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Do governance patterns of environmental regulation affect firm's technological innovation: Evidence from China

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ABSTRACT

In China, the environmental governance patterns of local governments differ significantly. This study explores the possible relationship between environmental governance patterns and firm's technological innovation. It firstly develops a quantitative method to describe environmental governance patterns by decomposing the environmental regulation intensity index into Normalized Governance Index (NGI) and Passive Governance Index (PGI). Then, this study employs Chinese city-level datasets in 2011–2015 to estimate High-Dimensional Fixed Effect model with instrumental variable (IV). The results show that, first, environmental regulations of governments positively affect technological innovation. Second, NGI has a positive moderating effect on the relationship between environmental regulation and technological innovation, whereas PGI has a negative moderating effect. Third, two opposite forces induced by governance patterns can explain the inverted U-shaped Porter effect. The results suggest energy, environmental, and technological innovation policy implications, as stable and expectable environmental regulation can better promote industrial sector technological innovation given the Porter effect.

1. Introduction

Given the increasingly serious environmental pollution and 2030 Agenda for Sustainable Development set by the United Nations, it is necessary to resort to technical innovation, which is a crucial strategy for addressing the synchronous challenges of economic development and environmental protection (Takalo et al., 2021). As the world's largest developing country, China has announced its intention to reach peak carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060. It will make the steepest cuts in the world of carbon emissions. In such a rapid green low-carbon transition, technological innovation will play a central role.

As the Porter effect theorizes, strict environmental regulations may trigger technological innovation and upgrade economic efficiency (Porter and Linde, 1995). Most studies focus on the environmental regulation intensity (Ouyang et al., 2020; Rubashkina et al., 2015; Wang et al., 2022), while little attention has been paid to the governance patterns of the environmental regulation. In fact, governance patterns differ significantly among regions. For example, in China, some regions form normalized laws, regularize and institutionalize the regulations, and ensure that the intensity of environmental governance is stable and expectable for firms. Other regions have unstable and fluctuating environmental governance intensities. Their intensity actively changes per external regulatory forces, such as central environmental supervision and environmental interview. When central governments strengthen the ecological and environmental supervision, such local governments increase their environmental regulation intensity. After the central inspection, they likely lose the incentive to execute environmental regulations. Given the huge and widespread governance patterns difference, do governance patterns of environmental regulation also affect technological innovation?

In addition, the evidence of the Porter effect remains controversial given the divergent empirical results across multiple countries and regions. Some studies support the idea that environmental regulation spurs technological innovation (Calel and Chezleprêtre, 2016; Ford et al., 2014; Rubashkina et al., 2015); others argue that environmental regulation affects technological innovation negatively (Gray and Shadbegian, 2003; Shao et al., 2020; Shi et al., 2018). Some studies explain these conflicting results by categorizing the environmental regulations into "command and control" and "market-based" regulations (Popp et al., 2010). The former assumedly, hinders technological innovation (Ford et al., 2014; Managi et al., 2005; Purvis and Outlaw, 1995),

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whereas the latter promotes technological innovation (Lange and Bellas, 2005; Popp, 2003; Yu et al., 2022). However, other studies reach opposing conclusions (Hwang and Kim, 2017; Ouyang et al., 2020; Testa et al., 2011). Thus, regulation instrument types are insufficient to explain the Porter effect controversy among countries and regions. Then, can the governance patterns of environmental regulation explain the Porter effect divergence?

The answer for this question lies in the firm's response to different governance patterns. Different governance patterns transfer distinct signals on whether the policy will remain stable for a long period, thus impacting firm expectations and long-term technological innovation strategies. When policy uncertainty increases, firms increase their financial liquidity and reduce R&D investments to address the potential increase in environmental fines and government-imposed production restrictions or shutdown measures. Consequently, firms' technological innovations are impeded. When the policy is more certain, firms expect environmental protection to be long-term policy, collusion with local governments to be difficult, and improving product and process technology (referred as "second sort of technological innovation" as Porter and Linde (1995)) to be the only way. This expectation will encourage firms to invest on technological innovation. Therefore, fluctuations in regulation policy can render firm expectations to be unstable and their technological innovation strategies, short-sighted, which decreases long-term R&D investment. Thus, different governance patterns can yield different results for the Porter effect. Hence, governance patterns may be key to explaining different relationships between environmental regulation and technological innovation. However, few studies address the differences in governance patterns, and no study explains the Porter effect divergence by governance patterns. Governance patterns in environmental regulation lack proper measurement and empirical testing, primarily because of the vagueness of the definition and the challenge of quantitatively measuring governance patterns.

This study uses two indicators Normalized Governance Index (NGI) and Passive Governance Index (PGI) to describe city governance pattern of environmental regulation. PGI and NGI can be viewed as two-dimensional coordinate axis. Some cities have both high (low) PGI and NGI. By employing two-digit industrial technological innovation data from China's cities, the examination supports that a stable normalized regulation pattern promotes a positive approach to technological innovation, whereas an unstable passive regulation pattern hinders it. These findings are also helpful to explain the controversial empirical results on the Porter effect.

This study contributes to the literature as follows. Firstly, it is the first study to focus on the governance pattern in environmental regulation. This study extends the current research of environmental regulation from intensity to governance pattern. Governance pattern analysis makes rich policy implications for local governments by suggesting normalized and stable regulation pattern. Secondly, this study forms a unique dataset of regulation intensity and pattern by adopting firm's punishment information for the illegal discharge. Such intensity index provides new measure for China's environmental regulation. Consequently, a quantitative method is constructed to measure governance patterns. Different from Xiao et al. (2018) this study further controls year fixed effect to eliminate effect from annually macro shocks. Governance pattern index addresses the data lack for governance pattern and makes econometric test possible. Thirdly, the governance pattern analysis offers new explanation the divergence of the Porter effect. This study primarily finds a potential explanation for the Porter effect difference among regions. Because of governance pattern difference, which stems from political and institutional environment, sampling bias can induce significant deviations in the results. This finding furnishes a potentially generalizable explanation of prior discoveries in the literature.

The remainder of this study is organized as follows. Section 2 reviews the literature. Section 3 introduces the study mechanism and hypotheses. Section 4 presents the main models, datasets, and variables used in the regressions and describes the key index construction process. Section 5 presents the regression results and analysis, discusses the connection with existing studies. Section 6 performs robustness checks. Section 7 summarizes the findings and discusses the emergent policy implications and scope for future research.

2. Literature review

2.1. Environmental regulation

Porter effect theorizes that strict environmental regulation can enhance technological innovation and promote long-term economic efficiency (Porter and Linde,1995). Jaffe and Palmer (1997) divide the Porter effect into "strong" and "weak" versions. The "strong" version indicates that environmental regulation can promote the competitiveness of companies by improving their productivity. The "Weak" version posits that certain technological innovations can be simulated. Popp (2003), Carrión-Flores and Innes (2010), Kneller and Manderson (2012), Rubashkina et al. (2015), and Wang et al. (2019) use empirical data to support the Porter hypothesis, while Conrad and Wastl (1996), Gray and Shadbegian (2003), Shao et al. (2020) find that environmental regulations hinder technological innovation, against Porter effect.

The existing literature attempts to explain the empirical divergence of the Porter effect across countries, by dividing environmental regulation tools into market-based and "command and control" (Popp et al., 2010). The former regards environmental policies and laws using economic measures like taxes and subsidies to incentivize companies to reduce pollutant emissions. The latter includes standards, commands and prohibitions to control pollutant emissions from inputs and outputs of polluting productivity (Testa et al., 2011). However, the empirical studies rarely form a broad consensus. Popp et al. (2010) pointed out that the market-based regulations promote technological innovation while "command and control" regulations block it. It's concluded that market-based and "command and control" tools can explain the Porter effect difference across regions. But recent studies (Li and Xiao, 2020; Ouyang et al., 2020) on the Chinese style of "government-motivated" environmental regulation also find a significant positive Porter effect. Thus, dividing market-based and "command and control" regulations is insufficient to explain the conflicting empirical results for the Porter effect.

Furthermore, other studies explore the differences from various perspectives. From the firm perspective, Shao et al. (2020) estimate the effect of regulation on enterprise technological innovation behavior, suggesting that empirical differences depend on enterprise characteristics and strategic goals. Smirnova et al. (2021) find that firm's high capital expenditure to curb pollution decreases technological innovation activity, while high operating expenditure increases technological innovation activity. From the government tools perspective, Li and Xiao (2020) find that strict pollution charges promote technological innovation, while subsidies hinder it. From the perspective of regulation intensity evolution, recent studies (Boakye et al., 2021; Ouyang et al., 2020; Wang et al., 2022; Zhao et al., 2018) find a non-monotonic (U-shaped) Porter effect between environmental regulation and economic behavior, suggesting that direction of the impact from environmental regulation intensity on technological innovation depends on whether the intensity reaches a threshold. When the regulatory intensity surpasses this threshold, excessive environmental regulation may inhibit corporate technological innovation. In addition, Zefeng et al. (2018) suggest that economic and social policies significantly affect the Porter hypothesis.

