

Article

“Emergence” and “Dissolution” of Green Innovation Bubbles in Power Industry Chain Enterprises

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Abstract

The clean and low-carbon transition of new-type power systems imposes increasingly stringent demands on green technology innovation among enterprises along the power industry chain. Identifying the drivers and potential remedies for green innovation bubble can offer China-originated solutions to the sustainable development of the global power sector. This paper focuses on Chinese power industry chain enterprises over the period 2016–2023. Drawing on the AMO framework, a three-dimensional analytical framework encompassing ability, motivation, and opportunity is developed. Double machine learning (DDML) is employed to perform benchmark regression and causal identification. Subsequently, gradient boosting trees (GBT) combined with SHAP interpretability analysis are applied to uncover nonlinear relationships and heterogeneous transmission pathways among key variables. The results indicate that energy-saving policies and green financial policies significantly inhibit the formation of the green innovation bubble in power industry chain enterprises. Specifically, these policies curb the green innovation bubble via three channels: an innovation incentive management mechanism, a peer imitation and convergence mechanism, and an industrial chain technology spillover mechanism. Upstream enterprises exhibit greater sensitivity to direct regulatory measures and backward technology spillovers from energy-saving and green finance policies, whereas midstream enterprises are more reliant on peer carbon emission pressure. The findings are validated through cross-verification among DDML, mechanism analysis, and interpretable analysis. The results provide empirical evidence and policy implications for optimizing energy-saving and green finance policies and for precisely deflating the green innovation bubble.

Keywords: green innovation bubble; power industry chain; AMO framework; environmental policy combination



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1. Introduction

Building a new-type power system oriented toward clean and low-carbon objectives is the core path to achieving the “dual carbon” strategic goal. This systemic change has put forward stringent demands for the green innovation capability of power industry chain enterprises. Upstream enterprises in the power industry chain focus on technology-driven and green process innovation (Chai et al., 2024), while midstream enterprises are more directly constrained by market mechanisms and institutional regulations (R. Zhang et al., 2024; Cheng et al., 2025). However, in the process of pursuing green transformation, enterprises generally face a dilemma: on the one hand, they entail long breakthrough cycles,

high risks, and substantial investment. On the other hand, external policy pressures and the urgent demand for clean energy in the market require enterprises to respond quickly and visibly. In this complex environment, some enterprises may exhibit behavioral biases when pursuing short-term compliance or policy incentives, tending to engage in symbolic, low-quality “green packaging” innovation rather than focusing on long-term value and substantial technological breakthroughs (Z. Xu et al., 2025). This transformation from real innovation demand to low-quality symbolic innovation gradually accumulates into a “green innovation bubble”. Different from ordinary low-quality innovation, the green innovation bubble is more strategic and selective, that is, enterprises deliberately increase low-quality patents or project outputs to send a signal of “active cooperation” to regulators, knowing that an innovation lacks commercialization prospects or environmental benefits. This behavior may not only lead to misallocation of innovation resources and the expulsion of good coins by bad ones, but also cause the green transformation of power industry chain enterprises to deviate from the core technological track that supports the stable and efficient operation of the new power system. Therefore, understanding the true logic and potential deviations of green innovation in enterprises under policy pressure is critically important for guiding innovative resources to effectively serve the national energy strategy.

Government implementation of environmental policies helps curb the emergence of the green innovation bubble. Energy conservation policies can strengthen rigid constraints and evaluate the authenticity of corporate green transformation through energy efficiency as a screening criterion. Green finance policies enhance the supervision and review of corporate green innovation achievements, increasing the credit risk associated with false green innovation through relevant information disclosure. Under the influence of the “dual carbon” strategy, environmental policies have become increasingly prominent in guiding and adjusting enterprises in the power industry chain. However, when the combination of restrictive policies and incentive policies is implemented, their impact presents complex characteristics. The implementation methods and target audiences of different policies vary, and a lack of coordination among them can easily lead to “policy crowding”, thereby undermining the effectiveness of policies (Bali et al., 2022). In this context, analyzing the impact of environmental policy combination on the green innovation bubble of power industry chain enterprises will not only help reveal its internal mechanism, but also help identify systematic obstacles in policy implementation.

To systematically deconstruct the complex drivers of corporate green innovation behavior, this paper introduces the AMO analysis framework (Appelbaum et al., 2000). This framework transcends the limitations inherent in the resource-based view (Barney, 1991), institutional theory (Powell, 1983), and externality theory (Romer, 1990) by conceptualizing green innovation as an outcome of the interplay between internal and external organizational factors. The AMO framework has been widely applied in employee behavior and organizational performance research to explain the formation pathways and internal logic of individual or organizational behavior (K. Jiang et al., 2012; Ngo & Ngo, 2023; Gupta et al., 2025). Within the power industry chain, the ability (A) dimension is manifested in enterprises’ endogenous capacity to absorb and generate technology based on R&D investment and talent reserves, constituting the resource foundation of green innovation. The motivation (M) dimension stems from competitive imitation and reputation-seeking triggered by peer effects (Wittmann et al., 2009), serving as the behavioral driving force of corporate innovation. The opportunity (O) dimension refers to the industry chain benefits derived from knowledge spillovers. Technological knowledge and human capital generate significant spillover effects along the industry chain. Enterprises integrate resources through business alliances and other collaborative arrangements to enhance the overall

knowledge accumulation and value creation capacity of the industry chain (Tian et al., 2023). The AMO framework thus offers a suitable theoretical lens for the present analysis.

This paper focuses on the upstream and midstream enterprises of the power industry chain as the research subjects. Based on the AMO framework, it systematically analyzes the impact of environmental policy combinations on enterprises' green innovation bubble and the underlying mechanisms. Theoretically, this paper integrates classical theories to reveal the internal logic and key decision-making nodes of green innovation behavior among power industry chain enterprises, thereby enriching the existing body of research on green technology innovation. In practice, the conclusions provide empirical references for local governments to optimize the design of energy-saving policies and green finance policies, offering both decision-making foundations and managerial insights for enterprises to adjust their green technology innovation strategies. The main marginal contributions are as follows: (1) Based on classical theories including the AMO framework and the resource-based view, this paper analyzes the internal logic of green innovation behavior in power industry chain enterprises, identifies key decision-making nodes, and provides new theoretical support for examining the indirect effects of environmental policy combinations. (2) Focusing on the green innovation bubble of power industry chain enterprises, this paper extends existing research on green technology innovation and reveals the internal mechanism through which environmental policy combinations deflate the green innovation bubble, from the three dimensions of ability (A), motivation (M), and opportunity (O). (3) By combining empirical analysis with interpretable analysis, this paper reveals the differentiated impact pathways of environmental policy combinations on the green innovation bubble of upstream versus midstream enterprises in the power industry chain. The remainder of this paper is structured as follows. Section 2 presents the research hypotheses. Section 3 describes the research design. Section 4 reports the empirical results. Section 5 concludes.

