the fixed effects model for empirical testing in this article.

Table 4. Hausman test

	Coef_lnGIE
Chi-square test value	15. 68
P−value	0. 0078

Table 5. Regression analysis results

Variables	(1) *lnGIE*	(2) *lnGIE*
ln Env_regu	0.677*** (0.062)	0.619*** (0.059)
L. GIE	0.458*** (0.034)	0.445**** (0.031)
ln AGDP		0.046*** (0.010)
ln UR		0.134*** (0.046)
ln ECS		-0.195*** (0.058)
ln HCL		-0.279*** (0.077)
Constant	0.187** (0.081)	2.005*** (0.744)
AR(1)	0.087	0.036
AR(2)	0.258	0.787
Hansen	0.614	0.182
Observations	7381	7381
R^2	0.220	0.208

*Note: Standard errors are shown in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.*

4.2. Benchmark regression and analysis

4.2.1. Benchmark tests

From **Table 5**, the regression analysis results indicate that AR (1) values are 0.087 and 0.036, both less than 0.1, while AR (2) values are 0.258 and 0.787, both greater than 0.1. This suggests that the system GMM model does not exhibit second-order residual autocorrelation issues, confirming the adequacy and effectiveness of the model setup regarding the impact of APER on GIE. According to regression models (1) and (2), the first-order lagged dependent variable significantly promotes enterprise green innovation efficiency at the 1% level, with coefficients of 0.677 and 0.619. This indicates a significant cumulative growth effect in enterprise green innovation efficiency, which requires continuous accumulation and reflects fully in the subsequent year. Therefore, the hypothesis H1 is validated, affirming that air pollution environmental regulations in China positively promote industrial enterprise green innovation efficiency.

The economic development indicator shows a positive coefficient on GIE but fails to pass the significance test. Previous studies suggest that economic development significantly promotes innovation, although some scholars draw on the Environmental Kuznets Curve, suggesting a significant U-shaped relationship between economic development and green innovation efficiency. Beyond the inflection point of the U-curve, as economic levels rise, there is a positive relationship with GIE, reflecting a development model driven by technological factors to pursue quantitative growth and economic growth.

Urbanization development exhibits a positive impact on GIE at the 1% significance level, with a coefficient of 0.134. This indicates that as urbanization leads to factor agglomeration triggered by large-scale urban influx, intensified production methods reduce per-unit air pollution emissions. Additionally, technological and population agglomeration due to factor concentration facilitates the collision and exchange of emission reduction technologies, thereby enhancing green technology innovation.

Energy consumption structure negatively affects GIE at the 1% significance level, with a coefficient of -0.195. Carbon emissions from energy consumption are the largest source of carbon emissions in China, posing challenges due to overall backwardness in energy technology. Amidst dual carbon goals, China is promoting energy structure transformation and upgrading to establish a clean, low-carbon, safe, and efficient energy system. Therefore, increasing the use of clean energy helps reduce regional pollution emissions, showing a certain substitutive effect with enterprise green innovation.

Human capital level negatively impacts GIE at the 1% significance level, with a coefficient of -0.279. Technological improvement and systematization in enterprises depend on domestic human capital conditions. However, due to the presence of technological lock-in effects, diffusion of external technologies triggered by human capital may induce rebound effects, conflicting with energy conservation and emission reduction efforts. This underscores the potential limitation of human capital in enhancing green development efficiency.

These findings contribute to understanding the complex interplay of economic, urbanization, energy, and human capital factors in influencing GIE within the context of environmental regulation frameworks.

4.2.2. Mediation analysis

In **Table 6**, models (4) and (5) indicate that the level of financial agglomeration partially mediates the connection between APER and GIE. Model (4) demonstrates a significant positive impact of air pollution environmental regulations on financial agglomeration (coefficient = 0.1195, $p < 0.05$), while model (5) shows that financial agglomeration significantly enhances industrial enterprise green innovation efficiency (coefficient = 0.1411, $p < 0.1$), supporting hypothesis H2. Theoretical analysis suggests that the impact of APER on GIE can be realized through the pathway of financial agglomeration, wherein environmental regulations influence financial deepening and optimization of financial structure. Financial agglomeration attracts production factors such as talent, technology, and capital, further boosting green innovation efficiency.

