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Research article

How does environmental regulations affect digital green innovation of high-pollution enterprises? Empirical evidence from China

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ABSTRACT

Digital green innovation (DGI) is crucial for high-pollution enterprises to improve green performance. However, there is a paradox regarding the impact of environmental regulations on DGI, primarily due to the varied effects of diverse regulatory tools. To resolve this paradox, based on Neoclassical Economics and the Porter Hypothesis, we empirically examine the influence of heterogeneous environmental regulations on DGI using a sample of high-pollution enterprises in China. The conclusions indicate that environmental protection tax has a pushing-forward effect on DGI, while environmental protection subsidy has a crowding-out effect. Moreover, enterprises' resource base and technological innovation capability positively moderate the impact of environmental protection tax. External pressure, internal incentives, pandering to governments, and managerial opportunism have mediating effects. Our research offers a new perspective to resolve the paradox of the effect of environmental regulations on DGI, explores potential mechanism as well as boundary condition, and proposes a new way of measuring DGI of enterprises with patents. Accordingly, we offer valuable policy recommendations about the formulation of environmental regulations, the facilitation of DGI, and the advancement of China's ecological civilization.

1. Introduction

Ecological civilization is of great importance to the Chinese government. Its government work report has repeatedly called for high-pollution enterprises to fulfill their environmental responsibilities. However, the ecological environment has specific unique attributes as a public good. Without institutional and normative guidance, individuals often lack the necessary motivation to protect the ecological environment [1]. Because of this unique attribute, a contradiction exists between the benefits and costs of high-pollution enterprises in environmental governance [2]. On the one hand, if high-pollution enterprises actively engage in environmental governance and ecological protection, external stakeholders will share the benefits of ecological improvement, while the costs incurred by environmental governance will be borne solely by high-pollution enterprises alone [3]. On the other hand, high-pollution enterprises do not have to pay for the costs of acquiring natural resources and enjoying a clean ecological environment. Therefore, a significant part of stimulating the active participation of high-pollution enterprises in environmental protection is internalizing the externality problem of environmental governance [4]. Specifically, the Chinese government employs two types of environmental

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regulations to internalize the externality problem: environmental protection taxes and environment protection subsidies. Environmental protection taxes involve imposing punitive charges on high-pollution enterprises for their ecological damage, while environment protection subsidies involve the government providing incentive compensation to encourage enterprises to reduce pollutants [5]. By these two types of environmental regulations, the Chinese government guides high-pollution enterprises to actively take environmental responsibilities, transform their development modes, and work towards sustainable development goals.

Digital green innovation (DGI) reshapes digital resources and incorporates digital technology into green innovation by integrating information, computation, communication, and connectivity technologies. Through integration, new products are developed, production processes are improved, organizational structures are altered, and business models are created and modified. The environment is greatly benefited by all these advancements [6]. Implementing digital strategies and promoting DGI in high-pollution enterprises are necessary and inevitable ways to enhance green performance and promote sustainable development [6,7]. The swift progress of digital technologies like artificial intelligence, big data, and industrial digitalization platforms have provided new perspectives and momentum for the combined growth of the economics and ecology [8]. Through DGI, high-pollution enterprises can reduce environmental damage, boost green development, and achieve sustainable development by improving their products, processes, and services [9]. DGI in product can promote pro-social product research and development and reduce the degree of environmental damage caused by high-pollution enterprises by improving the research and development efficiency and production quality of sustainable products [7]; By integrating digital processes with traditional production methods and implementing continuous iteration, high-pollution enterprises can reduce the environmental harm, striking a balance between individual benefits and environmental quality [10]; Digital platforms and ecosystems can also facilitate service innovation in high-pollution enterprises [6]. Leveraging big data technology, digital platforms enable quick collection and integration of product and green demand from various stakeholders, enabling enterprises to understand their product positioning better and make targeted improvements aligned with the sustainability needs of external stakeholders [11]. This will enhance the green performance in high-pollution enterprises. Therefore, encouraging the adoption of digital strategies and DGI in high-pollution enterprises holds tremendous practical significance in the digital era.

The analysis above indicates that implementing environmental regulations is essential for constructing ecological civilization and advancing sustainable development. At the same time, DGI is the proper and inevitable approach to increase the green performance in high-pollution enterprises [12,13]. Therefore, what is the possible relationship between environmental regulations and DGI? According to a review of previous studies, little have focused on the impact of environmental regulations on DGI [14]. Moreover, the multifaceted nature of environmental regulation, including punitive charges and incentive subsidies, contributes to varying effects on DGI. These effects encompass both a potential promotion of DGI (pushing-forward effect) and a potential inhibition of DGI (crowding-out effect), leaving a paradox regarding the impact of environmental regulations on DGI. Considering this gap, we propose a theoretical model supported by Neoclassical economics and the Porter Hypothesis to examine the impact of different types of environmental regulations on DGI [15,16]. Taking Chinese A-listed high-pollution enterprises from 2018 to 2022 as the sample, we verify the differential impact of heterogeneous environmental regulations on DGI in high-pollution enterprises and conduct endogeneity tests, robustness tests, mediating effect tests, moderating effect tests, and heterogeneity analysis to provide theoretical guidelines and policy recommendations for the formulation of environmental regulation in China.

2. Literature review and research hypothesis

2.1. Environmental protection tax and DGI

There are two distinct views regarding the impact of environmental protection tax on the DGI in high-pollution enterprises. On the one hand, the tax may occupy the resources of these enterprises, leading to a lack of necessary innovation resources and hindering their DGI. Firstly, following the principles of Neoclassical Economics, the government's imposition of an environmental protection tax adds to the "institutional compliance costs" faced by high-pollution enterprises [17]. The environmental protection tax penalizes firms for polluting the environment and destroying ecosystems during production and operation. While it forces enterprises to embrace the concept of sustainable development, the tax also increases their costs and operational burdens. To stay afloat, high-pollution enterprises will pass on the costs brought by environmental protection tax by misappropriating their technology research and development funds [18], thereby occupying the resources available for digital technology introduction and DGI. Secondly, DGI heavily relies on significant resource inputs from high-pollution enterprises, and the impact on green performance takes considerable time to materialize [10]. Considering the short-term costs imposed by this tax and the uncertainty surrounding the expected returns from DGI, managers in high-pollution enterprises will abandon DGI.