2. Hypothesis

2.1. Environmental Policy Combination and Green Innovation Bubbles of Power Industry Chain

The power industry chain is a cluster system with the coal industry and equipment manufacturing industry as its upstream starting point, the power industry as the linking sector, and high-energy-consuming industries as the downstream segment. Its internal structural relationships primarily manifest as input–output linkages, complementarities, and competitive dynamics. The upstream segment of the traditional power industry chain consisted solely of the coal industry. However, with the widespread deployment of clean energy production equipment, the equipment manufacturing industry has also come to be regarded as an important component of the upstream segment. A green innovation bubble refers to symbolic R&D and low-quality patent application behaviors undertaken by enterprises in response to internal innovation difficulties and external innovation pressure (C. Y. Li & Zhao, 2020). Compared with enterprises in other sectors, power industry chain enterprises are more prone to the formation of the green innovation bubble. On the one hand, despite breakthroughs in certain fields, high-precision and cutting-edge green technologies centered on clean energy continue to face persistent challenges and iterative pressure. Significant technological barriers exist between existing energy systems, and the collaborative optimization of the “source-grid-load-storage-carbon” chain faces substantial obstacles. High storage, transportation, and recycling costs limit the promotion and application of clean energy, particularly green hydrogen (Abdulaal et al., 2025). On the other hand, power industry chain enterprises face urgent demands for clean energy from the government, the market, and society. These demands are primarily reflected in the impact of governmental environmental policies, electricity price fluctuations, and

electric vehicle development on the green transformation of these enterprises (Liu et al., 2024; Y. Zhang et al., 2024). This dilemma reinforces the incentive for power industry chain enterprises to engage in false green innovation.

Promoting the green transformation of industrial chain/supply chains is critical for achieving the “dual carbon” strategic goal and controlling greenhouse gas emissions (Es-lamipoor, 2025). Energy-saving policies and green finance policies restrain the formation of green innovation bubbles in power industry chain enterprises through enhanced supervision and management. Energy-saving policies assess enterprise energy efficiency by establishing mandatory targets and stringent regulatory systems. False innovation hardly helps enterprises improve energy efficiency or meet government regulatory requirements. H. Xu et al. (2023) found that high energy consuming industries represented by energy and heavy industry are more sensitive to environmental regulation. Regions with weaker environmental regulations are prone to the carbon haven effect (CHE), attracting investment transfers from carbon-intensive industries (X. Zhao et al., 2020). Green finance policies strengthen the development and management of green finance products, lower the financial threshold and risks of green investment for enterprises, and assess green innovation quality while disclosing relevant information. The reputation constraint mechanism of green finance enhances investor attention to environmental violations by financed enterprises (He et al., 2022). Long-term green loans not only increase enterprises’ default risk but also strengthen enterprise–bank communication and improve banks’ ability to identify corporate greenwashing behavior (Y. Xu et al., 2022).

In summary, we propose the following hypothesis:

H1. *The combination of environmental policies can break the green innovation bubbles of power industry chain enterprises.*

2.2. *The Mediating Role of Innovation Incentives in the Dimension of Ability (A)*

The resource-based view suggests that the scarcity, non-imitability, and sustainability of green technology can create competitive advantages for enterprises. However, given the high cost, high risk, and high uncertainty of green innovation, enterprise output may not reach the socially optimal level without government support. Although the Porter hypothesis confirms that well-designed regulation can encourage enterprises to internalize compliance costs as innovation drivers through innovation compensation effects (Fernando & Wah, 2017), policies alone are unlikely to fully mobilize enterprises toward green innovation. Innovation subsidies can compensate for positive externalities from corporate green R&D activities or reduce the costs of green innovation (Z. Zhang et al., 2024). Government subsidies also carry a signaling effect, helping alleviate financing constraints faced by enterprises (Xinle et al., 2022). Beyond innovation subsidies, green finance serves as an instrument to incentivize corporate green technology innovation. The financial nature of green finance optimizes fund allocation and supports long-term green innovation. Compared to general innovation and quantity-based innovation, high-quality green innovation entails higher costs and longer cycles, thus requiring greater R&D support (S. Jiang et al., 2022).

Although innovation subsidies and green finance can improve enterprises’ technological ability and stimulate green innovation, some scholars argue that the so-called “fat cat effect” and rent-seeking behavior induced by high-intensity incentives distort green innovation and generate a green innovation bubble. Wu and Hu (2020) found that enterprises tend to divert high-tech R&D funds to other purposes, thereby rendering government subsidies ineffective. Entrepreneurs may establish rent-seeking relationships with government officials to obtain substantial financial subsidies. Government officials may provide additional financial subsidies to enterprises to maximize their own interests (e.g., securing

more political votes), thereby forming a two-way bribery dynamic (Sun & Yang, 2024). Moreover, to obtain green financial resources, enterprises may engage in strategic green innovation, leading to excessive innovation commitments (Q. Luo et al., 2019). Environmental policies exhibit a clear targeting effect. Under policy influence, governments and financial institutions enhance supervision over innovation subsidies and green financial resources, thereby preventing resource abuse or misuse and reducing resource misallocation.

In summary, we propose the following hypothesis:

H2a. *Innovation incentives will lead to the increase in green innovation bubbles of power industry chain enterprises.*

H2b. *Innovation incentives play a mediating role in the process of the environmental policy combination affecting the green innovation bubbles of power industry chain enterprises.*

2.3. The Mediating Role of Peer Effect in the Dimension of Motivation (M)

The impact of the peer effect on corporate behavior is explained by the imitative pressure emphasized in institutional theory. In the highly networked power industry chain, a significant peer effect exists among enterprises. The peer effect refers to the phenomenon of group convergence exhibited by enterprises through information dissemination, technological imitation, and behavioral learning, driven by mechanisms such as social learning, competitive imitation, and normative pressure (Seo, 2021; Chen et al., 2024). The peer effect amplifies external signals in policy transmission, promoting technological change and management innovation through demonstration diffusion and competitive imitation mechanisms (S. Luo et al., 2024; X. Zhao & Qian, 2024). Z. Li et al. (2025) found that the peer effect significantly enhances policy implementation and effectiveness, especially in resource-intensive industries, where the amplification effect is most pronounced. Compared with other enterprises, larger-scale, high-tech, and strictly regulated enterprises show a stronger willingness to transform (C. Xu & Lin, 2025).

The influence of peer effect on green innovation bubbles is mainly reflected in the peer transformation effect and peer reputation effect. To maintain competitiveness and stay aligned with market trends, peer enterprises exhibit similar behavioral decisions in corporate transformation, innovation output, and social responsibility (Chang et al., 2024; Kong et al., 2025; T. Zhao & Wang, 2024). In addition, the ESG behavior of peer enterprises influences the judgment of key enterprises within the group, whose ESG decisions tend to imitate the ESG performance of their peers. Peer effect triggers free-riding behavior, leading to a proliferation of strategic innovations in the industry (Wang et al., 2024). This type of innovation, which is primarily aimed at meeting external requirements or obtaining short-term benefits, may not necessarily yield substantial environmental improvements. Its characteristics include short-term orientation, low investment, low risk, low return, and superficial environmental benefits (Dang & Wang, 2022). The strategic green technologies of individual enterprises are disseminated within the industry through group learning and technological imitation, while environmental policies strengthen the government's green management of the industry, thereby preventing enterprises from adopting conceptual innovation.