2.2. Governance patterns

Most of the existing literature of environmental governance pattern focuses on its impact on the pollution control (Agrawal et al., 2022; Kostka and Nahm, 2017; Shen and Steuer, 2017). And the governance pattern effect on technological innovation only attracts sparse discussion, and no rigorous examination has been implemented. Only some studies explored the influence of government policies and behavior style (such as corruption, policy uncertainty etc.) on technological innovation, without focus on environmental regulation. Baker et al. (2016), and Kang et al. (2014) find policy uncertainty reduces R&D investment of firm. Gomes and Barros (2022) analyze the sustainability transitions in Brazil by case study and suggest that uncertainty significantly affects firms' technological innovation. Kyaw (2022), Le et al. (2022), Liu and Ma (2020) find that government policies uncertainty leads to a squeezing-out effect on corporate R&D investments. He et al. (2022) find that corruption can encourage firms to circumvent environmental regulations through rent-seeking, leaving firms with little incentive to increase R&D investment. Although these studies provide inspiration for this study, they have not answered whether governance pattern of environmental regulation impacts technological innovation directly.

One reason for insufficient study of governance pattern is the lack of indicators to describe governance patterns of regions, which consequently makes rigorous test impossible. For example, Nilsson et al. (2012) and Kroepsch (2018) use case analysis to distinguish different regulatory patterns. Nansikombi et al. (2020) use the non-parametric Wilcoxon test to compare the regulatory capablity gap among governments. Although there is no governance pattern measure for direct reference, Xiao et al. (2018) contribute a method to identify the relations-oriented firm by the changes in business entertainment expenses before and after the release of *the Eight Provisions of Central Government*. This index construction method gives this paper enlightenment.

Existing research has following knowledge gaps: Firstly, most of the existing literature analyzes the environmental regulation, but has not yet paid enough attention to the governance patterns of environmental regulation. Among the limited studies on the governance patterns, most of them are limited to exploring the governance pattern impact on pollution control. No studies focus on the governance pattern effect on technological innovation, and make rigorous test for it. Secondly, existing literature diverges on the Porter effect. Although some studies have attempted to explain it from many perspectives, no consensus has been reached. Therefore, it is necessary to explore from other perspective such as governance patterns. Third, the existing literature lacks measurement of governance patterns, and fails to put forward scientific indicators to describe cities governance patterns. Then it is impossible to incorporate governance pattern into the econometric analysis.

3. Mechanism and hypotheses

This study defines environmental governance patterns in two dimensions: Normalized Governance Index (NGI) and Passive Governance Index (PGI). The former, which relates to the internal self-willingness to improve the environment, represents a long-term regulation intensity adopted by city-level governments. The latter, which relates to external upper-level governments' supervision and requirements, represents the short-term fluctuation of regulation intensity sensitive to the central government's supervision. Notably, NGI and PGI are not mutually exclusive. A regional government may have a strong willingness to keep the regulation intensity stable at a high level and yet have a sensitive response to the central government's supervision and further enhance the regulation intensity.

Theoretically, the regulation patterns of governments can affect the expectations of firms to cope with regulatory stress, affecting their behavior toward technological innovation. For example, when a city-level government has a high NGI level, firms in the city are more inclined to expect long-term strict environmental regulations with stability and predictability. It would increase R&D investment and trigger technological innovation to avoid the high cost of regulation and vice versa. When a government has a high PGI level, firms are more inclined to expect that environmental regulations are temporary and may fluctuate with the central government requirements and supervision. Thus, they are encouraged to adopt short-term measures to address environmental regulations, like temporarily shutting down factories and colluding with the local government. Hence, governance patterns may moderate the relationship between environmental regulation and firms' technological innovation. Next, this study analyzes the mechanism of the moderation effect from governance patterns on the Porter effect.

3.1. *Environmental regulations*

On positive effects, Porter and Linde (1995) hold that appropriate environmental regulations can force enterprises to innovate. This positive impact can be divided into price and non-price mechanisms. Regarding price mechanisms, for firms that discharge pollutants, environmental regulations increase the polluting costs, motivating them to invest in green technologies and reduce pollutant emissions and polluting costs. For firms that do not discharge pollutants, regulations increase the price of intermediate inputs that produce pollutants, forcing enterprises to develop new technologies to reduce the use of such inputs. Thus, government environmental regulations may promote industrial technological innovation.

The non-price mechanism has four aspects. First, as Porter and Linde (1995) pointed out, regulation signals companies about likely resource inefficiencies and potential technological improvements. Even regulation focused on information gathering can achieve much by raising corporate awareness. Second, environmental regulation signals that governments hope to promote industrial upgradation and green transformation. This will encourage local enterprises to engage in R&D investment to obtain better political and business relations with local governments. Third, regulation reduces the uncertainty of innovation rewards that investments in environmental technological innovation will be valuable. More certainty leads to more investment in technological innovation. Fourth, the enhancement of government environmental regulation induces an increase in government expenditure on environmental protection, thus enhancing the demand for products from the environmental protection industry, increasing the revenue of relevant firms, and stimulating technological innovation. Therefore, this study proposes the following hypothesis.

Hypothesis 1. Governments' environmental regulation positively boosts technological innovation.

3.2. *Governance patterns*

For city-level governments, which are responsible for implementing environmental regulations, there are three key motivations to protect the environment: enhance people's welfare level; attract talent and investment; and conform to the supervision of upper-level governments, such as central governments. In China, local government motivation for environmental regulation highly depends on central government supervision (Hong et al., 2019). The central government sets different environmental protection goals per local conditions, and their implementation directly affects the central government's performance evaluation, affecting the promotion of individual officials. Thus, local officials are strongly motivated to respond actively to the central inspection for ecological and environmental protection. The regulation intensity of local government will vary with changes in central spot checks, emergency management and official tenure assessments. That is, the more active their response, the greater uncertainty and intensity fluctuation of environmental regulations. In this study, PGI represents policy uncertainty. A city with high PGI has an unstable policy environment because high PGI represents high fluctuates of regulation intensity.

Classical economic wisdom holds that firms increase their financial liquidity when market uncertainty is enhanced, reducing R&D investment. The research on uncertainty originated from Keynes' analysis, as individual confidence would be affected by uncertainty. According to real options theory and financial friction theory, firm's investments decrease when uncertainty increases. Given the irreversibility nature of investment projects, higher degree of uncertainty makes more return of waiting for future investment than current investment, hence a higher value on the option of waiting. Consequently companies have an incentive to postpone or cancel their current investment plans (Bernanke, 1983). Since the technological innovation investment return cycle is generally long and the failure risk is also relatively high, firm's investment will become more sensitive to uncertainty. Following empirical researches also reveal that policy uncertainty makes declines in investment, output, and employment both at firm-level and macro level (Baker et al., 2016; Kang et al., 2014), because of the investment irreversibility (Gulen and Ion, 2015). Especially, policy uncertainty incentivizes firms to delay investments in environmental research and developments (R&D) or postpone environmental projects that are costly (Kyaw, 2022; Le et al., 2022; Liu and Ma, 2020). For example, China's evidence shows policy uncertainty hinders investment in renewable energy and R&D (Jiao et al., 2022). That is, technological innovation investment triggered by environmental regulation would be affected by policy uncertainty. If local governments increase environmental regulation intensity with high PGI level, firms' willingness to invest in long-term technological innovation may be weakened. Thus, the policy uncertainty plays moderating effect in innovation (Li et al., 2021). Conversely, when the market is certain, waiting for future investment has no additional value. Firms will be encouraged to invest in production and innovation without delay.

Further, local governments with high PGI level more likely conspire with firms and use short-term methods for pollution reduction to address central government supervision. The collusion of government and firms would also erode the regulation impact on technological innovation, and negatively play moderation effect.