On the other hand, environmental protection tax may also have a pushing-forward effect, motivating high-pollution enterprises to apply digital technology and accelerate DGI. Firstly, from an internal view of the enterprise, the challenges posed by the tax can increase the innovation vitality and promote DGI [19]. Referring to the Porter Hypothesis, though environmental protection tax reduces high-pollution enterprises' directly realizable profits, it can motivate managers to actively reflect on the deficiencies of the enterprises' green development [20], effectively compensate for the inherent deficiencies of the governance mechanism, overcome the inertia that does not think about change [21], and create a sense of urgency for enterprises to innovate. Enterprises are compelled to offset the costs of the tax through the benefits of innovation, which helps to "push" enterprises to innovate. DGI can introduce new technologies to revolutionize enterprises' business models in terms of production, operations, and management, thereby enhancing operational efficiency, coordination, and cost reduction [22]. Therefore, leveraging DGI to offset the costs of environmental protection tax becomes a viable option for high-pollution enterprises [7]. Secondly, from an external view of the enterprise, the environment is a public good and enterprises need to respond to the pressures for sustainable development imposed by external stakeholders [23]. This demand compels managers to critically assess enterprises' production and operational decisions, considering the significant impacts of non-compliance with sustainable development requirements and prompting them to adopt new attitudes and approaches to comply with environmental regulations [24]. Green-focused enterprises are valued higher by investors than those penalized for environmental issues [25]. Through the implementation of DGI, high-pollution enterprises can mitigate environmental damages and enhance green development in terms of products, processes, and services [9], thus meeting the green development expectations of external stakeholders and reducing their negative perceptions arising from the ecological and environmental harm caused by high-pollution enterprises [26]. Therefore, whether it is to obtain "compensatory gains" to pass on the additional operating costs brought about by environmental protection taxes or satisfy the demands and pressures from external stakeholders on the environmental responsibility, managers in high-pollution enterprises will opt for a DGI strategy.

Accordingly, considering the crowding-out and pushing-forward effect of environmental protection tax, we propose two competitive hypotheses.

Hypothesis 1a. Environmental protection tax can promote DGI.

Hypothesis 1b. Environmental protection tax can inhibit DGI.

2.2. Environmental protection subsidy and DGI

A similar uncertainty surrounds the effect of environmental protection subsidy on DGI. On the one hand, the subsidy can have a compensatory effect on the resources required for enterprise innovation, thereby promoting the DGI. In existing research, it has been shown that government support and subsidies are beneficial to corporate innovation [27,28]. DGI, characterized by substantial upfront investments, complex technologies, and implementation challenges, demands significant resource allocation from high-pollution enterprises [29]. Resource scarcity is the primary obstacle hindering the implementation of digital strategies and the promotion of DGI in high-pollution enterprises [30]. Consequently, environmental protection subsidies effectively compensate for pollution charges and operational costs, enabling high-pollution enterprises to allocate more resources towards adopting digital technology and establishing digital platforms [31]. This, to some extent, mitigates the resource constraints faced by high-pollution enterprises when implementing digital strategies, reduces managers' concerns about the uncertainties associated with innovation, enhances their tolerance for innovation risks, and ultimately fosters DGI within high-pollution enterprises.

On the other hand, environmental protection subsidies may also have a negative impact on DGI, which is reflected in the crowding-out effect on their willingness and resources to implement digital strategies. Firstly, predatory hand theory suggests that when enterprises receive governments' support, they need to pander to the governments' demands, and even allocate resources at governments' behest, crowding out enterprises' incentives and resources to engage in technological innovation [32,33]. As a kind of specialized subsidy, Chinese environmental protection subsidy is governed by the Regulations on Strengthening the Management of Environmental Protection Subsidy Funds, stipulating that the subsidy should be only used for controlling key pollution sources as well as comprehensive environmental management and must not be diverted for other purposes. It is obvious that environmental protection subsidy mainly supports the direct environmental investment, but not specifically for DGI. Therefore, after obtaining environmental protection subsidy, high-pollution enterprises need to pander to the wishes of the government to carry out direct environmental investment, crowding out the resources for DGI. In addition, compared with environmental protection investment and direct environmental management, DGI is riskier, and the corresponding environmental and economic benefits need a longer period to return [34]. If high-pollution enterprises can meet the government's environmental requirements through direct environmental investment, their motivation to carry out DGI will be inhibited. Secondly, governments have difficulty monitoring the behavior of certain high-pollution

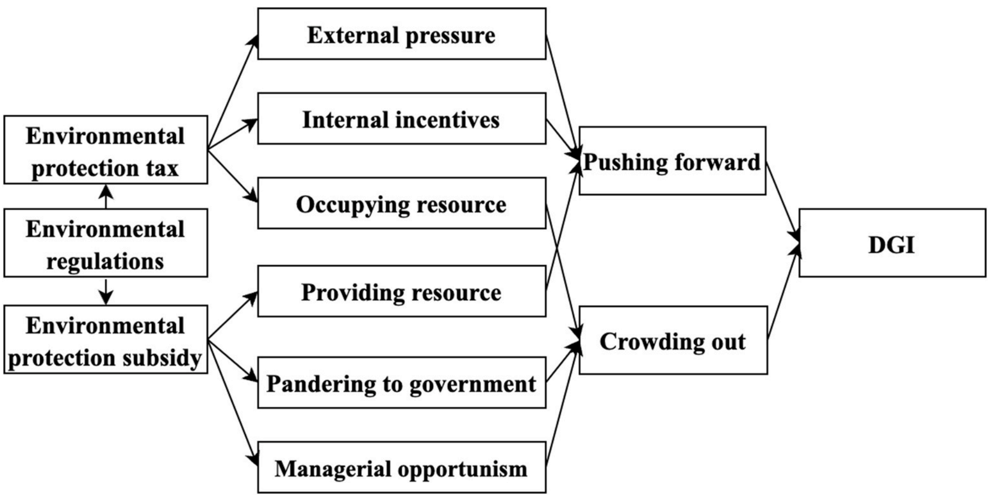

Fig. 1. Research framework.

enterprises directly because of information asymmetry [35]. The opportunistic of corporate management can easily cause resources to flow not into the field of creating enterprise value and social benefits, but into that of bringing private gains, distorting the direction of the optimal allocation of subsidies [36,37]. Therefore, when a high-pollution enterprise receives many environmental protection subsidies, the opportunistic of the management will be amplified and stimulated, and it will take possession of environmental protection subsidies or even more other resources of the enterprise [38], leading to the reduction in the resources to engage in DGI, thus inhibiting the DGI. Thirdly, excessive environmental subsidies may make high-pollution enterprises overly dependent on the government support, leading to the path dependency and reducing their endogenous motivation to implement DGI. At this point, enterprises will be more inclined to carry out simple and direct pollutant treatment and water purification by subsidies to meet the environmental requirements, rather than enhancing continuous sustainable development through continuous DGI.

Accordingly, considering the compensatory effect and crowding-out effect of environmental protection subsidy, we propose two competitive hypotheses.

Hypothesis 2a. Environmental protection subsidy can promote DGI.

Hypothesis 2b. Environmental protection subsidy can inhibit DGI.

The research framework for the competitive hypotheses is shown in Fig. 1, as below.