In summary, we propose the following hypothesis:

H3a. *The peer effect will lead to the increase in green innovation bubbles of power industry chain enterprises.*

H3b. *The peer effect plays a mediating role in the process of the environmental policy combination affecting the green innovation bubbles of power industry chain enterprises.*

2.4. The Mediating Role of Industry Chain Dividends in the Dimension of Opportunity (O)

The classic theory of externalities states that individual decisions often have spillover effects on other entities through knowledge diffusion, technological demonstration, and information dissemination. In the context of clean and low-carbon new power systems, knowledge spillovers and technology diffusion are more concentrated in highly interconnected environments such as digital infrastructure, energy information systems, and green financial platforms, which are substantially more systematic and large-scale than traditional industries. This enables enterprises to obtain “industrial chain dividends” while also providing a channel for the diffusion of green innovation bubbles. Digital platforms significantly improve knowledge diffusion efficiency by reducing technology search costs, enhancing reinforcement learning effects, and improving information transparency (B. Li et al., 2024). The higher the density and platformization of the industrial chain are, the more significant the spillover effect is, the faster the diffusion speed is, and the higher the technological synergy benefits are. The technology and products developed by upstream enterprises, as well as the special needs of downstream enterprises for technology and products, form market signals and feedback to midstream enterprises to promote their transformation (Wei et al., 2024), thereby reducing opportunities for false innovation among enterprises.

By reducing the cost of externalities, strengthening information disclosure and improving market transparency, environmental policies provide institutional guarantees for enterprises to capture external opportunities and also curb the diffusion of innovation bubbles in the industrial chain. Firstly, the information disclosure system related to energy conservation and emission reduction strengthens enterprises’ understanding and learning of substantive green innovation technologies by standardizing corporate reports and improving the availability of industry data (Ding et al., 2022). The carbon trading system and industry information platforms drive low-carbon technological innovation through price signals, credit constraints, and market expectations. Secondly, while providing external technological opportunities and lowering the innovation threshold, green financial policies strengthen the supervision and management of green technological innovation and financial resource allocation (T. Zhang, 2023), which inhibits the diffusion of green innovation bubbles in the industrial chain. The combination of environmental policies not only strengthens the transparency of technology diffusion and the effectiveness of supervision, but also inhibits the diffusion of false innovation in the industrial chain, thereby bursting the green innovation bubbles.

In summary, we propose the following hypothesis:

H4a. *Industrial chain technology spillovers will burst the green innovation bubbles of power industry chain enterprises.*

H4b. *Industrial chain technology spillovers play a mediating effect in the process of environmental policy combination affecting the green innovation bubbles of power industry chain enterprises.*

The theoretical framework is clearly shown in Figure 1.

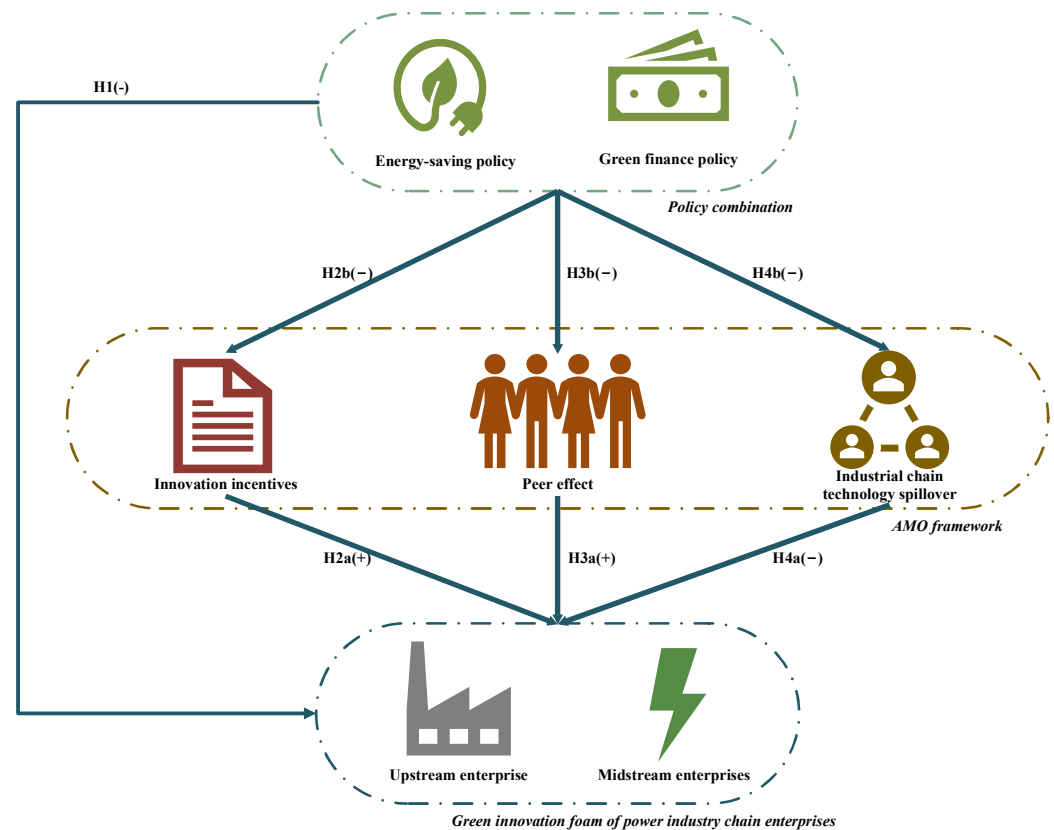


Figure 1. Theoretical framework.

3. Research Design

3.1. Model Design

The dual machine learning model overcomes the preset bias and the “curse of dimensionality” inherent in traditional models through machine learning and regularization algorithms and identifies the effects of energy-saving policies and green finance policies on enterprises’ green innovation bubbles. Therefore, this paper introduces a dual machine learning model (DDML) for estimation and constructs the following partial linear model:

$$CGI_bub_{it} = \theta_0 Policy_{it} + g(Control_{it}) + U_{it}, E(U_{it} | Policy_{it}, Control_{it}) = 0 \quad (1)$$

CGI_bub is the explained variable, representing the enterprise innovation bubble. $Policy$ is the treatment variable, including the energy-saving policy dummy variable (ESP) and the green finance policy dummy variable (GFP). $Control$ represents a high-dimensional set of control variables, and its specific functional form needs to be estimated through machine learning algorithms. U represents the random error term and follows the zero-mean assumption.

To address the estimation bias caused by the introduction of regularization terms in machine learning, the following auxiliary regression model is further constructed:

$$Policy_{it} = m(Control_{it}) + V_{it}, E(V_{it} | Control_{it}) = 0 \quad (2)$$

Among them, $m(Control)$ represents the regression function of $Policy$ on the control variable, and its specific function form also needs to be estimated through machine learning algorithms. V is a random error term that follows the zero-mean assumption. Regression analysis employs Lasso regression, random forest algorithm, and ridge regression, with the observation segmentation ratio set to 1:4.

3.2. Variable Selection and Data Sources

Explained variable: Referring to the research of [Elmawazini et al. \(2022\)](#) and [Guo et al. \(2021\)](#), this paper measures the quantity and quality of innovation using the number of green patent applications and green patent authorizations, respectively. Based on the method of [Geng et al. \(2024\)](#), the difference between quantity and quality is calculated and an index is constructed as a key indicator to measure the green innovation bubbles of enterprises. Specific operation: Green innovation bubbles = (number of green patent applications – number of green patent grants)/number of green patent applications. This indicator reflects the proportion of green patents applied by enterprises that are ultimately not authorized. The larger the ratio is, the more enterprises tend to apply for low-quality, easily rejected or voluntarily abandoned “bubble patents”, indicating obvious strategic patent applications. There is a difference between this indicator and “greenwashing” behavior and low-quality innovation. First, “greenwashing” behavior primarily emphasizes the exaggeration of environmental performance in environmental information disclosure, whereas the green innovation bubble is reflected in enterprises’ strategic behavior in the innovation output link. Secondly, low-quality innovation may stem from insufficient technological capacity or poor R&D management. In contrast, the green innovation bubble specifically refers to the systematic gap between the number of applications and authorizations, which arises when enterprises consciously shift R&D resources from high-quality, demanding substantive innovation to low-cost, easy-to-apply strategic patents under policy pressure.