Conversely, NGI will play positive moderating effect in technological innovation. Firstly, NGI represents the stability of regulation intensity, which represents the policy certainty. Policy certainty makes investment to address environment problems valuable, and greater certainty encourages more investment (Porter and Linde, 1995). As explained by (Bernanke, 1983), certainty means low value on the option of waiting, thus encourages current investment of technological innovation. Secondly, when regulation intensity is at steady high level, collusion between firms and local governments is fraught with risk. Firms have to comply environmental regulations with product and process cost increase. Thus, it's urgent to make technological innovations to offset the costs of compliance (Porter and Linde, 1995). Hence, this study proposes the following hypotheses.

Hypothesis 2. PGI has a negative moderating effect between environmental regulation and firms' technological innovation.

Hypothesis 3. NGI has a positive moderating effect between environmental regulation and firms' technological innovation.

4. Model, data, and variables

4.1. Models

This study implements Eq. (1) to estimate the effect of environmental regulation on technological innovation to prove Hypothesis 1:

$$lninnov_{cit} = \alpha_1 lnregu_{ct} + \omega X_{ct} + \sigma_{ci} + \omega_{it} + \mu_{cit}, \tag{1}$$

where $lnregu_{ct}$ is the key variable and is defined as the logarithmic form of environmental regulation intensity in city c in year t. The main outcome, $lninnov_{cit}$, is the logarithmic form of the technological innovation index in city c for industry i in year t. The variable X_{ct} is a set of city-level control variables. This study controls for higher-dimensional fixed effects, specifically city-industry fixed effect σ_{ci} and year-industry fixed effect ω_{it}, in addition to city and year fixed effects. This approach offers two advantages: first, it bolsters the robustness of the empirical findings by accounting for variations in developmental endowments across industries within the same city and divergent developmental trends among industries in the same year. Second, it tackles potential endogeneity concerns stemming from omitted variables, given the absence of industry-level control variables, thereby alleviating such issues.

Further, to estimate the moderating effect of governance patterns, this study implements Eq. (2) as follows:

$$\begin{aligned} lninnov_{cit} = {} & \beta_1 lnregu_{ct} + \beta_2 lnregu_{ct} \times NGI_c + \beta_3 lnregu_{ct} \times PGI_c \\ & + \gamma X_{ct} + \sigma_{ci} + \omega_{it} + \mu_{cit}, \end{aligned} \tag{2}$$

where NGI_c and PGI_c represent the city-specific NGI and PGI, respectively. In Eq. (2), this model focuses on the estimation of parameters β_2 and β_3, which represent the moderating effect of different governance patterns. This model reveals that the regulation effect on technological innovation depends on the governance pattern, NGI and PGI. According to the hypothesis 2 (3), β_2 (β_3) should be positive (negative), suggesting that NGI (PGI) enlarges (shrinks) the regulation effect on technological innovation.

4.2. Data and variables

4.2.1. Dependent variable

This study employs the industry-level technological innovation index of Chinese cities (Kou and Liu, 2017). This index uses patent data from the China National Intellectual Property Administration to ascertain the value of the retained patents for each industry in cities. The calculation formula is as follows:

$$V(T) = \sum_{t=1}^{T} \left[R_{0j} (1 - \delta_j)^t - C_{tj} \right] (1 + i)^{-t} \tag{3}$$

where $V(T)$ is the patent value, T is the patent age when the patentee stops paying annual fees, j is the year of patent application, t is the age of the patent calculated from the application date, R_{0j} and C_{tj} respectively indicate the revenue generated by the patent to the patentee at age t and the annual fee paid by the patentee, δ_j is the decay rate of the initial revenue of the patent, i is the discount rate. The formula signifies the present value of income generated by the patent over its lifespan. Notably, stopping patent fees and shortening the term of patent protection can reduce the technological innovation index according to the formula. Instead of directly using the number of patents as an technological innovation index, this index uses the econometric method to estimate the patent value of different patent ages.

4.2.2. Primary explanatory variables

This study uses data from China Institute of Public & Environmental Affairs (IPE) and *China Environmental Statistics Yearbook* to build regulation intensity and governance patterns indices. IPE has a detailed database of the number of firms subject to administrative punishment for the illegal pollution discharge. Contaminant emission data of 113 key cities (i.e., provincial capital cities and metropolises with large populations) are obtained from the *China Environmental Statistics Yearbook*. This study employs such data to build variables on regulation intensity, referring to Ye et al. (2018). See Appendix A for details.

For governance patterns, this study refers to Xiao et al. (2018), who use the difference in firms' business entertainment expenses before and after *the Eight Provisions of Central Government*. In China, many enterprises try to maintain good relationships (Guanxi) with government officials to improve cooperation opportunities and gain market facilities. Xiao et al. (2018) call firms whose main business relies on Guanxi with government officials as Guanxi-based firms. Most of their business entertainment expenses are used for rent-seeking from the government.

Therefore, after the release of *the Eight Provisions of Central Government*, the business entertainment expenses of such enterprises have dropped significantly. This index construction method gives this paper enlightenment: based on some special policy time nodes, we can calculate the changes of environmental regulation intensity to represent PGI pattern.

In May 2014, the Chinese Ministry of Environmental Protection signed the "*Interim Measures for Inquiry with the Ministry of Environmental Protection*"—a landmark event for central supervision. Inquiry and punishments mainly focus on city-level governments that fail to pass the annual environmental assessment, which influences the annual performance evaluation and promotion opportunities of officials. As of mid-2015, many prefecture-level city governments have been inquired, significantly enhancing the central supervision over local governments, thus drastically changing the regulation intensity in some cities. Therefore, this study uses the change of environmental regulation intensity before (2011–2013) and after (2014–2015) the signing of *Interim Measures for Inquiry* to measure the PGI. In order to control unobservable macro policy changes, this study improves the original method of Xiao et al. (2018) and construct Eq. (3) to divide NGI and PGI:

$$regu_{ct} = \gamma_1 \times I_1 + \gamma_2 \times I_2 + \delta_t + \rho_{ct}, \tag{4}$$

where $regu_{ct}$ is the regulation intensity of city c in year t, obtained from Eqs. (A.1)–(A.3). I_1 is a 112 $\times$1 vector, indicating the cities. I_2 is the interaction of I_1 with I (c & $t \geq$ 2014); it is also a 112 $\times$ 1 vector. Further, δ_t is the year fixed effect, and ρ_{ct} is the error term. γ_1 and γ_2 are 1 $\times$ 112 vectors. γ_1 is NGI_c, and γ_2 is PGI_c. This equation is similar to the Difference in Differences (DID) method in econometrics. When year t is below 2014, the expectation of the regulation intensity index is ($NGI_c + \delta_t$). When year t is equal to or above 2014, the year of establishment of *Interim Measures for Inquiry*—the expectation of the intensity index—is ($NGI_c + PGI_c + \delta_t$). Note that this method depends on a specific period in 2014. When important events that could weaken (enhance) the regulation intensity occur before (after) 2014, they can affect the accuracy of the estimation of regulation intensity. Thus, this study uses a placebo test to solve this problem and prove the robustness of the special period (2014).

Two points must be explained regarding the indicators of governance patterns. First, the indicators are time-constant variables. Second, NGI and PGI are not mutually exclusive. NGI and PGI levels of a city government can increase and decrease simultaneously as shown in Fig. 1. For example, in Shanghai, the levels of NGI and PGI are both far higher than those of other cities—the government of Shanghai has a strong willingness to enhance the regulation intensity and is also sensitive to the central government's supervision.

4.2.3. Other control variables

At the city level, city R&D expenditure will directly affect the technological innovation of all firms within the city, so this paper controls government R&D expenditure (*fisrd*). In addition, other city level variables are also controlled. For economy scale, the resident population (*pop*) and total GDP (*gdp*) are controlled. For economic development level, GDP per capita (*gdppc*) and per-labor wage (*wage*) are controlled. For economic structure, the proportion of industrial output (*ind*2) is controlled. For economic development driver, the human capital including the per capita financial expenditure on education (*fisedupc*), the proportion of college students (*highedu*), and physical capital-the total investment in fixed assets (*fixed*) are controlled. For public service, the total expenditure of city governments (*fisexp*), and the proportion of urban road areas in built-up areas (*road_p*) are also controlled. Further, to eliminate the impact of the inflation rate, this study deflates seven variables related to the price and inflation rate (*gdp*; *gdppc*, *wage*; *fisedupc*; *fisexp*; *fisrd*; *fixed*) according to the provincial consumer price index from 2011. The study obtained data from *the China Urban Statistical Yearbook* and the *China Statistical Yearbook*, and bridged missing values with the data from the previous and two subsequent years.