3. Research design

3.1. Data source

We take the Chinese A-listed high-pollution enterprises from 2018 to 2022 as research sample. Our data is obtained by matching multiple databases. The independent variables are obtained from annual reports of high-pollution enterprises in CNINFO Database, and dependent variables are from CNIPA Database. We collect all control variables form CSMAR Database. Mediating variables and moderating variables in the additional analysis part are from China Research Data Services Platform (CNRDS) and CSMAR. All these databases are widely used by scholars.

The original data are processed as follows. Firstly, we exclude the enterprises marked with ST to eliminate the interference of the enterprises' operational problems on DGI. Secondly, samples containing incomplete data are eliminated. Thirdly, we winsorize all continuous variables at their 1st and 99th percentiles to eliminate interference of extreme values. After sample selection and data cleaning, we obtained panel data of 7671 samples that can be used for empirical research.

3.2. Variables measurement

3.2.1. Independent variables

The environmental protection tax and subsidy are obtained from annual reports of high-pollution enterprises. We download these annual reports from the Wind database and organize them manually. To reduce the variability of both variables and improve readability of the empirical findings, we take the natural logarithm of the actual amount of environmental protection tax and subsidy after adding 1, respectively, which are used as proxy variables for environmental protection tax (*Tax*) and environmental protection subsidy (*Subsidy*).

3.2.2. Dependent variables

Patent is an important reflection of enterprises' innovation, and it has been generally recognized to use patent to measure an enterprise's innovation performance. DGI is the integration of information, computation, communication, and connectivity technologies to reshape digital resources and incorporate digital technology into green innovation [6]. Therefore, patents about DGI should encompass both green and digital technology dimensions. The specific process is as follows. Firstly, we obtain invention patents of all samples from CNIPA Database. Based on the "IPC Green Inventory" published by WIPO in 2010, we match the patent retrieved from CNIPA and screen out the green invention patents. Secondly, according to the "Comparison Table between Core Industry Classification of Digital Economy and International Patent Classification (2023)" published by CNIPA, we further filter out patents utilizing digital technology from the above green invention patents and calculate the number of invention patents possessed by enterprises for DGI. Finally, to overcome the right-skewed distribution problem of patent data, we use the natural logarithm of the number of all DGI patent after adding 1 as the proxy variable for DGI.

3.2.3. Control variables

According to previous studies, we identify and select 13 variables that may affect the DGI as control variables [39]. The variables and their measurements are as follows. (1) Age of the enterprise (*Age*): this is calculated by subtracting the year of establishment from current year; (2) Size of the enterprise (*Size*): we take the natural logarithm of its total assets; (3) Capital Structure (*Structure*): this variable is measured by the ratio of liabilities to total assets; (4) Cash flow (*Cash*): it is measured by the ratio of net cash flow to total assets; (5) Growth of enterprise (*Growth*): we measure it by the growth rate of the enterprise's current operating income; (6) Historical performance of the enterprise (*Roa*): it is characterized by the ratio of the previous period's net profit to total assets; (7) Market power of the enterprise (*Market*): the market power is measured using the natural logarithm of the ratio of sales revenue to operating costs; (8) Capital intensity of the enterprise (*Density*): li is measured by the ratio of total fixed assets to the number of employees; (9) Ownership of the enterprise (*Ownership*): for this variable, we set up a dummy variable, assigning a value of 1 if the high-pollution enterprise is state-owned capital holding, and 0 otherwise; (10) Equity Concentration of the enterprise (*Concentrate*): we characterize it by the shareholding ratio of the first largest shareholder of the high-pollution enterprise; (11) Political connection (*Politics*): similar to ownership, we set up a dummy variable. If the executives of the high-pollution enterprise have been or are currently serving as CCP representatives, deputies to the NPC, or members of CPPCC, the value is assigned: 1. Otherwise, it is assigned 0; (12) Board size of the enterprise (*Board*): we use the number of board members for measurement; (13) Two positions in one (*Dual*): this variable is also a dummy variable. The general manager and board chairman are assigned a value of 1 when the two positions are combined and 0 otherwise.

3.3. Model design

Since the dependent variable is continuous and numerical as well as conforms to normal distribution, and the scatter plot shows that the independent variable shows a linear relationship with the dependent variable, we propose a linear regression model [40].

$$DGI_{i,t} = \beta_0 + \beta_1 Tax_{i,t} + \beta_n Controls_{i,t} + +\mu_{i,t} + \sigma_{i,t} + \varepsilon_{i,t} \tag{1}$$

$$DGI_{i,t} = \beta_0 + \beta_1 Subsidy_{i,t} + \beta_n Controls_{i,t} + \mu_{i,t} + \sigma_{i,t} + \varepsilon_{i,t} \tag{2}$$

Model (1) examines the effect of tax on the DGI, while model (2) verifies the effect of subsidy on DGI. We introduce individual effect ($\mu_{i,t}$), time effects ($\sigma_{i,t}$) and cluster standard errors at firm level to control for differences over time, across firms and industries. *Controls* are the control variables mentioned above. Additionally, $\varepsilon_{i,t}$ represents a random perturbation term that the model cannot capture.

4. Empirical results

4.1. Descriptive statistics

In Table 1, the mean for DGI is 1.449, suggesting a generally low level of DGI among Chinese high-pollution enterprises. Furthermore, all high-pollution enterprises pay the environmental protection tax, while not all receive environmental protection subsidy from the government. Regarding the environmental protection tax, the mean is 13.46, while the mean for subsidy is 3.671. This implies that the amount of subsidy received by enterprises is relatively low. Additionally, the statistical distribution of each control variable aligns with the objective law and is consistent with existing related studies. This further strengthens the scientific validity and accuracy of our research samples.

4.2. Mean and median difference test between groups

Since not all high-pollution enterprises received environmental protection subsidy, it provides an opportunity to conduct difference test between-groups. Therefore, we use the T-test, one-way ANOVA, median difference test, and Kruskal-Wallis test according to whether the enterprises received environmental protection subsidy. The mean of DGI in the group that did not receive environmental protection subsidy is 1.521, while DGI in the group that received subsidy is 1.252, and the difference between the means and the median was significant at the 1 % level. In the one-way ANOVA, SSA is 108.721 and SSE is 5193.644, F value equals to 160.54 and significant at 1 % level. In Kruskal-Wallis test, Chi2 value is equal to 145.863 and significant at 1 % level. These tests imply that DGI of subsidized firms is higher compared to enterprises that do not receive environmental protection subsidy, which tentatively supports the crowding-out effect.

Table 1
Descriptive statistics.