Explanatory variables: The explanatory variables include dummy variables for energy-saving policy (*ESP*) and green finance policy (*GFP*). The policy variable is measured using an interaction term ($Treat \times Post$). *Treat* is a policy indicator variable, equal to 1 if the industry of the enterprise is affected by the policy, and 0 otherwise. *Post* is a time indicator variable, equal to 1 for the year of policy implementation and thereafter, and 0 for the period before. The industry scope of energy-saving policies is determined based on documents such as the “Energy Conservation Management Measures for Key Energy Using Units”, while green finance policies are defined based on documents such as the “Guiding Opinions on Building a Green Finance System”.

Mechanism variables: The dimension of capability (*A*) mainly involves government subsidies and green finance. Innovation subsidies (*Subsidies*) and an urban green finance index (*Finance*) are used to measure the levels of government subsidies and green finance, respectively. This paper uses text analysis to extract “government subsidy details” from the “non-operating income” account in the annual financial statements of listed enterprises. More than 800,000 government subsidy records were identified, and subsequent keyword searches yielded over 130,000 innovation subsidy records. The total amount of government innovation subsidies received by an enterprise in a given year is aggregated, and its ratio to total assets is used as a proxy variable for government innovation subsidies in the model. By collecting and organizing data on seven indicators including green credit, green investment, green insurance, green bonds, green support, green funds, and green equity in various prefecture-level cities in China, the entropy method is used to measure the level of urban green finance development and match it with the registered location of the enterprise. The specific evaluation system is shown in Table 1.

The dimension of motivation (*M*) mainly involves the peer effect. Construct Formula (3) based on the calculation method proposed by [Tan et al. \(2022\)](#), measuring the same group effect of enterprises from the industry dimension and using the average carbon emission intensity of same group enterprises (*Peer_Carbon*) and the average ESG score of same group enterprises (*Peer_ESG*). In Formula (1), *i*, *j*, and *t* respectively represent the enterprise, industry,

and year, and N represents the number of enterprises in the industry to which enterprise i belongs.

$$Peer_x = \sum_{i=1}^N x_{i,j,t} - x_{i,j,t} \quad (3)$$

The opportunity (O) dimension mainly involves the technology spillover effects between enterprises in the power industry chain. This paper uses the number of enterprise technology patent applications to measure the level of enterprise technology innovation. Select the lagged term of technology variables in adjacent industries of the industrial chain to evaluate spillover effects, as shown in the specific Formula (4). Among them, w_{ij} represents the upstream and downstream relationship between industry i and industry j , taking the value of 1 when they exist and 0 otherwise. $\bar{Y}_{ij}$ represents the mean lagged term of industry i , and the impact of adjacent industries on this industry usually lags behind. $Spill_{it}$ characterizes the spillover effects of adjacent industries on the industry itself. In order to further analyze the impact of spillover effects, they are divided into forward spillover effects (F_Spill) and backward spillover effects (B_Spill). Forward spillover effect refers to the spillover effect of downstream industries on upstream industries, while backward spillover effect refers to the spillover effect of upstream industries on downstream industries.

$$Spill_{i,t} = \sum_{j \neq i} w_{i,j} \bar{y}_{j,t-1} \quad (4)$$

Control variables: Mainly including establishment age (Age), asset size ($Size$), asset liability ratio (Lev), independent director shareholding ratio ($Indep_ratio$), and return on net assets (NPM).

Table 1. Green finance evaluation system.

Dimension	Indicator	Calculation Method
Green credit	Proportion of environmental project credit	Total credit amount for environmental protection projects/total credit amount
Green investment	Proportion of investment in environmental pollution control to GDP	Investment in environmental pollution control/GDP
Green insurance	Promotion level of environmental pollution liability insurance	Environmental pollution liability insurance income/total premium income
Green bonds	Development level of green bonds	Total issuance of green bonds/total issuance of all bonds
Green support	Proportion of fiscal environmental protection expenditure	Financial environmental protection expenditure/general budget expenditure
Green funds	Proportion of green funds	Total market value of green funds/total market value of all funds
Green equity	Depth of green equity development	Total amount of carbon trading, energy use rights trading, emissions trading/equity market trading

This paper takes A-share listed enterprises on the Shanghai and Shenzhen stock exchanges in China from 2016 to 2023 as the research sample. The upstream of the power industry chain includes coal mining and washing (B06), oil and gas extraction (B07), general equipment manufacturing (C34), special equipment manufacturing for mining, metallurgy, and construction (C351), as well as electrical machinery and equipment manufacturing (C38). The midstream of the power industry chain is primarily composed of electricity and heat production and supply (D44). To avoid estimation bias due to missing, erroneous, or incomplete data, the following data verification and screening criteria are applied. First, firm-level data are cross-checked against raw data from multiple mainstream databases, including THS Finance and Wind Consulting. For variables with discrepancies, the corre-

sponding annual reports are consulted for verification and correction. Second, observations of key variables that are either unavailable in any database or clearly abnormal are removed. Third, firms in the financial industry, ST and *ST firms, and observations with missing key variables are excluded. Finally, all continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. Firm-level data are mainly sourced from the CSMAR database and the China National Intellectual Property Administration, while regional data come from the China City Statistical Yearbook. After the above processing, a final sample of 5574 valid firm-year observations is obtained. Table 2 presents the descriptive statistics of the selected variables.

Table 2. Descriptive analysis of variables.

Variable	Mean	SD	Min	Max	Size
<i>CGI_bub</i>	0.0855	1.5187	−9.0251	40.033	5574
<i>ESP</i>	0.478	0.4996	0	1	5574
<i>GFP</i>	0.6347	0.4815	0	1	5574
<i>Subsidies</i>	35,101	24,313	0	1,061,021	5574
<i>Finance</i>	0.4204	0.1038	0.0769	0.6575	5574
<i>Peer_Carbon</i>	344,231	355,011	328.183	991,579	5574
<i>Peer_ESG</i>	0.5022	0.1431	0	1	5574
<i>F_Spill</i>	24.9542	66.1666	0	360.333	5574
<i>B_Spill</i>	8.6799	14.6863	0	32.625	5574
<i>Age</i>	10.6981	7.8859	1	34	5574
<i>Asset</i>	237.3928	1285.078	0.4646	27,527.1	5574
<i>Lev</i>	0.4346	0.1881	0.0131	1.1498	5574
<i>Indep_ratio</i>	0.3761	0.0539	0.2	0.8	5574
<i>NPM</i>	0.0659	0.2969	−11.0743	4.1752	5574

Data source: Compiled by the author.

4. Results and Analysis

4.1. Benchmark Regression

Table 3 reports the benchmark regression results. Columns 1 to 3 present the results of Lasso regression, random forest algorithm, and ridge regression, respectively, testing the relationship between energy-saving policies and the green innovation bubble. Except for the random forest algorithm results, the estimates from the other methods are significant at the 1% level, all indicating that *ESP* has a negative impact on *CGI_bub*. Columns 4 to 6 use Lasso regression, random forest algorithm, and ridge regression, respectively, to test the relationship between green finance policy and the green innovation bubble. The results from all three methods indicate that *GFP* has a negative impact on *CGI_bub* at the 1% level. These results support Hypothesis 1, confirming that energy-saving policies and green finance policies are consistently associated with the resolution of the green innovation bubble in power industry chain enterprises.