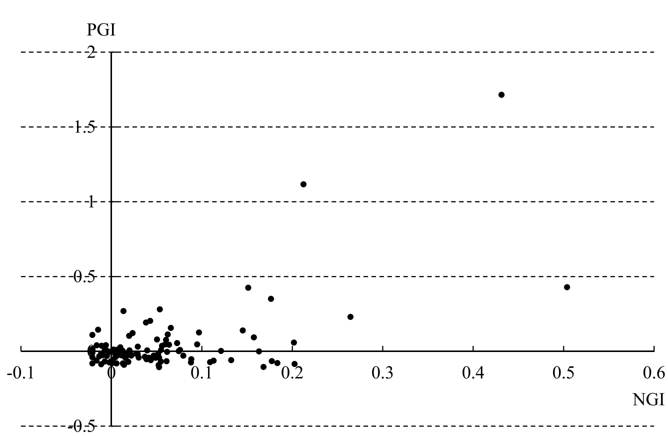

Fig. 1. Scatter of NGI & PGI index.

4.2.4. Descriptive result

By scattering the technological innovation and regulation intensity grouped by different governance patterns (as shown in Fig. 2), we find the coefficients of the fitted value line are positive, for all the subplots, according with the Hypothesis 1. The coefficient for the cities in the top third of the NGI index (subplot 1) is 0.618; that in the bottom third of the NGI index (subplot 3) is 0.112. Thus, an increase in the NGI index may induce a rise in the coefficients, consistent with Hypothesis 2. For the PGI index, the coefficient of the cities in the top third of the PGI index (subplot 4) is 0.440, less than 0.548—that of the bottom third of the PGI index (subplot 6). This result accords with Hypothesis 3.

4.3. Endogeneity and instrument variable

Besides the endogeneity problem noted above, the models and equations have two other significant endogeneity problems. First, the model has significant omitted variable problems. For example, government ability is an important control variable that affects both the regulation intensity and city-level technological innovation; even so, it is challenging to measure government ability quantitatively. Second, cities with high levels of technological innovation have a higher standard of environmental protection, which can stimulate local governments to enhance the regulation intensity. Thus, the model has a reverse causality problem.

Therefore, this study uses air ventilation coefficient as an instrumental variable (IV) to solve the endogeneity problem above. A synthesized air ventilation coefficient is the arithmetic product of wind speed and mixing height, two main forces acting on pollutant dispersion in the atmosphere (Broner et al., 2012). When the dispersion of pollutants in the atmosphere is facilitated (i.e., a country has a relatively high air ventilation coefficient), the pollution problem is relatively moderate, and the air pollution regulation is laxer. Thus, this IV affects the regulation intensity but is exogenous to technological innovation, as it does not affect city-level technological innovation and R&D investment. The air ventilation coefficient is widely used in recent studies (Chen and Chen, 2018; Han et al., 2023; Hering and Poncet, 2014; Shen et al., 2017). The IV is highly based on the hypothesis that atmospheric circulation has a strong impact on environmental regulation. Following the checklist from Lal et al. (2021), KP-rk LM and KP-F statistics using bootstrapped standard errors (SEs) for under identification test and weak identification test are reported, to avoid an overestimation of the F statistic. Young (2022) shows that conventional SEs underestimate the uncertainties in sampling and induce false discoveries. Hence, this study employs the bootstrap method to obtain SEs and confidence intervals.

The ERA-Interim data provide wind speed at 10 m height and mixing height for a global grid of 751 $\times$ 751 cells (approximately 83 km^2). This study employs the data following Hering and Poncet (2014) to obtain

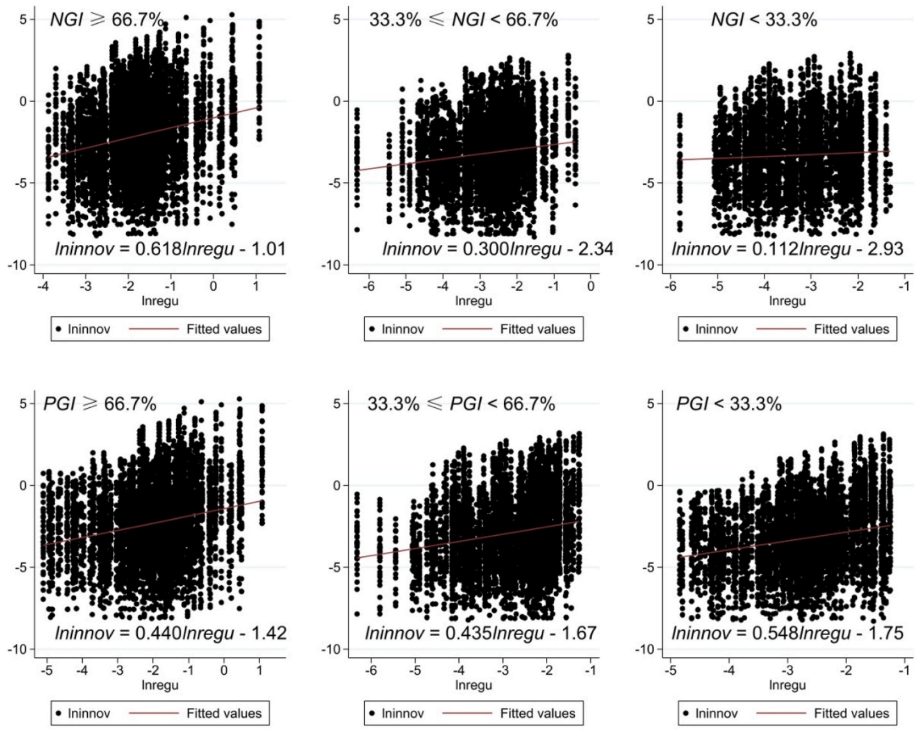

Fig. 2. Scatter plots of innovation index and regulation intensity index. *Notes*: The red line is the OLS regression result between the logarithmic form of the innovation index (*lninnov*) and regulation intensity index (*lnregu*). The figure shows the coefficients and intercepts. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

the city-level air ventilation.

4.4. Datasets

The panel datasets used in this study include 41 two-digit industries in 113 key cities for five years (2011–2015). The total sample size is 23,165. Table 1 presents the details of the data and summarizes the city-level control variables—regulation intensity variable and city-industry level technological innovation index. Note that for the regulation intensity (*regu*), the mean value is 0.119, and the 10th percentile is 0. Thus, more than 10% of the main explanatory variable is zero, as no firm illegal discharge is publicly disclosed at that year in prefecture-level city, indicating extremely low supervision level. Some cities have weak environmental regulation, as reflected in the low regulation intensity.

For the technological innovation index, the 10th percentile is also 0 because some two-digit-level industries have not developed in some cities, and not all industries have patents and innovations in a city. For extreme values, the maximum regulation intensity is 2.931, which is more than 20 times the mean value. The maximum technological innovation index is 196.412, which is more than 300 times the mean value. Thus, 2% of the data from the dataset are deleted, including 1% extremely large and 1% small values on technological innovation and regulation intensity indices. See Table 2 for results on the cities with high NGI and PGI indices.

Table 1
Descriptive statistics.

	N	Mean	Percentile				
			Min	10%	50%	90%	Max
1. City-level variables							
regu	565	0.119	0.000	0.000	0.070	0.248	2.931
NGI	565	0.051	−0.021	−0.011	0.022	0.157	0.504
PGI	565	0.037	−0.105	−0.078	−0.012	0.145	1.715
fisexp	565	0.047	0.003	0.013	0.027	0.082	0.532
fisrd	565	13.886	0.148	1.104	3.683	31.227	246.937
pop	565	537.196	29.970	169.970	507.900	878.900	3371.840
gdp	565	0.330	0.019	0.086	0.189	0.724	2.159
gdppc	565	5.484	1.578	2.536	4.761	9.441	42.157
ind2	565	50.876	19.250	38.380	51.240	62.380	89.340
fixed	565	0.207	0.012	0.053	0.143	0.458	1.343
wage	565	4.510	2.476	3.429	4.323	5.780	9.702
highedu	565	325.858	16.416	68.907	195.027	905.478	1293.687
road_p	565	14.570	3.889	8.773	12.658	20.032	201.273
fisedupc	565	0.149	0.029	0.075	0.118	0.229	1.049
2. City-Industry level variables							
innov	23,165	0.573	0.000	0.000	0.026	0.795	196.412

Table 2
Cities with high NGI & PGI index.