Variable	N	Mean	SD	Min	Max
DGI	7671	1.449	0.832	0	5.561
Tax	7671	13.46	1.502	7.937	20.65
Subsidy	7671	3.671	6.247	0	20.81
Age	7671	20.63	5.180	6	55
Size	7671	22.43	1.308	19.63	28.30
Structure	7671	0.416	0.183	0.014	0.900
Cash	7671	0.056	0.064	−0.454	0.471
Growth	7671	0.110	0.243	−0.859	0.994
Roa	7671	0.039	0.076	−1.057	0.541
Market	7671	1.095	0.173	0.229	3.690
Density	7671	12.79	0.960	7.149	17.54
Politics	7671	0.270	0.444	0	1
Ownership	7671	0.283	0.451	0	1
Board	7671	8.329	1.606	4	17
Dual	7671	0.301	0.459	0	1
Concentrate	7671	0.312	0.137	0.0184	0.900

4.3. Baseline regression results

Table 2 presents the effects of tax and subsidy on DGI in high-pollution enterprises. Since we focus more on examine the effect of the amount of subsidy on DGI, only enterprises receiving subsidies are included in our following research. Specifically, Columns 1 and 2 display the effects after excluding control variables, while Columns 3 and 4 represent the findings after considering control variables. Additionally, Columns 5 and 6 examine combined effects of tax and subsidy, both excluding and considering control variables, respectively. In Column 3, the regression coefficient suggests that the tax exerts a pushing-forward effect on DGI and promotes the enterprise's DGI. In column 4, the regression coefficient indicates that subsidy has a crowding-out effect on DGI and inhibits DGI in high-pollution enterprises. As seen in Column 6, the conclusion is still valid after simultaneously considering the environmental protection tax and subsidy.

4.4. Heterogeneity analysis

4.4.1. Ownership

China's economy exhibits a distinctive "dualistic characteristic," with variations in the institutional environment and market position of state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs), potentially impacting the relationship between environmental regulations and DGI. On the one hand, non-SOEs, driven by profit maximization, display greater sensitivity to economic losses [41]. Furthermore, non-SOEs are relatively more fragile regarding their reputation and relationships with stakeholders because they do not have a governmental background. Therefore, the loss in economic benefits and external pressure from environmental protection taxes could further push forward non-SOEs to apply digital technology and accelerate DGI, thus promoting DGI.

On the other hand, compared with SOEs, non-SOEs enjoy relatively greater discretionary power. The opportunistic motivation of corporate management inspired by environmental protection subsidies and the greater discretionary can increases the likelihood of misappropriating subsidies, which crowding out the resources for conducting DGI. Therefore, environmental protection subsidies may further inhibit DGI in non-SOEs.

In our research, we divide the sample based on the ownership of high-pollution enterprises. The coefficient in Table 3 indicates that compared to SOEs, tax has a stronger pushing-forward effect on DGI in non-SOEs, while subsidy has a stronger crowding-out effect on DGI in non-SOEs as well. This suggests that the ownership of high-pollution enterprises needs to be fully considered when formulating policies on environmental protection taxes and subsidies.

4.4.2. Political connection

Political connections signify the strength of an enterprise's relationship with the government, enabling it to access resources and enhance its ability to resist risks [42]. These factors influence environmental regulations' impact on high-pollution enterprises' DGI. On the one hand, enterprises with weak political connections have limited access to resources, lower risk resistance, and heightened sensitivity to economic losses compared to those with strong political connections. Due to a lack of government endorsement, enterprises with weak political connections are prone to signal to outsiders that their social capital is weak. Thus, their relationships with stakeholders are relatively more fragile. Therefore, enterprises with weak political connections experience more significant external pressure from environmental protection taxes and are more likely to implement DGI.

On the other hand, enterprises with weak political connections have a relatively higher degree of information asymmetry between government and enterprises due to lacking direct relationship and are subject to relatively less supervision. As a result, executives have more opportunities to manipulate the allocation of environmental protection subsidies, leading to a crowding out of innovation resources and inhibiting DGI. Besides, to improve the governments' impression and improve the political connection, enterprises with weak political connection are more likely to try to actively pander to the governments through direct environmental investments. Such direct environmental investments can occupy the subsidy and crowd out the DGI.

Our research classifies high-pollution enterprises into the weak and strong connection group based on their political connections.

Table 2
Baseline regression.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	DGI	DGI	DGI	DGI	DGI	DGI
Tax	0.146***		0.116***		0.281***	0.253***
	(0.011)		(0.013)		(0.022)	(0.027)
Subsidy		−0.088***		−0.077***	−0.070***	−0.068***
		(0.007)		(0.006)	(0.006)	(0.006)
_cons	−0.567***	2.354***	−24.018***	−23.509***	−1.702***	−8.833***
	(0.148)	(0.092)	(2.435)	(3.080)	(0.332)	(3.333)
Controls	YES	YES	YES	YES	YES	YES
Firm/Year FE	YES	YES	YES	YES	YES	YES
N	7671	2053	7671	2053	2053	2053
Adj R^2	0.073	0.194	0.103	0.276	0.298	0.333
F	91.94***	52.23***	37.54***	22.67***	76.62***	28.09***

Table 3
Heterogeneity analysis based on ownership.

Variable	(1)	(2)	(3)	(4)
	Non-SOEs	SOEs	Non-SOEs	SOEs
	DGI	DGI	DGI	DGI
Tax	0.110***	0.108***		
	(0.016)	(0.024)		
Subsidy			−0.008***	−0.007***
			(0.001)	(0.002)
_cons	−0.187	−33.577***	−0.826	−41.687***
	(0.596)	(4.141)	(0.588)	(3.677)
Controls	YES	YES	YES	YES
Firm/Year FE	YES	YES	YES	YES
N	5497	2174	5497	2174
Adj R^2	0.063	0.192	0.062	0.190
F	17.06***	22.96***	16.90***	22.66***

Table 4 reveal that compared to enterprises with strong political connections, tax has a stronger pushing-forward effect on the DGI in enterprises with weak political connections, while subsidy has a stronger crowding-out effect on the DGI in enterprises with weak political connections as well. It implies that environmental protection taxes and subsidies should be heterogeneous for enterprises with different political connection to maximize the utility of environmental regulations.

4.4.3. Enterprise size

Significant differences exist between large firms and small and medium-sized enterprises (SMEs) regarding internal controls, external constraints, and profitability [43], which will impact the efficacy of environmental regulations. On the one hand, large enterprises have more redundant resources and stronger profitability, making them less sensitive to the economic impact of environmental protection taxes. Conversely, SMEs have tighter financial chains and lower profitability, making them more susceptible to economic losses from environmental protection taxes. Therefore, environmental protection taxes will increase the external pressure and internal incentives on SMEs, and further exert a pushing-forward effect on high-pollution enterprises' DGI.

On the other hand, constrained by the development conditions and resources, internal institutionalization of SMEs is relatively inadequate. SMEs have relatively weaker internal controls than large enterprises, leading to less effective control of executive opportunism. Executives are more likely to distort the optimal allocation direction of environmental protection subsidy and divert the subsidy. Therefore, the environmental protection subsidy will further exert a crowding-out effect on the DGI in high-pollution enterprises.