Table 3. Benchmark regression results.

Model	Lasso	RF	Ridge	Lasso	RF	Ridge
Variable	<i>CGI_bub</i>	<i>CGI_bub</i>	<i>CGI_bub</i>	<i>CGI_bub</i>	<i>CGI_bub</i>	<i>CGI_bub</i>
<i>ESP</i>	−0.0104 *** (0.0018)	−0.0023 (0.0024)	−0.0101 *** (0.0018)			
<i>GFP</i>				−0.0055 *** (0.0011)	−0.0042 *** (0.0012)	−0.0056 *** (0.0011)
<i>Constant</i>	0.0000 (0.0005)	−0.0002 (0.0005)	−0.0000 (0.0005)	−0.0001 (0.0005)	−0.0005 (0.0005)	−0.0000 (0.0005)

Table 3. Cont.

Model	Lasso	RF	Ridge	Lasso	RF	Ridge
Control	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
ID	YES	YES	YES	YES	YES	YES
N	5774	5774	5774	5774	5774	5774

Note: *, **, *** represent statistical significance of 10%, 5%, and 1%, respectively. Standard errors are reported in parentheses.

4.2. Placebo Test

A placebo test based on random sampling indirectly determines whether the baseline regression has omitted important variables, thereby avoiding estimation errors caused by other confounding factors during the study period. The distribution of the estimated coefficients from sampling, the p -value distribution, and the relationship between the true coefficients and the sampling estimates are derived from 1000 random sample regressions. Figure 2 shows the placebo test results of *ESP* and *GFP* on *CGI_bub*, where the horizontal axis represents the sampling estimation coefficient, the left vertical axis represents the p -value distribution corresponding to the regression coefficient, and the right vertical axis represents the kernel density distribution of the coefficient. The horizontal dashed line represents the significance of 10%, and the vertical dashed line represents the true estimate of the baseline regression. The estimated coefficients from the 1000 random samples exhibit a normal distribution centered at zero. Most sampling coefficients have p -values above the 10% significance level, and their magnitudes deviate substantially from the benchmark regression results. This indicates that the coefficient estimates of *ESP* and *GFP* in the baseline regression are extreme and low-probability events in the placebo test distribution, whereas most randomly sampled coefficients are not statistically significant at the 10% level. The baseline regression model of this study did not miss important explanatory variables, and the baseline regression results are robust.

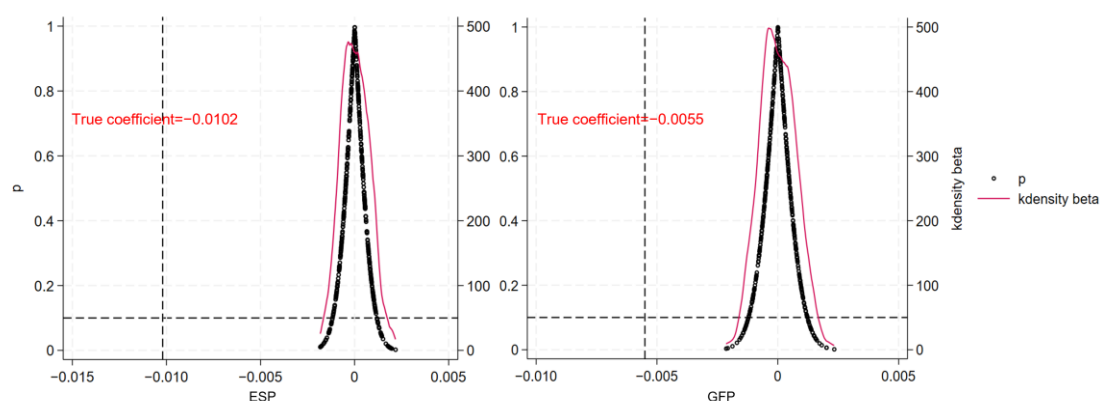


Figure 2. Placebo test results.

4.3. Mechanism Analysis

This paper constructs a mediation effect model to examine the relationship between policy combinations and the green innovation bubbles of power industry chain enterprises, viewed from the three dimensions of ability (A), motivation (M), and opportunity (O). The model also tests the mediating roles of innovation incentives, peer effects, and technology spillovers along the industrial chain.

$$M_{it} = \beta_0 + \beta_1 Policy_{it} + \varepsilon_{it} \quad (5)$$

$$CGI_bub_{it} = \beta_0 + \beta_1 Policy_{it} + \beta_2 M_{it} + \varepsilon_{it} \quad (6)$$

The explained variable is the enterprise green innovation bubble (*CGI_bub*). *Policy* is the explanatory variable, including the energy-saving policy dummy variable (*ESP*) and the green finance policy dummy variable (*GFP*). *M* is a mediating variable, including government innovation subsidies (*Subsidies*), green finance level (*Finance*), carbon emissions of peer enterprises (*Peer_Carbon*), ESG scores of peer enterprises (*Peer_ESG*), forward spillover effects (*F_Spill*), and backward spillover effects (*B_Spill*). ε_{it} is a random interference term.

Following Yuan et al. (2025), this paper first employs multiple linear regression (LR) to estimate the mediation effect model. The regression results for the full sample are presented in Tables 4–6. The first and second columns in Table 4 examine the mediating effect of government innovation subsidies. The results show that *ESP* and *GFP* have a significant negative effect on *Subsidies* and *CGI_bub* at the 1% level, while *Subsidies* has a significant positive effect on *CGI_bub* at the 1% level. Columns 3 and 4 test the mediating effect of the urban green finance level. The results show that *ESP* and *GFP* have a significant negative effect on *Finance* and *CGI_bub* at the 1% level, while *Finance* has a significant positive effect on *CGI_bub* at the 1% level. This result validates assumptions 2a and 2b. From the perspective of capability (A), improvements in government innovation subsidies and the green finance level are often accompanied by a “fat cat effect”, which may lead to a green innovation bubble in the power industry chain. Policy combinations strengthen government supervision and management of innovation subsidies and green financial resources, thereby achieving the policy effect of bursting the green innovation bubble.

Table 4. Mechanism test—Ability (A) dimension.

Variable	Subsidies	CGI_bub	Finance	CGI_bub
ESP	−0.0044 *** (0.001)	−0.0053 *** (0.0013)	−0.0215 *** (0.0043)	−0.0074 *** (0.0014)
GFP	−0.0069 *** (0.0011)	−0.0094 *** (0.0014)	−0.0128 *** (0.0045)	−0.0129 *** (0.0015)
Subsidies		0.5201 *** (0.018)		
Finance				0.0094*** (0.0047)
Constant	1.5676 *** (0.3052)	−0.1978 (0.3854)	−1.2323 *** (1.2674)	0.7883 (0.4243)
Year	YES	YES	YES	YES
ID	YES	YES	YES	YES
N	5774	5774	5774	5774

Note: *, **, *** represent statistical significance of 10%, 5%, and 1%, respectively. Standard errors are reported in parentheses.