4.2.3. Threshold effect analysis

The mechanism of how air pollution environmental regulations affect industrial enterprise green innovation efficiency is complex, thus necessitating the use of a panel threshold model. Industrial agglomeration (*AGG*) is used as the threshold variable, following Hansen (1999)'s approach to verify whether there is a threshold effect of industrial agglomeration on enterprise innovation efficiency.

Table 6. Regression analysis of intermediation effects

	Model (3)	**Model (4)**	**Model (5)**
	lnGIE	***lnFC***	***lnGIE***
lnEnv_regu	0.1749^{**}(2.1807)	0.1195^{**}(2.0208)	0.1600^{**}(1.9839)
lnfc			0.1411^{*}(1.7089)
lnur	-1.0345^{**}(-2.5842)	0.8011^{***}(2.7909)	-1.1826^{***}(-2.9455)
lnagdp	-0.0965(-0.7611)	-0.8479^{***}(-9.2680)	0.0235(0.1641)
lnecs	0.0698(0.5821)	-0.1631^{*}(-1.9242)	0.0797(0.6649)
lnhcl	0.4590^{**}(2.4338)	-0.1525(-1.1227)	0.4943^{***}(2.6404)
Constant	7.6362^{***}(5.0906)	9.7552^{***}(8.9081)	6.3860^{***}(3.7624)
N	7381	7381	7381
R^2	0.0807	0.4560	0.0907

Firstly, the existence of panel thresholds is tested, with the results from Bootstrap resampling 300 times yielding threshold numbers and values as shown in **Table 7**. The findings indicate that during the ongoing phase, industrial agglomeration fulfills the conditions for passing both the single and double threshold tests at the 1% significance level, warranting a double threshold analysis. The LR trend in **Figure 4-11** for double threshold estimation shows that the LR values corresponding to the first and second threshold values of 2.1152 and 2.7513 respectively fall below the 10% critical value and approach 0. This indicates that the estimated threshold values equal the true threshold values, accurately dividing industrial agglomeration levels into three stages.

The estimation outcomes for the parameters of the double threshold model are presented in **Table 8**. Industrial agglomeration positively impacts GIE. When industrial agglomeration is below the threshold value (AGG ≤ 2.1152), the coefficient indicating its impact on GIE is 0.006, significant at the 5% level. This suggests that under these conditions, industrial agglomeration significantly positively affects GIE. When industrial agglomeration exceeds the threshold value (i.e., 2.1152 < AGG ≤ 2.7513), the promotion effect of industrial agglomeration on GIE significantly decreases (-0.009) at the 10% level. Thus, industrial agglomeration has varying effects on GIE at different levels, thereby validating hypothesis H3 (**Figure 3**).

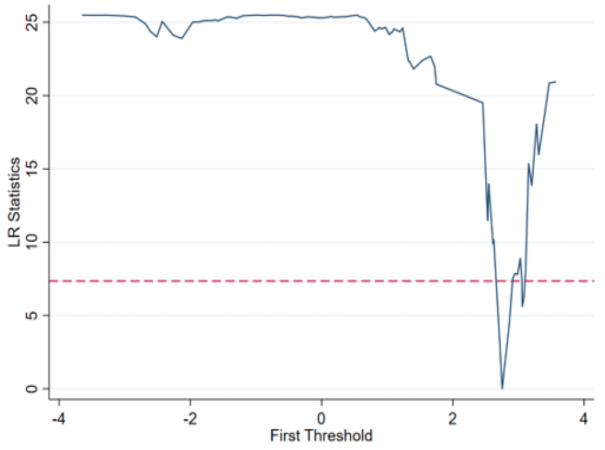


Figure 3. Threshold effect diagram

When industrial agglomeration is below the threshold value (AGG ≤ 2.1152), it significantly positively impacts enterprise green innovation efficiency. However, when industrial agglomeration surpasses a certain threshold (2.1152 < AGG ≤ 2.7513), it exhibits a restraining effect. This could be attributed to higher investment levels and longer investment cycles leading to increased input costs and financial constraints, reducing the addition of production capacity. Additionally, dispersed investments without focused construction exacerbate investment inefficiencies, hindering economic development and not favoring enterprise growth.