Top 10 cities of NGI index		Top 10 cities of PGI index	
City	NGI index	City	PGI index
Shenzhen	0.5037	Beijing	1.7151
Beijing	0.4313	Xiamen	1.1170
Yangquan	0.2642	Shenzhen	0.4292
Xiamen	0.2123	Haikou	0.4254
Xining	0.2025	Jinan	0.3510
Changsha	0.2018	Shaoxing	0.2813
Wuxi	0.1834	Zhuhai	0.2697
Hangzhou	0.1773	Yangquan	0.2306
Jinan	0.1764	Xi'an	0.2042
Taiyuan	0.1681	Yantai	0.1930

Notes: NGI = Normalized Governance Intensity; PGI = Passive Governance Intensity.

5. Results, analysis, and discussion

5.1. Regulation intensity

This study uses a fixed-effects model with IV to estimate the effect of regulation intensity on city-industry-level technological innovation. Table 3 lists the results of Eq. (1). Column (1) is the result of the pooled ordinary least squares (POLS), and Column (2) is the result of the fixed-effect model. Columns (3), (4), and (5) use the IV to eliminate the endogeneity of the regulation intensity. Note that the result of the OLS (IV) estimation is negative (positive); the IV estimation is more credible because of eliminating endogeneity problems. In the first-stage regression results, all bootstrapped F-statistics are above 10 and statistically significant at the 1% level, indicating that the results in Columns (3)–(5) do not have a weak IV problem. Note that conventional SEs have the potential for underestimation (Lal et al., 2021); thus, we report bootstrapped SEs and obtain confidence intervals.

In Column (3), a 1% rise in regulation intensity induces a 0.5639% increase in the technological innovation index, statistically significant at the 1% level. Thus, environmental regulation positively affects technological innovation. Technological innovation may differ in annual trends and fluctuations per industry. For example, technological innovation in emerging industries has faster growth than that in traditional industries. Thus, in Column 4, the year-industry fixed effects are controlled to avoid the influence of different time trends in industries on the results. The result remains positive, with a significance level of 1%. In Column 5, more control variables are added in the model, such as *fixed*, *ind2*, and *road_p* to observe the influence of omitted variables on the estimation and the changes in the estimation parameters. The result remains positive, and the coefficient is 0.5370, only changing within 5% of the estimation in Column (3). Therefore, the results support Hypothesis 1. Compared to other similar studies, Xiaoqing Li et al. (2021) employs Chinese provincial panel data and finds that a 1% increase in regulatory intensity leads to a 0.644% increase in the patent index. Result in Column (5) of this study is relatively close to their findings. Thus, the omitted variable has a limited influence on the final estimation result. Note that using the conventional robust error may underestimate SEs and report false significance; thus, we employ the bootstrap method clustered at the city-industry level to obtain SEs and confidence interval.

Table 3
Estimates of the effect of regulation intensity on the innovation index.

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	IV	IV	IV
	lninnov	lninnov	lninnov	lninnov	lninnov
lnregu	0.0714[a]	−0.0236[a]	0.5639[a]	0.5582[a]	0.5370[a]
	(0.0255)	(0.0051)	(0.1654)	(0.1633)	(0.1563)
Main Control Variables	Yes	Yes	Yes	Yes	Yes
fixed、*ind2* and *road_p*	No	No	No	No	Yes
City × Industry2 FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Year × Industry2 FE	No	No	No	Yes	Yes
N	16,658	16,454	16,454	16,454	16,454
Estimation of First-stage Regression					
VC	–	–	−0.0003[a]	−0.0003[a]	−0.0003[a]
			(0.0001)	(0.0001)	(0.0001)
KP-rk LM			21.41	21.45	21.68
KP-F	–	–	13.17	13.05	15.78
P	–	–	0.0000	0.0000	0.0000

Notes: All observations are from 113 key cities from the 2011–2015 period. Columns have bootstrapped standard errors clustered at the city-industry level in parentheses. The main control variables are all variables except *fixed*, *ind2*, and *road_p*, including *gdp*, *pop*, *fisexp*, *fisedupc*, *fisrd*, *gdppc*, *highedu,* and *wages*. We use the bootstrap method clustered at the city-industry level to obtain the KP-rk LM and KP-F statistics.
**Significant at the 5% level.
*Significant at the 10% level.
[a] Significant at the 1% level.

5.2. Governance patterns

Table 4 shows the estimation results of the governance patterns via Eq. (2). The results are IV estimations with all control variables, including *fixed*, *ind2*, and *road_p*, consistent with Column (5) in Table 3. From Column (1) ([2]), the estimation of the NGI (PGI) effect is positive (negative), both of which are statistically significant at the 1% level. Thus, the results confirm Hypotheses 2 and 3. We put NGI and PGI indices together as the main independent variables in Column (3) to see if the coefficient changes significantly. The estimation in Column (3) is larger than that in Columns (1) and (2). Nevertheless, the direction of the positive or negative sign does not change, indicating no changes on our main result.

The negative coefficient of *lnregu* × *PGI* suggests negative moderation effect of PGI for technological innovation. As the regulatory intensity increases, regulatory intensity in cities with higher PGI, triggers less technological innovations. This is because high PGI represents greater uncertainty and intensity fluctuation of environmental regulations. Then firms increase their financial liquidity when market uncertainty is enhanced, reducing R&D investment. As contrast, high NGI signals that strong regulation will be stable and that investing in technological innovation is profitable. Thus, regulatory intensity in cities with higher NGI, triggers more technological innovation.

Returning to the study focus, governance patterns crucially impact how the Porter effect changes across different governments. We count the environmental regulation marginal effect based on coefficients in

Table 4
Estimations of governance patterns.

	(1)	(2)	(3)
	IV	IV	IV
	lninnov	lninnov	lninnov
lnregu	0.4551***	0.4925***	0.2028***
	(0.1305)	(0.1354)	(0.0539)
lnregu × *NGI*	1.6311***		3.8071***
	(0.5020)		(0.8668)
lnregu × *PGI*		−0.3600***	−1.0999***
		(0.0894)	(0.2373)
All Control Variables	Yes	Yes	Yes
N	16,454	16,454	16,454

Notes: All columns have bootstrapped standard errors clustered at the city-industry level in parentheses. "All control variables" means ten city-level control variables, including *fixed*, *ind2*, and *road_p,* as in the estimation in Table 3, Column (5). City-industry and year-industry fixed effects are included in the estimation.

Column (3) in Table 4 and show the result in Table 5. If environmental regulation follows the hypotheses, the Porter effect $\partial y/\partial x = \beta_1 + \beta_2 NGI - \beta_3 PGI$ $(\beta_1, \beta_2, \beta_3 > 0)$, as expressed in Eq. (2), is positive when NGI is high and PGI is low. This effect expression indicates that governance patterns can reverse the direction of the Porter effect. In Table 5 Part 1, as NGI and PGI indices in certain regions reach some level, the negative effect can offset the positive effect, reversing $\partial y/\partial x$ to negative. The sign of $\partial y/\partial x$ depends on the two opposite forces from governance patterns. When NGI is low and PGI is high, enterprises in the local market face fluctuating environmental supervision. Further, distorted incentives for R&D investment and rent-seeking behavior breed in this governance pattern, hindering the motivation to innovate.

For geographical analysis of technological innovation, this study divides cities into three groups, East, Middle and West regions. China shows an "East-Middle-West" stepwise decline in economic development. For regulation effect on technological innovation, cities in the Middle Group have the highest marginal effect on technological innovation while the West cities have the lowest, as shown in Table 5 Part 2. The East cities do not have the highest marginal effect because they have higher PGI index than national average level in Table 1, which offset positive NGI effect. The West cities have lower NGI index than national average level, which hinder their marginal effect. This part suggests that East cities should avoid governance pattern with high PGI level and fluctuating regulations while the West cities should strengthen their long-term regulation intensity. Table 5 Part 3 shows some cases of typical cities. For example, the regulation intensity of Beijing is higher than that of Shanghai. However, the regulation effect on technological innovation in Beijing is negative, while that in Shanghai is positive. Compared with Shanghai, Beijing has extreme high NGI and PGI indices, but PGI is overwhelmingly high, and the fluctuation of regulation harms expectation, which consequently, impedes the technological innovation. This is a typical case that governance style, rather than regulation intensity, matters technological innovation. Another comparison of two West cities, Xi'an and Chengdu, reveals that Chengdu, the city with less passive level, has higher marginal effect of regulation on technological innovation. This conclusion suggests that the rapid economic and technological innovation development in Chengdu may be due to low PGI, which constructs a stable expectation and encourages technological innovation.

Table 5
Marginal effect in each governance pattern group.