The first and second columns in Table 5 test the mediating effect of carbon emissions from the peer enterprises. The results show that *ESP* and *GFP* have a significant negative effect on *Peer_Carbon* and *CGI_bub* at the 1% level, while *Peer_Carbon* has a significant positive effect on *CGI_bub* at the 1% level. The third and fourth columns examine the mediating effect of ESG ratings on peer enterprises. The results show that *ESP* and *GFP* have no significant effect on *Peer_ESG*, but they have a significant negative effect on *CGI_bub* at the 1% level. *Peer_ESG* has a significant positive effect on *CGI_bub* at the 1% level. This result verifies assumptions 3a and 3b. From the perspective of motivation (M), high carbon emissions from peer enterprises lead to free-riding behavior, which may breed a green innovation bubble. After the introduction of policy combinations, industry management becomes more stringent: peer carbon emissions decline, strategic innovation decreases, and

the green innovation bubble shrinks accordingly. In addition, although peer ESG scores are positively associated with the innovation bubble, policy combinations do not generate a clear transmission effect through this channel.

Table 5. Mechanism test—Motivation (M) dimension.

Variable	Peer_Carbon	CGI_bub	Peer_ESG	CGI_bub
ESP	−0.0137 *** (0.0016)	−0.0007 * (0.0012)	0.0091 (0.0062)	−0.0078 *** (0.0014)
GFP	−0.0168 *** (0.0016)	−0.0045 *** (0.0012)	−0.0051 (0.0064)	−0.0129 *** (0.0015)
Peer_Carbon		0.5046 *** (0.0109)		
Peer_ESG				0.0258 *** (0.0032)
Constant	1.4846 (0.4553)	−0.1316 (0.3469)	4.1727 (1.8264)	0.5098 (0.4134)
Year	YES	YES	YES	YES
ID	YES	YES	YES	YES
N	5774	5774	5774	5774

Note: *, **, *** represent statistical significance of 10%, 5%, and 1%, respectively. Standard errors are reported in parentheses.

Table 6. Mechanism test—Opportunity (O) dimension.

Variable	F_Spill	CGI_bub	B_Spill	CGI_bub
ESP	−0.0113 (0.0103)	−0.0076 *** (0.0014)	−0.0399 *** (0.0077)	−0.0079 *** (0.0014)
GFP	−0.0168 (0.0107)	−0.0131 *** (0.0015)	−0.0537 *** (0.008)	−0.0134 *** (0.0015)
F_Spill		−0.0034 ** (0.002)		
B_Spill				−0.008 *** (0.0026)
Constant	10.4092 (3.0222)	0.6524 (0.4162)	6.098 (2.2525)	0.6665 (0.4157)
Year	YES	YES	YES	YES
ID	YES	YES	YES	YES
N	5774	5774	5774	5774

Note: *, **, *** represent statistical significance of 10%, 5%, and 1%, respectively. Standard errors are reported in parentheses.

The first and second columns in Table 6 examine the mediating effects of forward spillovers. The results show that *ESP* and *GFP* have no significant effect on *F_Spill*, but they have a significant negative effect on *CGI_bub* at the 1% level, while *F_Spill* itself has a significant negative effect on *CGI_bub* at the 5% level. The third and fourth columns examine the mediating effect of backward spillovers. The results show that *ESP* and *GFP* have a significant negative effect on both *B_Spill* and *CGI_bub* at the 1% level, and *B_Spill* also has a significant negative effect on *CGI_bub* at the 1% level. The research results validate assumptions 4a and 4b. From the perspective of opportunity (O), backward spillover serves as an effective mediating channel through which policies restrain the bubble. This suggests that policy combinations are associated with the resolution of the innovation bubble by strengthening quality control of green innovation and providing

upstream feedback. Although forward spillovers are also related to the resolution of the innovation bubble, they do not play a mediating role in the policy transmission process.

4.4. Interpretability Analysis

Referring to the research of P. Zhang et al. (2025), this paper uses Gradient Boosted Trees (GBT) and Shapley Additive Explanations (SHAP) for local interpretability analysis. The specific models are shown in the Appendix A. To assess model accuracy, this paper compares the GBT model with Random Forest (RF), Decision Tree (DT), and Multiple Linear Regression (LR). The panel data of upstream and midstream enterprises in Chinese power industry chains from 2016 to 2023 are divided into training and testing sets at a 4:1 ratio. The learning rate is set to 0.1 to control the iteration update step size, and both the subsample sampling rate and the feature column sampling rate are set to 0.8 to enhance model generalization and robustness. The model's prediction performance is shown in Table 7. Among the four models, GBT achieves the highest R^2 and lower MAE, MSE, RMSE, and MAPE than the other models. Thus, the GBT model outperforms other models in prediction accuracy and error control, and its predictions better capture the underlying dynamics of the green innovation bubble under the influence of energy-saving policies and green finance policies.

Table 7. Evaluation of prediction performance under different machine learning models.

	R^2	MAE	MSE	RMSE	MAPE
GBT	0.686	0.004	0.001	0.015	0.02
RF	0.603	0.005	0.001	0.017	0.021
DT	0.621	0.005	0.001	0.016	0.021
LR	0.012	0.006	0.001	0.027	0.027

Compared with linear regression analysis, SHAP analysis offers distinct advantages and is more necessary for explaining model results. SHAP is based on game theory and provides consistent and additive explanations for any complex model, including nonlinear and black box models. It can quantify the marginal contribution of each feature to the prediction results and reveal individual differences and overall importance rankings. This paper presents the SHAP-based interpretability analysis results using raincloud plots and scatter plots. A high absolute SHAP value for a given feature indicates that the feature is highly important for model prediction.

Figure 3 presents the interpretability analysis results for the mediating effects of government innovation subsidies and urban green finance level within the ability (A) dimension. In Figure 3a, compared with midstream enterprises (M), upstream enterprises (U) have a larger mean absolute SHAP value of *Subsidies* for *ESP* and *GFP*, indicating that government innovation subsidies have a more significant impact on upstream enterprises. In Figure 3b, the SHAP values of *CGI_bub* for *Subsidies* are mainly distributed above zero and increase with *Subsidies*. The SHAP values of upstream enterprises fluctuate more significantly. In Figure 3c, compared with upstream enterprises (U), midstream enterprises (M) have larger mean absolute SHAP values of *Finance* for *ESP* and *GFP*, indicating that urban green finance level has a more significant impact on midstream enterprises. In Figure 3d, the SHAP values of *CGI_bub* for *Finance* are mainly distributed above zero and increase with *Finance*. The SHAP values of midstream enterprises fluctuate more significantly. This result not only verifies the robustness of the findings in Table 4, but also reveals that the policy transmission effect varies significantly across different links of the power industry chain. Upstream enterprises are more sensitive to changes in government subsidies, and subsidy growth significantly expands their green innovation

bubbles. Midstream enterprises respond more strongly to the regional green finance level, and improvements in the financial environment significantly stimulate the formation of their bubbles.