Table 7. Threshold effect test findings

Threshold variables	Number of thresholds	Threshold value	F value	P value	95% confidence interval
AGG	single threshold	2.1152	16.07*	0.0967	[1.9201,2.1863]
	double threshold	2.7513	10.04*	0.0900	[2.6601,2.8567]

Table 8. Analysis of threshold regression results

Explanatory variable	β	P 值
lnEnv_regu(AGG≤2.1152)	0.006** (1.75)	0.088
lnEnv_regu(2.1152＜AGG≤2.7513)	-0.009* (-1.72)	0.063
lnEnv_regu(AGG＞2.7513)	0.013 (1.42)	0.163

5. Robustness tests

Several robustness tests were conducted in this study to support the robustness of the main findings.

5.1. Use of alternative variables

In order to verify the robustness of the findings and to reduce potential measurement errors, this study used proxy variables for analysis. Specifically, the number of green patents (*Patent*) submitted by firms is used as a proxy indicator for green innovation efficiency (*GIE*). The number of green patents is an important indicator of an enterprise's green innovation activities, as it directly reflects the enterprise's achievements in green technology development and application. Green patents usually involve technological innovations in the fields of energy saving and emission reduction, resource recycling and environmental protection, and are a visual representation of an enterprise's green innovation capability.

As shown in **Table 9** (1), the results of regression analysis using the number of green patents (*Patent*) as the dependent variable show that the coefficient of influence of Air Pollution Environmental Regulation (*APER*) on Green Innovation Efficiency (*GIE*) is 0.737, and it is significant at 1% significance level. This result is consistent with the results of green innovation efficiency (*GIE*) calculated using the Super-SBM model in the main effects analysis, indicating that air pollution environmental regulation has a significant role in promoting green innovation activities of enterprises. Specifically, the strengthening of environmental regulations can incentivize enterprises to increase the number of green patent applications, thus promoting green technological innovation.

5.2. Generalized least squares (GLS)

Heteroskedasticity and autocorrelation are common problems in panel data analysis, which may lead to inconsistency and bias in the estimation results. In order to ensure the reliability and stability of the findings and to minimize the bias caused by measurement errors in the selection of explanatory variables and samples, this study adopts the Generalized Least Squares (GLS) method for the robustness test. GLS is an improved least squares estimation method that can effectively deal with heteroskedasticity and autocorrelation problems, thus improving the accuracy and robustness of the estimation results.

The results of the robustness test are shown in **Table 9** (2). As can be seen from the table, the results estimated using the GLS method are highly consistent with those in the main effects analysis. Specifically, the coefficient of the effect of Air Pollution Environmental Regulation (*APER*) on Green Innovation Efficiency (*GIE*) is 0.624 and is significant at the 1% significance level. This result is very close to the results obtained in the main effects analysis using the system GMM method (coefficient of 0.677 and significance level of 1%), indicating that air pollution environmental regulation has a significant contribution to the green innovation efficiency of firms.

In addition, the coefficients of other control variables are similar to the results in the main effects analysis. For example, the coefficient of economic development is 0.045, indicating that the level of economic development has a positive effect on green innovation efficiency; the coefficient of urbanization level is 0.134, indicating that the development of urbanization has a significant positive effect on green innovation efficiency; the coefficient of the energy consumption structure is -0.195, indicating that the optimization of the energy consumption structure has a negative effect on the green innovation efficiency; and the coefficient of human capital level is - 0.279, indicating that the level of human capital has a significant negative effect on green innovation efficiency. These results further validate the robustness of the main effects analysis.

5.3. Generalized method of moments (GMM)

In empirical research, endogeneity problem is one of the important factors affecting the accuracy and reliability of estimation results. Endogeneity problems usually stem from omitted variables, measurement errors, simultaneity bias, etc., which may cause the explanatory variables to be correlated with the error terms, thus making the estimation results biased. In order to ensure the accuracy and reliability of the results, this study used the generalized method of moments (GMM) for robustness testing.

In dynamic panel data modeling, systematic GMM and differential GMM are two commonly used GMM estimation methods. Differential GMM eliminates individual fixed effects by first-order differencing the equations, but this method may lead to the problem of weak instrumental variables, especially when the sample size is small. System GMM, on the other hand, combines the moment conditions of the level and difference equations, and is able to utilize the data information more effectively to improve the accuracy and efficiency of the estimation results. Therefore, the system GMM is usually more effective than the differential GMM in limited sample situations.