The Division of Statistically Large, Small, Medium, and Micro Enterprises, issued by NBSC, classify industrial enterprises with 1000 or more employees as large enterprises. Accordingly, based on the number of employees, we categorize high-pollution enterprises into the large enterprise group and the SMEs group. Table 5 indicate that, compared to large enterprises, tax has a stronger pushing-forward effect on DGI in SMEs, while subsidy has a stronger crowding-out effect on DGI in SMEs as well. These results show that the government should adopt different flexibility measures for enterprises of different sizes when formulating environmental regulations. For those SOEs, private enterprises, and low political connection enterprises, governments should enhance environmental protection tax, increase the amount and collection of tax, and strengthen the penalties for tax evasion by these enterprises. Subsidies supported for these enterprises should be strictly regulated and supervised to enhance the DGI.

Table 4
Heterogeneity analysis based on political connection.

Variable	(1)	(2)	(3)	(4)
	Weak	Strong	Weak	Strong
	DGI	DGI	DGI	DGI
Tax	0.122***	0.046*		
	(0.015)	(0.025)		
Subsidy			−0.008***	−0.006***
			(0.001)	(0.002)
_cons	−1.263**	−28.580***	−2.087***	−30.650***
	(0.631)	(2.839)	(0.627)	(2.383)
Controls	YES	YES	YES	YES
Firm/Year FE	YES	YES	YES	YES
N	5602	2069	5602	2069
Adj R^2	0.081	0.180	0.077	0.185
F	23.03***	19.88***	21.87***	20.64***

Table 5
Heterogeneity analysis based on enterprise size.

Variable	(1)	(2)	(3)	(4)
	SMEs	Large	SMEs	Large
	DGI	DGI	DGI	DGI
Tax	0.166***	0.091***		
	(0.024)	(0.016)		
Subsidy			−0.019***	−0.004***
			(0.002)	(0.001)
_cons	−18.489***	−0.169	−26.719***	−0.600
	(2.869)	(0.635)	(2.495)	(0.632)
Controls	YES	YES	YES	YES
Firm/Year FE	YES	YES	YES	YES
N	1792	5879	1792	5879
Adj R^2	0.193	0.080	0.207	0.077
F	16.11***	22.75***	17.67***	21.73***

5. Endogeneity tests and robustness tests

5.1. Endogeneity tests

5.1.1. Two-stage least squares regression analysis

The regression analysis above may suffer potential endogeneity from omitted variables and variable measurement errors. To address this concern, we employ 2SLS regression to examine potential endogeneity further. For environmental protection tax, referring to Hering and Poncet (2014), we construct a year-city air flow coefficient as the instrumental variable (*IV1*) using wind speed and atmospheric boundary layer height indicators from European Centre for Medium-Range Weather Forecasts Database [44]. The choice of this instrumental variable has some rationality. In terms of theoretical basis, the larger the air flow coefficient is, the stronger the air mobility is, and the more lenient the environmental protection tax will be. So, there is an obvious negative correlation between the air flow coefficient and the environmental protection tax. Regarding exogeneity, the air flow coefficient is directly affected by both wind speed and atmospheric boundary layer height. Both are only determined by natural conditions and cannot directly affect the DGI, which can satisfy the requirement of exogeneity of instrumental variables.

For environmental protection subsidy, we choose the fiscal deficit as the instrumental variable (*IV2*). The fiscal deficit of the local government in one year will be closely related to the number of subsidies [45]. However, the DGI of a listed enterprise in a certain year

Table 6
Endogeneity analysis I

Variable	I	II	I	II	I	II
	(1)	(2)	(3)	(4)	(5)	(6)
	Tax	DGI	Subsidy	DGI	IfSubsidy	DGI
Tax		0.639***				
		(0.112)				
Subsidy				−0.406***		−0.077***
				(0.044)		(0.001)
IV1	0.003***					
	(0.001)					
IV2			−0.001***			
			(0.001)			
IV3					0.088***	
					(0.008)	
Imr						0.012
						(0.065)
_cons						−30.544***
						(2.318)
Controls	YES	YES	YES	YES	YES	YES
Firm/Year FE	YES	YES	YES	YES	YES	YES
Industry & Year FE	NO	NO	NO	NO	NO	NO
N	7498	7498	1592	1592	7671	2053
F	100.76***		83.84***			34.60***
Pseudo R^2					0.072	
Log likelihood					−4135	
LR chi2					641.23***	
Anderson LM Statistics		99.36***		79.06***		
C-D Wald F Statistics		100.75***		83.84***		

form the micro perspective is unlikely to affect the government's fiscal deficit. And the fiscal deficit cannot directly influence the DGI without subsidies, which satisfying the requirement of exogeneity of instrumental variables. Therefore, we argue that fiscal deficit of cities can be estimated as reasonable instrumental variables.

Columns 1–4 in Table 6 report results of 2SLS. In Stage I, the coefficient of instrumental variables (*IV1* and *IV2*) indicates that they meet the necessary correlation requirements. In the Stage II, the Anderson LM statistic is 99.36 and 79.06, and C-D Wald F-statistic is 100.75 and 83.84, respectively. Both are greater than the significance threshold, indicating no weak instrumental variable problem. Analysis show that coefficient of tax and subsidy is consistent with the conclusion above. Therefore, our conclusions maintain a robustness even after accounting for potential endogeneity.

5.1.2. Heckman two-stage selection model

To solve sample self-selection bias, we utilize Heckman two-stage selection model. In Stage I, since all high-pollution enterprises in the sample pay environmental protection taxes and not all high-pollution enterprises receive environmental protection subsidies, we introduce the dummy variable called *IfSubsidy*. *IfSubsidy* indicates whether high-pollution enterprises receive subsidies. Meanwhile, to exclude the influence of other enterprises in the same industry and region on the decision-making of high-pollution enterprises, we introduce instrumental variable called *IV3*, which is the mean of other enterprises in the same industry and region obtaining subsidy. In Stage II, Inverse Mills Ratio, calculated based on Stage I, is incorporated into regression model. From Column 5 in Tables 6, in Stage I, *IV3* is significant. In Stage II, coefficient of subsidy indicates that it inhibits the DGI in high-pollution enterprises. Accordingly, our conclusions remain robust even after accounting for sample self-selection bias.

5.1.3. Propensity score matching

We employ PSM as a further testing method to address potential endogeneity resulting from sample selection bias. We divide the sample based on mean of tax and subsidy. All control variables are treated as characteristic variables. Propensity scores are calculated using the logit model and nearest neighbor matching algorithm, and only samples that meet the assumption of equilibrium test as well as common support are retained. We re-estimate the model after selecting samples satisfying the common support test. From Column 1 and 2 in Table 7, coefficients are consistent with baseline regression. Accordingly, even after accounting for sample selection bias, our conclusions remain supported.