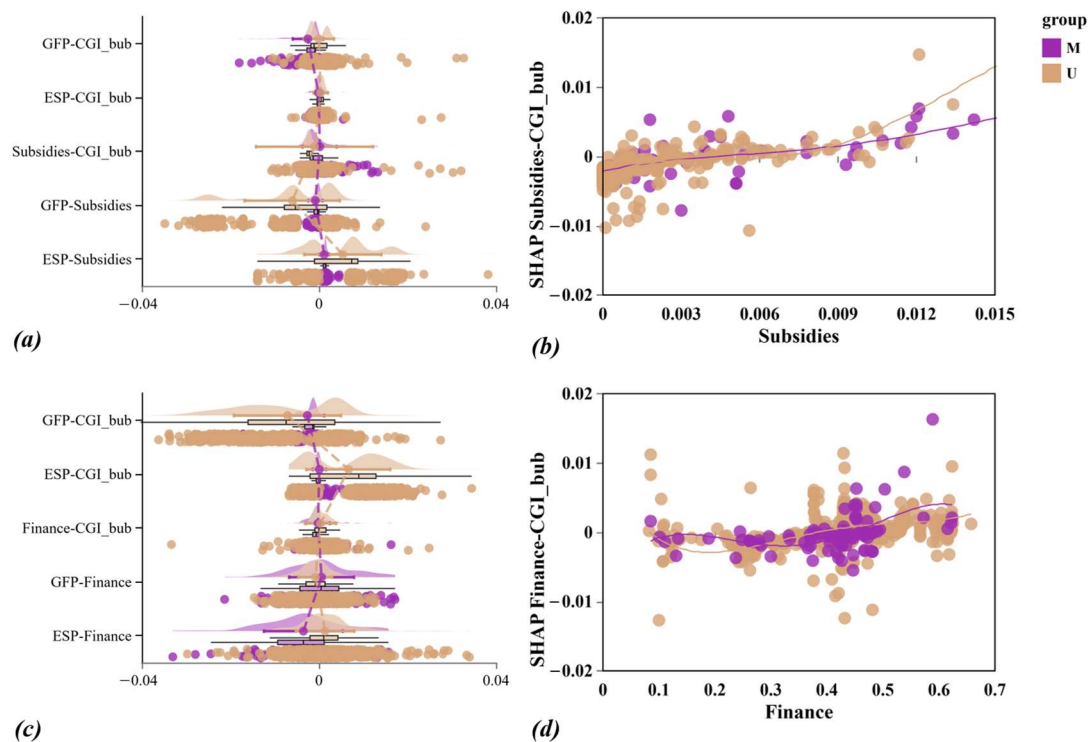


Figure 3. Interpretability analysis of ability (A). Each scatter point in the figure represents the SHAP value of a specific firm-level characteristic. Positive and negative values denote favorable and adverse effects, respectively. Orange and purple indicate upstream and midstream enterprises, respectively. (a,c) present the global SHAP-based interpretability analysis of the mediating effects of *Subsidies* and *Finance*. In these panels, the vertical axis, labeled A-B, represents the effect of explanatory variable A on outcome variable B, while the horizontal axis shows the SHAP value. (b,d) depict the local interpretability analysis of the impact of *Subsidies* and *Finance* on *CGI_bub*. In these two panels, the vertical axis corresponds to the SHAP values of *Subsidies* and *Finance* for *CGI_bub*, and the horizontal axis represents the raw feature values of *Subsidies* and *Finance*.

Figure 4 presents the interpretability analysis results for the mediating effects within the motivation (M) dimension, specifically for peer carbon emissions and peer ESG ratings. In Figure 4a, the mean absolute SHAP values of *Peer_Carbon* for ESP and GFP, as well as those of *CGI_bub* for *Peer_Carbon*, are near zero for both upstream (U) and midstream (M) enterprises. By contrast, the mean absolute SHAP values of *CGI_bub* for ESP and GFP are relatively large for upstream enterprises. However, the mean absolute SHAP values of *CGI_bub* for ESP and GFP are relatively large for upstream enterprises. In Figure 4b, the SHAP values of *CGI_bub* for *Peer_Carbon* are mainly distributed above zero but slowly decrease as *Peer_Carbon* increases. There is no significant difference in the fluctuation trend between upstream enterprises (U) and midstream enterprises (M). In Figure 4c, compared with upstream enterprises (U), midstream enterprises (M) have a larger mean absolute SHAP value of *Peer_ESG* for ESP and GFP, indicating that ESG scores have a more significant impact on midstream enterprises. In Figure 4d, the SHAP values of *CGI_bub* for *Peer_ESG* are mainly distributed above zero and increase with *Peer_ESG*. There is no significant difference in the fluctuation trend between upstream enterprises (U) and midstream enterprises (M). This result not only validates the robustness of the results in Table 5, but also further demonstrates the heterogeneity of the mediating effect. The direct

impact of policy combinations on the green innovation bubble of upstream enterprises is significant but not transmitted through the peer effect path, whereas their impact on midstream enterprises requires mediation through the peer effect channel.

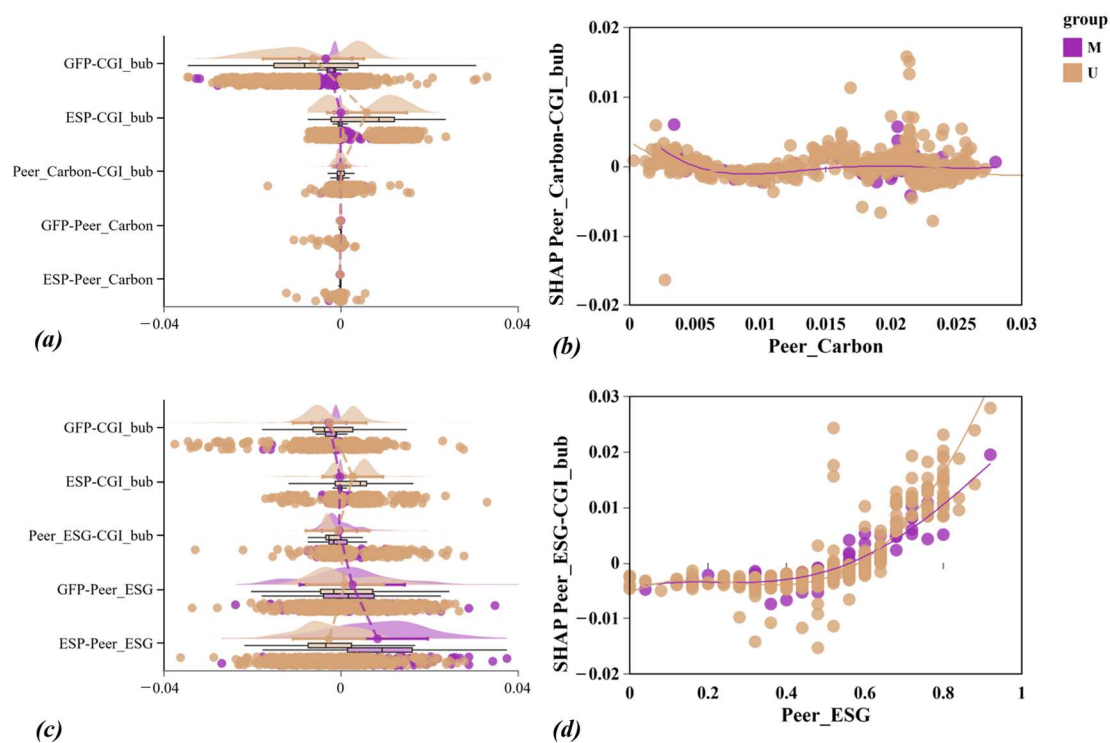


Figure 4. Interpretability analysis of motivation (M). Each scatter point in the figure represents the SHAP value of a specific firm-level characteristic. Positive and negative values denote favorable and adverse effects, respectively. Orange and purple indicate upstream and midstream enterprises, respectively. (a,c) present the global SHAP-based interpretability analysis of the mediating effects of *Peer_Carbon* and *Peer_ESG*. In these panels, the vertical axis, labeled A-B, represents the effect of explanatory variable A on outcome variable B, while the horizontal axis shows the SHAP value. (b,d) depict the local interpretability analysis of the impact of *Peer_Carbon* and *Peer_ESG* on *CGI_bub*. In these two panels, the vertical axis corresponds to the SHAP values of Subsidies and Finance for *CGI_bub*, and the horizontal axis represents the raw feature values of *Peer_Carbon* and *Peer_ESG*.