Table 9. Robustness tests

Variable	**(1)**	**(2)**	**(3)**
	lnPatent	***lnGIE***	***lnGIE***
ln Env_regu	0.737^{***}	0.624^{***}	0.584^{***}
	(0.073)	(0.109)	(0.069)
L. GIE	0.034^{**}	0.045^{***}	0.058^{***}
	(0.012)	(0.010)	(0.019)
ln AGDP	0.035^{***}	0.134^{***}	0.124^{***}
	(0.009)	(0.046)	(0.029)
ln UR	0.032^{***}	0.195^{***}	0.227^{***}
	(0.007)	(0.058)	(0.059)
ln ECS	-0.038^{***}	-0.279^{***}	-0.424^{***}
	(0.008)	(0.077)	(0.109)
ln HCL	-0.004^{***}	-0.012	-0.024^{***}
	(0.001)	(0.012)	(0.008)
Contant	0.245^{***}	2.205^{***}	0.624^{***}
	(0.041)	(0.744)	(0.109)
AR1	0.062	0.036	0.041
AR2	0.615	0.787	0.689
Hansen	0.247	0.182	0.172
Observations	7381	7381	7381
R^2	0.324	0.245	0.229

The results of the robustness test of the system GMM method are shown in Table 9(3). As can be seen from the table, the results estimated using the system GMM and differential GMM methods are highly consistent with the results in the main effects analysis. Specifically, the coefficient of the first lagged term of green innovation efficiency (*GIE*) on current green innovation efficiency is 0.584 and is significant at 1% level of significance. This result is very close to that obtained in the main effects analysis using the system GMM method (coefficient of 0.677 and significance level of 1%), indicating a significant cumulative growth effect of green innovation efficiency. In addition, the coefficient of Air Pollution Environmental Regulation (*APER*) on green innovation efficiency is 0.584 and significant at 1% significance level, which is consistent with the results in the main effects analysis, further verifying the positive impact of APER on green innovation efficiency.

The coefficients of other control variables are also similar to the results in the main effects analysis. For example, the coefficient of economic development is 0.058, indicating that the level of economic development has a positive effect on green innovation efficiency; the coefficient of urbanization level is 0.124, indicating that the development of urbanization has a significant positive effect on green innovation efficiency; the coefficient of the energy consumption structure is -0.227, indicating that the optimization of the energy consumption structure has a negative effect on the green innovation efficiency; and the coefficient of human capital level is - 0.424, indicating that the level of human capital has a significant negative effect on green innovation efficiency. These results further validate the robustness of the main effects analysis.

6. Conclusion and recommendations

The economic significance of this study is to provide policy makers with scientific and reasonable policy recommendations to realize the win-win goal of environmental protection and economic growth. Specifically: firstly, by strengthening the environmental regulation of air pollution, enterprises can be guided to invest more resources in green technology research and development and application, so as to improve the efficiency of resource utilization and promote the sustainable development of the economy. The mediating role of financial agglomeration further suggests that optimizing the allocation of financial resources is important for enhancing the efficiency of green innovation. The results of the study show that environmental regulatory policies can effectively promote the green innovation activities of enterprises. This not only helps to reduce environmental pollution, but also promotes the transformation of enterprises to a green, low-carbon and circular economic model, and enhances their market competitiveness and economic efficiency. Secondly, the threshold effect of industrial agglomeration suggests that policymakers need to consider the actual situation of regional industrial agglomeration when formulating environmental regulatory policies. For regions with a low level of industrial agglomeration, infrastructure construction and policy support should be strengthened to promote the development of industrial agglomeration; while for regions with a high level of industrial agglomeration, attention should be paid to optimizing the industrial structure, avoiding the negative effects of over-agglomeration, and realizing the coordinated development of the regional economy.

This study employed a two-step system GMM model as the primary regression model to analyze the effects of APER on GIE. The empirical analysis reveals:

1. APER significantly promote GIE.
2. By revealing the "black box" of the relationship between APER and GIE, the study confirms that financial agglomeration plays an intermediary role in enhancing green innovation efficiency under air pollution control regulations.
3. This study introduces industrial agglomeration as a threshold variable, indicating a dual threshold effect between APER and GIE. However, as industrial agglomeration levels increase, the promotion effect of APER on GIE diminishes.