5.1.4. Controlling for industry-year fixed effect

We further control for industry-year fixed effects on the basis of firm and year fixed effects. To a certain extent, this can solve endogeneity problems caused by variable omitting, such as the technology shocks form industry-level and other industrial policy support. From Column 7 and 8 in Table 7, our conclusions maintain a robustness even after accounting for potential endogeneity caused by variable omitting.

5.2. Robustness tests

5.2.1. Alternative measurements for independent variable

We divide the actual amount of tax and subsidy by total assets, respectively, and re-fit baseline regression model. The Columns 1 and 2 of Table 8 demonstrate that coefficients for *Tax2* and *Subsidy2* remain the main findings of our research. We also divide the actual amounts of environmental protection tax and subsidy by operating income (*Tax3 & Subsidy3*), re-fitting the model using Model 1 and Model 2. Furthermore, we also divide each of the tax and subsidy by 100 million to obtain new proxy variables (*Tax4 & Subsidy4*) and re-fit the model. Columns 3 to 6 of Table 8 reveal the robustness of our research conclusions.

5.2.2. Alternative measurements for dependent variables

In addition to invention patents, patents in China also include appearance patents and utility model patents. In our research, we

Table 7
Endogeneity analysis II

Variable	(1)	(2)	(3)	(4)
	DGI	DGI	DGI	DGI
Tax	0.127		0.301***	
	(0.013)		(0.028)	
Subsidy		−0.077		−0.078***
		(0.006)		(0.006)
_cons	−23.180	−23.498	−13.020***	−23.474***
	(2.435)	(3.081)	(3.485)	(3.078)
Controls	YES	YES	YES	YES
Firm/Year FE	YES	YES	YES	YES
Industry-year FE	NO	NO	YES	YES
N	7123	2051	2053	2053
Adj R^2	0.106	0.276	0.261	0.277
F	35.78***	22.61***	19.84***	21.65***

Table 8
Robustness test I

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DGI	DGI	DGI	DGI	DGI	DGI	DGI2	DGI2
Tax2	5.821***							
	(0.293)							
Subsidy2		−1.443***						
		(0.141)						
Tax3			0.140***					
			(0.017)					
Subsidy3				−0.732***				
				(0.072)				
Tax4					0.559***			
					(0.031)			
Subsidy4						−0.094***		
						(0.007)		
Tax							0.088***	
							(0.017)	
Subsidy								−0.018**
								(0.009)
_cons	−28.711***	−29.702***	−21.509***	−11.573***	−5.032*	−25.205***	−15.540***	−17.716***
	(2.250)	(3.064)	(2.591)	(3.634)	(2.681)	(2.978)	(3.315)	(4.235)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm/Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	7671	2053	7671	2053	7671	2053	7671	2053
Adj R^2	0.148	0.251	0.101	0.250	0.139	0.306	0.019	0.059
F	56.73***	19.90***	36.61***	19.87***	52.50***	26.22***	6.37***	3.73***

further extend indicator range of DGI to appearance patents and utility model patents, recalculate DGI, and re-fit the model using Model 1 and Model 2. From Columns 7 and 8 of Table 8, the regression coefficient of *Tax* and *Subsidy* both still supports our main conclusions.

5.2.3. Replacement for estimation model

Since the dependent variable in our research is a positive value greater than 0 and belongs to the left-truncated model, we employ the Tobit model to re-estimate the main effects. From Columns 1 and 2 of Table 9, it suggests that the main effects remain consistent even after replacing the estimation model.

5.2.4. Controlling for province fixed effect and industry fixed effect

For alleviation of the concern on industry-level and region-level time-invariant missing variables not included in the regression model, industry-level and region-level fixed effects are controlled in the regression analysis. As Columns 3 and 4, *Tax* and *Subsidy* are both significant, which supports our main conclusions.

5.2.5. Changing the range of sample

As Beijing, Shanghai, Tianjin, and Chongqing are the four municipalities directly under the central government in China, they have obvious political and economic advantages. Compared with other cities, they have a higher quality level of development. Therefore,

Table 9
Robustness test II

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DGI	DGI	DGI	DGI	DGI	DGI	DGI	DGI
Tax	0.129***		0.113***		0.136***		0.123***	
	(0.011)		(0.013)		(0.014)		(0.016)	
Subsidy		−0.107***		−0.076***		−0.082***		−0.079***
		(0.005)		(0.006)		(0.007)		(0.008)
_cons	3.358***	2.687***	−24.987***	−23.103***	−23.320***	−22.802***	−29.425***	−28.465***
	(0.310)	(0.469)	(2.461)	(3.133)	(2.460)	(3.165)	(3.442)	(4.191)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm/Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry/Province FE	NO	NO	YES	YES	NO	NO	NO	NO
N	7671	2053	7671	2053	6665	1809	6131	1738
Adj R^2			0.124	0.289	0.109	0.290	0.121	0.289
F			13.73***	12.61***	34.61***	21.29***	34.89***	18.85***
Log likelihood	−5530	−1843						
Wald chi2	687.36***	655.05***						

we re-estimate the model after excluding the four municipalities. In addition, given the economic impact of the COVID-19 in 2020 and fiscal support policies including the reductions of environmental tax and fee to help enterprises tide over the difficulties from the government, which may confound our identification of the effects of tax. Therefore, we try to exclude the sample in 2020 and re-fit baseline regression. The results in Columns 5 to 8 show that our findings remain robust.

5.2.6. Placebo test

We randomly assign environmental protection tax and subsidy to each firm-year observation and re-examine the baseline regression model. If the main regression remains significant, the relationship between two kinds of environmental regulations and DGI will lose statistical significance. To address this concern, we conduct 1000 placebo tests described above and draw the distribution of the regression coefficients of virtual DGI. In Figs. 2 and 3, the distribution is symmetric in the graph about the vertical line over the origin, implying that the expectation value of the coefficient of the virtual DGI will not be different from 0. It indicates that the virtual relationship between two kinds of environmental regulations and DGI does not exist, and our conclusion remains robust.

6. Additional analysis

6.1. Mechanism test

6.1.1. The mediating effect of external pressure and internal incentives

According to theoretical mechanism of our research, external pressure and internal incentives serve as specific pathways through which the environmental protection tax exerts the pushing-forward effect on DGI. First, media coverage is employed to measure external pressure on enterprises. Media coverage will give enterprises wider external attention, influence stakeholders' evaluation of enterprises, increase the chances of enterprises being regulated [46], and enhance managers' crisis awareness. Our research uses natural logarithm of the number of high-pollution enterprises reported in media as a proxy variable (*Media*). From Columns 1 and 2 in Table 10, external pressure mediates the relationship between taxes and DGI.

Second, we utilize the compensation of the top three executives as a measurement of internal incentives. Executives are critical in formulating and spearheading a firm's DGI strategy. Whether a firm undertakes innovative activities depends mainly on the extent to which executives are incentivized [47]. We employ natural logarithm of the total compensation received by the top three executives in high-pollution enterprises as a proxy variable (*Salary*). As Columns 3 and 4 of Table 10, internal incentives mediate the relationship between taxes and DGI. Table 11 shows the mechanism test using the Sobel and Bootstrap test. The mediating effect of external pressure as well as internal incentives remains significant.