1. Governance pattern group			
PGI / *NGI*	Low	Medium	High
Low	0.2445	0.1725	−0.0002
Medium	0.3717	0.2997	0.1270
High	0.8877	0.8157	0.6430
2. Cities grouped by geography			
Geography groups	*NGI*	*PGI*	Marginal effect
East	0.0671	0.0827	0.3673
Mid	0.0561	0.0038	0.4122
West	0.0237	−0.0054	0.2990
3. City cases			
City	*NGI*	*PGI*	Marginal effect
Beijing	0.4313	1.7151	−0.0416
Shanghai	0.0968	0.1266	0.4321
Xi'an	0.0428	0.2042	0.1411
Chengdu	0.0758	0.0098	0.4806

Notes: Part 1 represents the marginal effect of environmental regulation intensity on innovation in each governance pattern group. Low, medium and high correspond to the 10th, 50th, and 90th percentile of each governance pattern index. Part 2 represents average NGI and PGI indices and marginal effect in each geography groups. East includes cities in Heilongjiang, Liaoning, Jilin, Beijing, Tianjin, Hebei, Shandong, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong and Hainan; Mid includes cities in Shanxi, Henan, Anhui, Jiangxi, Hubei, Hunan; west includes cities in Inner Mongolia, Ningxia, Shaanxi, Gansu, Qinghai, Xinjiang, Tibet, Chongqing, Sichuan, Guizhou, Yunnan, Guangxi. Part 3 represents 4 city cases. We use estimation results in Table 4 Column (3) to count the marginal effect for each part, the equation is $\beta_1 + \beta_2 \times NGI_G + \beta_3 \times PGI_G$, where G is governance pattern groups.

Therefore, the Porter effect changes among regions in China because of the different government patterns and styles. From the economic theory perspective, the NGI (PGI) represents the predictable (unpredictable) and stable (unstable) parts of the environmental regulation. Different patterns of governance affect the market expectations of regulation policy and the long-term regulation stability, influencing the R&D investments and technological innovation strategies of firms.

5.3. Discussion: can governance patterns explain prior findings?

This study primarily finds a potential explanation for why the Porter effect differs among regions. Thus, the main results should explain some common prior empirical findings. We use the inverted U-shaped Porter effect as an example. Studies like Zhao et al. (2018) and Boakye et al. (2021) incorporate the quadratic term of environmental regulation into their regressions and find a negative coefficient, suggesting a decreasing Porter effect when regulation is strengthened. However, others (Ouyang et al., 2020; Pan et al., 2019) find a positive U-shaped Porter effect. This study discovers that governance patterns and potential sampling bias may explain such differences.

First, we divide all the sampling cities into weak and strong groups per annually-averaged regulation intensity. Then we divide cities into "Good" (NGI high and PGI low) and "Bad" (NGI low and PGI high) groups in 113 cities. Table 6 shows the FE model results.

For the moderating model in this study, $\partial y/\partial x = \beta_1 + \beta_2 NGI - \beta_3 PGI$ $(\beta_1, \beta_2, \beta_3 > 0)$. Thus $\partial y/\partial x$ is larger in the Good Group than that in the Bad Group. This is supported by the results in Table 6. Both Weak Group (Column (1)–(3)) and Strong group (Column (2)–(4)) show $\partial y/\partial x$ of "Good" samples is larger than that of "Bad" samples.

For the inverted U-shaped Porter effect, $\partial y/\partial x = \alpha_1 - \alpha_2 x$ $(\alpha_1, \alpha_2 > 0)$ decreases with the rise of x. Thus $\partial y/\partial x$ is negative in the Strong Group while positive in the Weak Group. This study reveals that the real reason of negative (positive) $\partial y/\partial x$ in the Strong (Weak) Group may lie in the governance patterns, which can be concluded from Column (2)–(3).

In Column (2) ([3]), when the regulation pattern is "Bad" ("Good") and intensity is Strong (Weak), there is a significant negative (positive) coefficient of regulation intensity. That is, if we only choose the "Bad" pattern samples when regulation intensity is strong (Column (2)), and "Good" pattern samples when intensity is weak (Column (3)), we can observe changes of signs for regression coefficient, which is in accordance with inverted U-shaped Porter effect.

This study furnishes a potential implication on the Porter effect. Ignoring analyses of the political and institutional environment,

Table 6
Estimation of the Porter effect grouped by regulation intensity.

	(1)	(2)	(3)	(4)
Governance Pattern Group	NGI low and PGI high (Bad)		NGI high and PGI low (Good)	
Intensity Group	Low (Weak)	High (Strong)	Low (Weak)	High (Strong)
	lninnov	*lninnov*	*lninnov*	*lninnov*
lnregu	−0.0437***	−0.0704***	0.1247**	−0.0080
	(0.0130)	(0.0156)	(0.0556)	(0.0145)
N	2489	919	608	2824

Notes: All columns have standard errors clustered at the city-industry level in parentheses. There are 113 cities in the dataset. Weak/Strong Regulation Groups have 57/56 cities. All regressions in this table use the fixed effect model and control for year-industry and city-industry fixed effects.

sampling bias can induce significant deviations in the results. Some studies (Boakye et al., 2021; Zhou et al., 2020) bear potential concerns by using biased data (i.e., parts of regions or listed firm that mostly agglomerates in economically developed cities) to yield an inverted U-shaped Porter effect. This study provides a new perspective to explain such results. Thus, future studies should discuss in-depth comparability of governance patterns among samples.

The governance patterns of environmental regulation also differ significantly worldwide. Our study supports the global governance patterns improvement, and provides rich policy implication for innovation process in the context of global sustainable development.

6. Robustness and heterogeneity analysis

6.1. Control pollution-related variables

Table 3 Column (5) considers some omitted variables, but issues remain. Current control variables don't account for the main explanatory variables' composition or pollution treatment levels in cities. Therefore, this paper includes the logarithmic form of the emissions of the four major categories of pollutants as control variables to control important components of the index, and controls the proportion of industrial water and gas pollutant emissions to the total production, in order to control the pollution treatment levels in various cities. The results are estimated by Eq. (2). shown in Table 7 Column (1)–(2). The direction of all estimates is consistent with Table 4 Column (3), indicating that the omitted relevant variables do not affect the main regression results.

6.2. Lag terms

Technological innovation does not always have an instantaneous output. Thus, this study uses the regulation intensity index with a lag of one year to analyze the lag effect. Table 7, Column (3), shows that the estimation is 0.1464, less than 0.5370 in the benchmark estimation result in Table 3, Column (5); it remains significant at the 1% significance level. Therefore, environmental regulations have a lag effect on the following year's technological innovation level. The effect decreases over time per the natural trend.

6.3. Sampling change

The difference in the administrative hierarchy and history of cities can affect the technological innovation ability and regulation intensity, affecting the result's causal identification. Thus, this study eliminates four province-level municipalities (Beijing, Shanghai, Tianjin, and Chongqing) that have a higher administrative hierarchy to avoid a selection bias in the samples in Table 8, Column (1). As data from Xinjiang and Tibet might have low quality, this study eliminates cities in Xinjiang and Tibet in Table 8, Column(2). The direction of all estimates is consistent with Table 4 Column (3), remaining at the 1% significance level.

Table 7
Robustness check A.

	(1)	(2)	(3)
	IV	IV	IV
	lninnov	lninnov	*lninnov*
lnregu	0.2722***	0.2453***	
	(0.0721)	(0.0635)	
lnregu_l1			0.1464***
			(0.0462)
lnregu × NGI	5.3450***	4.4890***	
	(1.2244)	(1.0305)	
lnregu × PGI	−1.3848***	−1.2894***	
	(0.3121)	(0.2811)	
Four polluants emissions	Y	Y	
Two emission proportions	N	Y	
N	16337	16337	12,960

Notes: All columns have bootstrapped standard errors clustered at the city-industry level in parentheses. All the estimation results control for the city-level control variables and city-industry and year-industry fixed effects.

6.4. Placebo test

The NGI and PGI indices rely on 2014 when the *Interim Measures for Inquiry* were signed and implemented. Therefore, we must identify the significance of the estimation from this specific year rather than other years. For example, if we use other years to count the NGI and PGI indices and obtain a significant result, the significance will lose its economic meaning. Therefore, this study uses a placebo test to identify if the significant result only comes from 2014. We set different policy transition year and obtain new NGI and PGI indices. For each year (2012–2015), average of regulation intensity before this year is used as NGI index, and difference of regulation intensity after and before this year as PGI index. Then, with these new NGI and PGI, the coefficients of Eq. (2) are estimated as placebo test. Robustness will be proved if NGI coefficient is significantly positive and PGI coefficient is significantly negative only in year 2014. Table 9 shows the results that only the estimation for 2014 is consistent with our hypothesis: NGI coefficient is significantly positive, and PGI is significantly negative. The estimation for year 2012 and 2013 is positively significant both in PGI and NGI indices. The coefficient of PGI index in 2015 is not statistically significant. This result provides an important evidence that 2014 *Interim Measures for Inquiry* is the most crucial policy transition point for governance patterns.