Drawing upon these research findings, the following perspectives are offered:

This optimization enhances resource allocation efficiency, fosters a green development philosophy in regional business operations, thereby promoting economic output and ecological conservation, and improving green innovation efficiency. Environmental regulations act as effective external measures to enforce pollution reduction by enterprises, necessitating the involvement of financial intermediaries to strengthen the "investment screening effect" and mitigate "resource allocation distortion effects". Depending on the level of financial development in different regions, heterogeneous environmental regulation tools should be employed to construct multi-level environmental rights markets, thereby achieving a mutually beneficial outcome for both economic development and environmental conservation.

Based on the advantages of industrial agglomeration, various regions should establish strategic alliances in agglomeration areas and regional cooperative innovation networks to promote GIE. On one hand, provinces and cities should accelerate the concentration of innovative factors in agglomeration areas, encourage leading enterprises in these areas to form industrial-technological innovation alliances with universities and research institutes, and leverage the advantages of industrial agglomeration to create internationally competitive industrial agglomeration areas or clusters. On the other hand, agglomeration areas should expedite the cultivation and improvement of industrial chains, conduct technological innovation activities around industrial chains, integrate innovation chains into industrial chains, fully achieve the integration and coordination between innovation chains and industrial chains, thereby boosting the efficiency of innovation endeavors within agglomeration zones.

7. Limitations and future prospects

7.1. Limitations

First, the limitation of data scope and sample. The study is based on panel data for only 28 manufacturing sectors in Shandong Province from 2012 - 2023. This geographic and industry limitation may limit the generalizability of the study's findings. Other regions or industries may face different environmental regulatory policies and market conditions, thus affecting the extrapolation of the study's findings. Although the sample size (7,381 observations) is relatively large for a panel data analysis, the sample may still be insufficiently diverse and representative. The study may not cover other important economic sectors such as services, which may also be significantly affected by environmental policies.

Second, variable selection and measurement issues are flawed. The measurement of green innovation efficiency (GIE) Although the Super-SBM model was used to measure GIE, the model may not fully capture all aspects of green innovation. The impact of non-quantifiable factors (e.g., green management practices within firms) on green innovation may be overlooked. Financial agglomeration is measured based on location entropy, but this measure may not fully capture the dynamic flow of financial resources and agglomeration effects. In addition, the impact of financial agglomeration on green innovation may be moderated by factors such as financial market efficiency and financial regulation, but these factors are not fully considered in the study.

Finally, the variability of policy implementation and institutional context. The study assumes that environmental regulatory policies are implemented uniformly across the country, but in practice there may be significant differences in policy implementation across regions and industries. Local governments may selectively implement environmental regulation policies due to economic interests or political pressure, and such differences may lead to bias in the study results. The study does not fully consider the impact of China's unique institutional context on environmental regulation and green innovation. China's environmental regulation policies are often integrated with the country's macroeconomic development strategy, and this institutional context may affect firms' innovation decisions and the actual effects of the policies.

7.2. Future prospects

First, future research could be expanded to more regions and industries across the country to verify the generalizability and applicability of the findings. Especially for other economic sectors such as the service industry, studying the response of their green innovation efficiency to environmental regulation may provide a more comprehensive reference for policy making.

Second, comparing China's environmental regulation and green innovation efficiency with other countries may provide a better understanding of the policy effects and differences in firms' behavior under different institutional contexts. Such international comparative studies can help reveal commonalities and peculiarities in global environmental governance.

Again, a more comprehensive measure of green innovation efficiency, combining quantitative and qualitative indicators, should be developed to reflect the level of green innovation of firms in a more comprehensive way. The long-term dynamic effects of environmental regulation can be further explored by using dynamic panel models to analyze lagged effects and long-term impacts. This can help to more accurately assess the long-term effects of environmental regulation policies and firms' adaptation strategies.

Finally, future research can combine the methods of environmental science and economics to deeply analyze the scientific basis and economic mechanism of environmental regulation on green innovation. Research on how the physicochemical properties of environmental pollutants affect firms' innovation decisions and how to achieve pollutant reduction through technological innovation. Introduce the perspectives of sociology and management to study the impact of social factors (e.g., employees' environmental awareness, corporate culture, etc.) and management practices (e.g., green supply chain management, environmental management system, etc.) within enterprises on green innovation. This contributes to a comprehensive understanding of the drivers and impediments of green innovation from a multidisciplinary perspective.

With the above improvements and outlook, future research can explore the impact of environmental regulation on green innovation efficiency in a more comprehensive and in-depth manner, and provide more valuable references for policy making and business practices.

Competing interests

The authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article.

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