6.1.2. The mediating effect of pandering to governments and managerial opportunism

According to the theoretical mechanism of our research, pandering to governments and managerial opportunism are potential pathway through which the environmental protection subsidy exerts a crowding-out effect on DGI. First, for the measurement of pandering to governments, we choose the direct environmental investment as a proxy variable and take logarithms of the investments (*Invest*). From Columns 5 and 6 in Table 10, pandering to governments mediates the relationship between subsidies and DGI. Second, information asymmetry between governments and high-pollution enterprises creates a situation where these subsidies are susceptible to being exploited by managers for their personal gains [36]. Roychowdhury (2006) [37] pointed out that the manipulation of production and operation activities is an essential approach for managers to satisfy short-term interests, and the real earnings management model proposed by Roychowdhury has been taken to portray the opportunistic behavior of managers. We use the enterprise's current period Roychowdhury (2006) [37] model regression residuals as a proxy variable for managerial opportunism (*REM*). In column 5 and column 6 of Table 10, managerial opportunism mediates the crowding-out effect of subsidies on DGI. Table 11 demonstrates that the mediating effect of pandering to governments and managerial opportunism are still significant with the Sobel test and Bootstrap test.

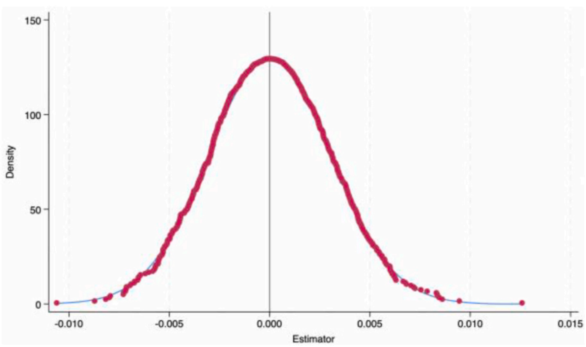

Fig. 2. Placebo test of pushing-forward-effect.

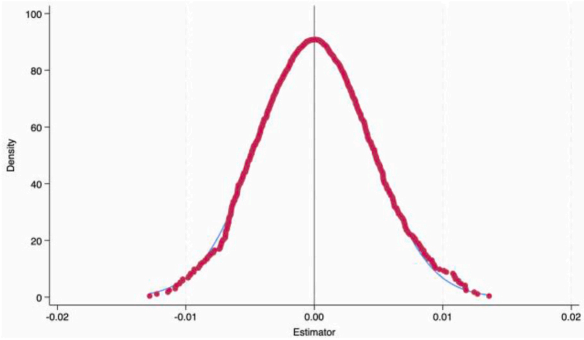

Fig. 3. Placebo test of crowding-out-effect.

Table 10
Mechanism test.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Salary	DGI	Media	DGI	Invest	DGI	REM	DGI
Tax	0.282***	0.089***	0.149***	0.114***				
	(0.015)	(0.013)	(0.049)	(0.013)				
Subsidy					0.119***	−0.075***	0.010***	−0.070***
					(0.044)	(0.006)	(0.002)	(0.006)
Salary		0.098***						
		(0.011)						
Media				0.013***				
				(0.003)				
Invest						−0.023***		
						(0.004)		
REM								−0.750***
								(0.119)
_cons	−63.552***	−17.804***	−59.439***	−23.260***	99.923***	−21.231***	5.239***	−19.579***
	(2.897)	(2.516)	(9.211)	(2.441)	(21.300)	(3.073)	(0.774)	(3.090)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm/Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	7671	7671	7671	7671	2053	2053	2053	2053
Adj R^2	0.282	0.116	0.341	0.105	0.095	0.294	0.192	0.302
F	127.75***	40.28***	168.45***	36.36***	6.25***	23.44***	14.18***	24.33***

Table 11
Sobel and Bootstrap test.

Path	Sobel			Bootstrap				Outcome
	Sobel	Z	P	Ind_eff	P	Low 95 %	High 95 %	
Tax-Media-DGI	0.005	4.159	0.000	0.005	0.006	0.001	0.009	Support
Tax-Salary-DGI	0.013	6.388	0.000	0.012	0.000	0.006	0.018	Support
Subsidy-Invest-DGI	−0.003	−2.382	0.017	−0.003	0.024	−0.131	−0.001	Support
Subsidy-REM-DGI	−0.007	−4.312	0.000	−0.001	0.062	−0.003	0.001	Support

6.2. Moderating effect test

6.2.1. The moderating effect of resource base

Resources are crucial in influencing enterprises' decision-making processes and strategic choices. The extent of redundancy in an enterprise's resources and reliance on them directly impact how it responds to environmental regulations. Enterprises possessing diverse and abundant resources, with less dependence on a specific resource, are better equipped to navigate environmental regulations comfortably and minimize risks [48]. Given the high uncertainty of DGI, enterprises often consider their resource base when making decisions regarding digital strategy. In contrast to enterprises with strong resource bases, those with relatively weak ones are often confined by their limited resources, thus concerned about the expected benefits and risks associated with DGI. Consequently, their inclination to participate in DGI is usually minimal. Therefore, we further examine the moderating effect of resource base.

We assess the resource base in financial and human aspects. To measure financial resources, we employ SA index, proposed by Hadlock & Pierce (2010) [49]. In measuring human resources, we utilize the ratio of managers' shares to the total shares of the enterprise [50]. From Columns 1 and 2 of Table 12, *Tax* × *Finance* and *Tax* × *Human* suggest a more significant promotion of DGI through tax when the enterprise's resource base is stronger. However, Columns 3 and 4 indicate that *Subsidy* × *Finance* and *Subsidy* × *Human* are insignificant.

6.2.2. The moderating effect of technological innovation capability

Technological innovation capability holds a crucial position in innovation activities and is an essential source of forming the competitive advantage of enterprises. On the one hand, it reflects the material foundation for engaging in innovation [51]; on the other hand, it denotes the ability for firms to transform knowledge and reconfigure resources [52]. Compared to enterprises with relatively low technological innovation capability, those with high can leverage their endowment advantage of innovation resources to alleviate concerns arising from the uncertainty of DGI. Moreover, the strong abilities of knowledge acquisition and resource reconfiguration, facilitated by technological innovation capability, can also enhance enterprises' adoption of digital technologies, allocation of innovation factors, and promotion of DGI. Therefore, we further examine the moderating effect of technological innovation capabilities. Referring to Krafft (2014) [53], we employ number of patents granted to enterprises as a proxy variable for technological innovation capability. In Column 5 of Table 12, regression coefficient of *Tax* × *Capability* indicates that tax has a stronger pushing-forward effect on DGI when accompanied by strong technological innovation capability. However, Column 6 reveals that *Subsidy* × *Capability* is insignificant.