6.5. Intra-provincial spillover

To consider spatial spillover among cities, the regulation intensity of neighbor cities should be controlled. But the dataset only contains 113 key cities, not covering all prefecture cities. Hence, this study employs total provincial emissions data from *the China Statistical Yearbook*, which allows for establishing a provincial-level regulation intensity index and using it in the regression as a control variable. Table 10 shows the results. The direction and significance of all estimates are consistent with Table 4 Column (3), indicating that spatial spillover has limited effect on main estimation result. The negative coefficient of *lnregu_prov* suggests that provincial environmental regulation has a significant negative spillover effect on technological innovation, possibly due to increased pollution costs raising the overall price of intermediate input goods in the provincial market, crowding out firms' innovation investment.

6.6. Heterogeneity analysis

All industries in the theoretical analysis are affected by regulation policies regardless of whether pollutants are discharged. Given a price

Table 8
Robustness check B.

	(1)	(2)
	IV	IV
	lninnov	lninnov
lnregu	0.2107***	0.2301***
	(0.0487)	(0.0471)
lnregu × NGI	2.3541***	2.7389***
	(0.5678)	(0.5507)
lnregu × PGI	−1.8863***	−1.8209***
	(0.3488)	(0.3168)
N	15,640	15,339

Notes: All columns have bootstrapped standard errors clustered at the city-industry level in parentheses.

Table 9
Placebo test.

	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
	lninnov	lninnov	lninnov	lninnov
lnregu	0.6898***	0.8148***	0.7890***	0.9477***
	(0.1562)	(0.1572)	(0.1606)	(0.2056)
lnregu × *PGI_2012*	0.0909***			
	(0.0258)			
lnregu × *NGI_2012*	0.1404***			
	(0.0302)			
lnregu × *PGI_2013*		0.0434**		
		(0.0195)		
lnregu × *NGI_2013*		0.1820***		
		(0.0334)		
lnregu × *PGI_2014*			−0.1740***	
			(0.0417)	
lnregu × *NGI_2014*			0.1425***	
			(0.0298)	
lnregu × *PGI_2015*				0.0008
				(0.0280)
lnregu × *NGI_2015*				0.2142***
				(0.0442)
N	12,701	14,162	15,189	15,504

Notes: All columns have bootstrapped standard errors clustered at the city-industry level in parentheses.

Table 10
Intra-provincial spillover.

	IV
	lninnov
lnregu	0.2494***
	(0.0564)
lnregu × *NGI*	2.7272***
	(0.5831)
lnregu × *PGI*	−0.8062***
	(0.1589)
lnregu_prov	−0.2398***
	(0.0482)
N	16,818

Notes: All columns have bootstrapped standard errors clustered at the city-industry level in parentheses. Although we use the provincial-level *lnregu* index as an independent variable, the estimation remains at on the city-level to maintain comparability with previous regression.

mechanism, environmental regulation should have a more obvious impact on the industries with high pollution, as they face tougher regulations and higher costs. Therefore, following Zhao (2003), this study divides all the two-digit-level industries into low-, medium-, and high-pollution groups and regress them separately (as shown in Table 11A). We also compare these coefficients by Chow test (as shown in Table 11B). Appendices B and C present details of the index construction and classification of industries. Table 11A shows the regression results.

The overall estimation results confirm the expectations based on the theoretical analysis. The estimation result for the high-pollution industry group in Table 11A, Column (3), is 0.9491, significant at the 5% significance level. The low- and medium-pollution groups observe no significant results in Columns (1) and (2) at the 5% significance level. Further, the coefficient in high-pollution industry group is significantly larger than that in medium-pollution industry (as shown in Table 11A), conforming that industries with higher pollution levels face stronger regulation, thus making the cost of environmental regulation therein more influential. The low-pollution group coefficient is also significantly larger than that of the medium-pollution group (as shown in Table 11B). The reason may be that many low-pollution industries are technology intensive and more capable of technological innovation.

Further, to see if the moderating effect of governance patterns changes across different pollution groups, we regress Eq. (2) separately for each group; Table 12A shows the results. For moderating effects, the estimation of PGI and NGI indices is significant at the 1% level in the low- and high-pollution groups in Columns (1) and (3). Both PGI and NGI moderating coefficients of the high-pollution group and low-pollution group are significantly larger than those of the medium-pollution group (as shown in Tables 12A,12B). These results suggest that both high-pollution and low-pollution industry suffer bigger impact from regulation governance patterns than medium-pollution. It's because that for high-pollution industry, environmental policy changes its cost most, as it faces most severe regulation intensity. For low-pollution industry, which is more active in technological innovation, environmental policy changes it's innovation more.

Table 11A
Industry-level heterogeneity analysis.

	(1)	(2)	(3)
Pollution Group	Low	Medium	High
VARIABLES	*lninnov*	*lninnov*	*lninnov*
lnregu	0.6172*	0.4871	0.9491**
	(0.3150)	(0.3505)	(0.4826)
N	5773	5221	5824

Table 11B
Chow test of industry-level heterogeneity analysis.

	(1)
VARIABLES	*lninnov*
lnregu × *I*(Low Group)	0.4591**
	(0.2022)
lnregu × *I*(High Group)	0.7567**
	(0.3498)
N	16,247

Notes: All columns have bootstrapped standard errors clustered at the city-industry level in parentheses. There are 41 industries in the dataset. Low- and high-pollution industries include 14 two-digit industries separately, and the medium-pollution industry has 13 two-digit industries, inducing a shortage of observations in the medium group. We don't include the Medium Group indicator variable in Table 11B to make Medium Group as baseline. All regressions in this table use the IV method and control for year-industry and city-industry fixed effects.

7. Conclusion and policy implications

The existence of the Porter effect remains controversial in the academic field. Merely categorizing regulation instruments into command-and-control and market-based methods is insufficient to explain the

Table 12A
Industry-level analysis with governance patterns.

	(1)	(2)	(3)
Pollution Group	Low	Medium	High
VARIABLES	*lninnov*	*lninnov*	*lninnov*
lnregu	0.2002**	0.1708*	0.3228***
	(0.0927)	(0.1020)	(0.1108)
lnregu × *NGI*	4.2647***	2.8792*	5.5470***
	(1.4596)	(1.6462)	(1.8369)
lnregu × *PGI*	−1.1688***	−0.8676*	−1.6181***
	(0.3980)	(0.4483)	(0.5017)
N	5773	5221	5824

Table 12B
Chow test of industry-level analysis with governance patterns.

	(1)
VARIABLES	lninnov
lnregu × *NGI* × *I*(Low Group)	5.4984***
	(1.8279)
lnregu × *NGI* × *I*(High Group)	6.6024***
	(2.1766)
lnregu × *PGI* × *I*(Low Group)	−1.3676***
	(0.4821)
lnregu × *PGI* × *I*(High Group)	−1.8436***
	(0.5595)
N	16,247

Notes: All columns have bootstrapped standard errors clustered at the city-industry level in parentheses. We don't include the Medium Group indicator variable in Table 12B to make Medium Group as baseline.

differences in empirical analyses across regions. Thus, it is vital to analyze the regulation styles using their patterns, as different environmental regulation patterns influencing firms, and markets directly affect firms' R&D investments and innovation behavior. Hence, this study quantifies governance patterns and empirically shows that different governance patterns can determine whether regulations promote or hinder technological innovation.

First, this study finds support for the Porter effect in the city-level dataset of China. Generally, environmental regulations promote industrial innovation across 113 Chinese cities. 1% change in regulation intensity induces a 0.54% increase in the technological innovation index, which is similar to Li et al. (2021). Second, and importantly, this study quantifies governance patterns to estimate how they affect the relationship between regulation and technological innovation. The results demonstrate the importance of expectations in the field on the Porter effect, showing that governance patterns are an essential adjustment variable moderating regulation effect on technological innovation and can even change the direction of the Porter effect. Further, the results reveal that governance patterns and the potential sampling bias of prior studies can explain the inverted U-shaped Porter effect of prior studies. By choosing the "Bad" pattern samples when regulation intensity is strong and "Good" pattern samples when intensity is weak, we can observe changes of signs for regression coefficient, which is in accordance with inverted U-shaped Porter effect. Similarly, some studies with inverted U-shaped Porter effect (Boakye et al., 2021; Zhou et al., 2020) also bear potential concerns by using partial samples (i.e., parts of regions or listed firm). The results suggest four implications for environmental, energy, and technological innovation policies. First, given the Porter effect, environmental regulation can promote industrial sector technological innovation. Second, as stable and expectable policies are preferable, governance patterns with high NGI level can benefit enterprises by stable expectations, increase R&D investments to save energy, and decrease contaminants emissions. Third, fluctuating policies with high passive level motivated by central government supervision negatively reduce regulation effect on innovation. Enterprises can adopt rent-seeking and temporary emission reduction measures to address regulation rather than achieve technological innovation. Fourth, high-pollution industries are more sensitive to environmental regulation; thus, stringent regulations perform powerful push to promote more technological innovation. Associate with China style environmental regulation, spot checks and short-term energy use regulations have become important tools for local governments to achieve energy conservation and emission reduction goal. This study shows that such fluctuating governance patterns may harm technological innovation and hinder the development of clean energy. This result is more alarming than other studies. Some optimistic research find that national environmental governance have a positive effect on air quality (Wang, 2021; Tan and Mao, 2021). Some relatively cautious study, such as Liu et al. (2022), only supports short-term positive effect and recognizes long-term fail of national supervision. As contrast, our study shows that extremely high PGI level may result in negative effects. Then we need to be fully aware of the risks and dangers from PGI. It's the NGI construction, such as laws and institutions development, that can motivate enterprises to invest in long-term innovation strategies and reduce contaminant emissions via technological innovation while ensuring environmental protection.

Despite the study implications, it bears notable limitations that give scope for further studies. First, though the study reveals the necessity of exploring the subdivision of "command and control" tools into two governance patterns, it only explains why the division of regulation tools into market-based and "command and control" tools is not sufficient to explain the divergent empirical results for the Porter effect. Future studies on environmental regulations can probe further and shed light on this controversial topic. Moreover, the Porter effect changes across regions and governments, because of the different expectations that firms establish from the regulation policies. Command and control regulation methods can provide a stable expectation for firms and the market by regularizing and institutionalizing the regulation. However, some market-based regulations could squeeze technological innovation given their fluctuations and instability. Hence, as the instruments do not matter as much as the expectations, further research can focus on such expectations and employ more indicators and data for the empirical research.

CRediT authorship contribution statement

Ye Yang: Methodology, Software, Data curation, Formal analysis, Writing – original draft. **Ying Xu:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Data availability

Data will be made available on request.

Appendix A

Method to calculate the environmental regulation intensity.

First, we assume that if two cities share the same environmental regulation intensity, the illegal firms to contaminant emissions proportion is the same in both cities. The IPE (2009) used 20 cities as reference cities to calculate the reference proportions: $compnum_r/pollu_r$. Here, $compnum_r$ is the number of firms facing administrative punishment for illegally discharging contaminants into the sewage in the reference cities. Further, $pollu_r$ is the total emission of contaminants in the reference cities. Thus, the regulation intensity index of city i can be measured by comparing the proportions of city i with the reference proportion, as expressed by Eq. (A.1). Thus, if an increase of one unit of contaminant emissions in two cities promotes the same number of illegal firms detected by local governments, the two cities have the same intensity of environmental regulation.

$$RE_{cxt} = \frac{compnum_{cxt}}{pollu_{cxt}} \bigg/ \frac{compnum_r}{pollu_r} \tag{A.1}$$

As the reference proportion is the same for all cities, $RE_{cxt} \propto compnum_{cxt}/pollu_{cxt}$, where $compnum_{cxt}$ is the number of firms under administrative punishment for the illegal discharge of contaminant x in city c in year t. The meaning of this indicator is: under the same amount of pollutant emissions, the more illegal enterprises found and disclosed by the government, the stricter the law enforcement and the greater the environmental supervision intensity in that area.

Further, to make the intensity index for each contaminant comparable, we normalize the intensity index using Eq. (A.2):

$$RE^s_{cxt} = \frac{[RE_{cxt} - \min(RE_x)]}{[\max(RE_x) - \min(RE_x)]} \tag{A.2}$$

where $\max(RE_x)$ and $\min(RE_x)$ are the maximum and minimum intensities, respectively, measured across all cities and for all years. By normalizing the intensity index, we can add all indices for different contaminants to build an integrated intensity index $regu_{ct}$ in Eq. (A.3):

$$regu_{ct} = \sum_x RE^s_{cxt} \tag{A.3}$$

where $regu_{ct}$ is the final regulation intensity index in city c in year t. A higher $regu_{ct}$ means a larger number of illegal companies are detected, representing a higher enforcement effort and environmental regulation intensity level.

Appendix B

Method to calculate the industrial pollution intensity.

Following Xikang Zhao (2003), we construct the following equations and methods to calculate the pollution intensity index, rank the index, and group all the two-digit industries into low-, medium-, and high-pollution industries. An industry's pollution intensity depends on its emission level per unit output. First, we calculate the pollution intensity for different contaminant types:

$$pi_{ix} = \frac{pollu_{ix}}{output_i} \tag{B.1}$$

where pi_{ix} is the pollution intensity for industry i contaminant type x, $pollu_{ix}$ is the contaminant emission for industry i pollutant type x, and $output_i$ is the output for industry i. Further, to aggregate the index at the pollutant level, we normalize the pi_{ix} index:

$$pi^s_{ix} = \frac{pi_{ix} - \min(pi_x)}{\max(pi_x) - \min(pi_x)} \tag{B.2}$$

where min (pi_x) is the minimum of pi_{ix} across all industries, and max (pi_x) is the maximum. Next, we use

$$PI_i = \frac{1}{n}\sum_x pi^s_{ix} \tag{B.3}$$

to aggregate the final pollution intensity index PI_i for industry i, where n is the number of contaminant types. Contaminant emission data were obtained from the *China Environmental Statistics Yearbook*, and the output data were obtained from the *China Industrial Yearbook*. As the industry classification standards in the two yearbooks were different in 2011, we used data from 2012 to calculate the pollution intensity index. Further, as the China Bureau of Statistics canceled the statistics for the total output for industries, we used the sales output.

Appendix C

Table C.1
Classification of industries by pollution intensity index

Industry	PI Index	Group	Industry	PI Index	Group
Production and Supply of Water	0.00	Low	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products	0.93	
Manufacture of Furniture	0.08		Mining and Processing of Non-metal Ores	1.34	
Manufacture of Electrical Machinery and Equipment	0.10		Mining and Washing of Coal	2.15	
Manufacture of Articles for Culture, Education, and Sport Activity	0.12		Smelting and Pressing of Ferrous Metals	2.18	
Ancillary Activities for Exploitation	0.14		Smelting and Pressing of Non-ferrous Metals	2.63	
Manufacture of Measuring Instrument	0.18		Processing of Petroleum, Coking, Processing of Nuclear Fuel	2.84	
Manufacture of Special Purpose Machinery	0.19		Other Manufactures	2.89	Large
Manufacture of General-Purpose Machinery	0.19		Manufacture of Non-metallic Mineral Products	3.36	
Manufacture of Automobile	0.20		Manufacture of Medicines	3.82	
Manufacture of Tobacco	0.24		Manufacture of Leather, Fur, Feather, and Related Products and Footwear	3.94	
Printing, Reproduction of Recording Media	0.31		Mining and Processing of Non-metal Ores	4.03	
Manufacture of Computers, Communication, and Other Electronic Equipment	0.32		Manufacture of Foods	5.02	
Manufacture of Rubber and Plastic	0.50		Processing of Food from Agricultural Products	5.47	

(continued on next page)

Table C.1 (*continued*)

Industry	PI Index	Group	Industry	PI Index	Group
Production and Supply of Gas	0.51		Manufacture of Textile	5.64	
Mining and Processing of Ferrous Metal Ores	0.62	Medium	Mining of Other Ores	5.89	
Manufacture of Railway, Shipbuilding, Aerospace, and Other Transportation Equipment	0.66		Manufacture of Raw Chemical Materials and Chemical Products	6.51	
Manufacture of Textile Wearing and Apparel	0.66		Manufacture of Wine, Drinks, and Refined Tea	9.84	
Metal Products, Machinery and Equipment Repair	0.68		Production and Supply of Electric Power and Heat Power	10.11	
Utilization of Waste Resources	0.71		Manufacture of Chemical Fibers	11.26	
Extraction of Petroleum and Natural Gas	0.78		Manufacture of Paper and Paper Products	26.45	
Manufacture of Metal Products	0.83				

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