7. Discussion

7.1. Conclusion

Our findings are as follows: (1) Environmental protection tax is of pushing-forward effect on DGI, while environmental protection subsidy is of crowding-out effect. (2) External pressure and internal incentives mediate pushing-forward effect of environmental protection tax. Pandering to governments and managerial opportunism have mediating effect. (3) Enterprises' resource base and technological innovation capability have a moderating effect on the main effect. (4) For those enterprises that are non-SOEs, weak politically connected, or large enterprises, the tax has a stronger pushing-forward effect on DGI and the subsidy has a stronger crowding-out effect on DGI as well.

7.2. Theoretical implication

We develop a theoretical model of different types of environmental regulations on DGI and validate it using data from high-pollution enterprises in China. There are three theoretical implications of our research. (1) We offer a new perspective to resolve the paradox of the effect of environmental regulation on DGI, i.e., clarifying the role of environmental regulation on DGI by decomposing it into two different types of policy instruments and discussing the heterogeneous effects separately. In addition, our research extends the literature on antecedents of DGI. Previous research regarding antecedents focusses more on digital green knowledge creation, digital green value co-creation behavior [54], digital green network embedding [55], and digital technology application [56]. Our research is the first to supplement the antecedents of DGI from the perspective of environmental regulations, which filling the research gap. (2) Our research explores the potential mechanism and boundary condition of environmental regulations on DGI. On one hand, DGI is a potentially effective way for enterprises to solve pollution and achieve sustainable development. From the aspect of external pressure, internal incentives, pandering to governments, and managerial opportunism, we empirically investigate the mechanisms between environmental regulations and DGI, opening the "black box" between them. It makes up for the shortcomings of previous studies and provides new ideas for the government to formulate environmental protection policies. In fact, our research further supplement and develop the study of Hu et al. (2023) [56]. On the other hand, we introduce resource base and technological innovation capability as the moderator variables and consider the heterogeneous effect of the enterprises' conditions on the relationship between environmental regulations and DGI, further expanding our conclusions' boundary. (3) Previous research often uses questionnaires to measure the DGI [16,57]. However, questionnaires may be influenced by interviewees' subjective factors, leading to inaccurate measurements on DGI. By calculating the number of patents encompassing both green and digital technology dimensions, we propose a new way of measuring DGI in enterprises with patents, providing a reference for the subsequent related research.

7.3. Policy recommendations

We propose some policy recommendations.

(1) The punitive charges on high-pollution enterprises for damaging the environment should be further strengthened. The government should enforce environmental protection tax more rigorously, leveraging its pushing-forward effect on DGI and thus promoting the environmental performance of high-pollution enterprises. In the implementation process, governments should actively involve the public and the media, exposing and condemning the environmentally harmful practices of these enterprises. Meanwhile, the managers of high-pollution enterprises and R&D personnel who have developed DGI intellectual property rights and widely applied DGI achievements in production should be commended, publicized, and materially rewarded.

Table 12
Moderating effects test.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	DGI	DGI	DGI	DGI	DGI	DGI
Tax	0.406***	0.051***			0.095***	
	(0.110)	(0.014)			(0.013)	
Subsidy			−0.232**	−0.054***		−0.049***
			(0.103)	(0.007)		(0.007)
Finance	0.205***		2.774***			
	(0.054)		(0.344)			
Human		5.790***		4.818***		
		(0.628)		(0.623)		
Capability					0.187***	0.340***
					(0.031)	(0.034)
Tax × Finance	0.086***					
	(0.028)					
Tax × Human		0.499***				
		(0.049)				
Subsidy × Finance			−0.045			
			(0.026)			
Subsidy × Human				−0.232		
				(0.049)		
Tax × Capability					0.014***	
					(0.002)	
Subsidy × Capability						−0.025
						(0.002)
_cons	−16.934***	−14.282***	0.545	−16.516***	−19.163***	−12.497***
	(3.131)	(2.562)	(3.377)	(3.059)	(2.533)	(3.119)
Controls	YES	YES	YES	YES	YES	YES
Firm/Year FE	YES	YES	YES	YES	YES	YES
N	7671	7671	2053	2053	7671	2053
Adj R^2	0.127	0.123	0.386	0.330	0.111	0.344
F	42.46***	41.07***	33.63***	26.33***	36.45***	28.07***

(2) With regard to the environmental protection subsidy, the government should make up for its defects by strengthening the monitoring and control of subsidy funds and implementing the mechanism for earmarking subsidy funds to prevent managers' opportunistic behavior. Additionally, the government should provide guidance for DGI among high-pollution enterprises, supporting them in adopting digital technologies to enhance their sustainable development capabilities.
(3) To realize the economic growth and environmental protection, governments should strengthen support for DGI of high-pollution enterprises rather than limiting it to direct environmental investment. Meanwhile, when supporting DGI, to prevent some high-pollution enterprises from seizing subsidy through rent-seeking activities, a reasonable evaluation mechanism should be set up, and the procedure should be transparent.
(4) In the process of coping with environmental regulations, direct environmental investment is certainly an important manifestation of high-pollution enterprises' active participation in environmental governance and social responsibility. However, as a profit-seeker, to realize the creation of shareholders' wealth, high-pollution enterprises should strengthen their DGI, motivate managers to set up the concept of DGI, formulate a DGI strategy, and cultivate the awareness of DGI among R&D personnel. This is conductive to minimize negative externalities and create a unique competitive advantage at the same time.
(5) When formulating environmental regulations, governments should consider the heterogeneity of high-pollution enterprises and adopt different approaches based on their innovation capabilities, resource bases, ownership, political connection, and enterprise size. For high-pollution enterprises with strong resource bases and technological innovation capabilities, governments should intensify supervision to overcome inertia of enterprises with insufficient motivation for DGI and fully utilize the pushing-forward effect of environmental protection tax. For high-pollution enterprises with a poor resource base and weak technological innovation capability, governments should broaden financing channels and compensate for the disadvantage of the technological innovation capability through cooperation among industries, universities, and research institutes, to enhance pushing-forward effect of environmental protection tax. For those SOEs, private enterprises, and low political connection enterprises, governments should enhance environmental protection tax, increase the amount and collection of tax, and strengthen the penalties for tax evasion by these enterprises. Subsidies supported for these enterprises should be strictly regulated and supervised to enhance the DGI.

7.4. Limitations and future research

Our research may have two limitations. (1) In addition to the external pressure, internal incentives, and manager opportunism that we have examined, there may be additional mediation mechanisms through which environmental regulations impact DGI. For instance, the executives' environmental protection awareness could play a role and require further investigation. (2) There are contextual variables, including level of regional digital economy development and legalization, which may moderate the conclusions of our research. It also needs to be further explored and researched.

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Jinyu Chen: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Zekun Chen:** Software.

Declaration of competing interest

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

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