Figure 5 presents the interpretability analysis results for the mediating effects of forward and backward spillovers in the opportunity (O) dimension. In Figure 5a,c, for upstream firms (U), the mean SHAP values of *F_Spill* for *ESP* and *GFP* is positive. For midstream firms (M), the mean SHAP values of *F_Spill* for *ESP* and *GFP* are negative. The *ESP* and *GFP* of upstream enterprise (U) have a relatively large absolute mean SHAP for *CGI_bub*. In Figure 5b, the SHAP values of *CGI_bub* for *F_Spill* are mainly distributed below zero and decrease as *F_Spill* increases. The fluctuation trend is more pronounced for upstream enterprises. In Figure 5d, the SHAP values of *CGI_bub* for *B_Spill* are mainly distributed below zero, and there is an inverted U-shaped relationship between *B_Spill* and *CGI_bub*, with more pronounced fluctuations for upstream enterprises. This result not only verifies the robustness of Table 6 but also demonstrates the asymmetric impact of policy combinations on technology spillover mechanisms at different positions in the industrial chain. Policy combinations promote technology spillovers for upstream enterprises in both forward and backward directions, making upstream enterprises more sensitive to policy shocks, while suppressing the spillover effects experienced by midstream enterprises.

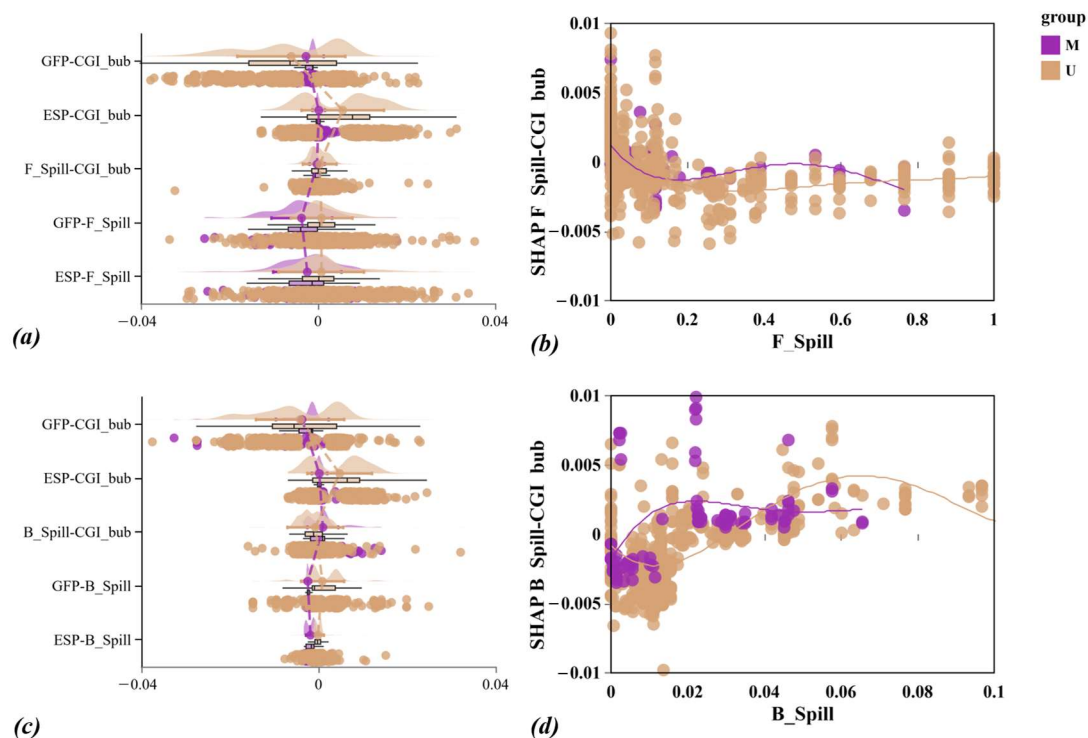


Figure 5. Interpretability analysis of opportunity (O). Each scatter point in the figure represents the SHAP value of a specific firm-level characteristic. Positive and negative values denote favorable and adverse effects, respectively. Orange and purple indicate upstream and midstream enterprises, respectively. (a,c) present the global SHAP-based interpretability analysis of the mediating effects of F_Spill and B_Spill . In these panels, the vertical axis, labeled A-B, represents the effect of explanatory variable A on outcome variable B, while the horizontal axis shows the SHAP value. (b,d) depict the local interpretability analysis of the impact of F_Spill and B_Spill on CGI_bub . In these two panels, the vertical axis corresponds to the SHAP values of Subsidies and Finance for CGI_bub , and the horizontal axis represents the raw feature values of F_Spill and B_Spill .

The interpretability analysis of ability (A), motivation (M), and opportunity (O) reveals that energy-saving policies and green finance policies exert heterogeneous impact mechanisms on the green innovation bubble of upstream and midstream enterprises in the power industry chain. Upstream enterprises are highly sensitive to government subsidies. Increased subsidies directly lower their strategic innovation costs and significantly expand the bubble, with the effect operating mainly through direct transmission. The mediating effect of peer carbon emissions and ESG scores is not significant. At the same time, energy-saving policies and green finance policies impose an inverted U-shaped constraint on the upstream bubble by promoting forward and backward technology spillovers: moderate spillovers inhibit the bubble, while excessive pressure may still trigger strategic innovation. Midstream enterprises have a stronger response to the level of urban green finance. Improvements in the green financial environment stimulate the formation of the green innovation bubble by reducing financing costs. This effect partly depends on the mediating amplification of peer ESG scores, whereas the mediating effect of peer carbon emissions is not significant. In contrast, the technology spillover effects of energy-saving policies and green finance policies on midstream enterprises are mainly inhibitory. Midstream enterprises find it difficult to effectively absorb external technology spillovers under policy shocks, and instead strengthen their dependence on financial resources for strategic innovation. Upstream enterprises are mostly technology-intensive and asset-heavy industries. They have large R&D investment, long cycles, strong dependence on government subsidies, and are located at the source of industrial chain technology, which can easily generate

two-way technology spillovers. Therefore, increased subsidies directly stimulate strategic innovation, whereas moderate technology spillovers inhibit the innovation bubble through technology learning and imitation. Midstream enterprises belong to the asset operation sector of natural monopoly. Their innovation activities rely more on external financing and the regional green finance environment, and they are highly sensitive to financing costs. Peer ESG ratings, as a source of social legitimacy pressure, amplify enterprises' motivation to imitate strategic innovation. In addition, because the technological absorption capacity of midstream enterprises is constrained by their monopoly position, they cannot effectively utilize external technology spillovers. This instead strengthens their dependence on financial resources for “green packaging” innovation.

4.5. Sensitivity Test

To further test the heterogeneous impact of policy combinations on the green innovation bubble of upstream and midstream enterprises, this paper employs the Bootstrap method for sensitivity analysis. The specific results are shown in Table 8. The Bootstrap test results (1000 repetitions) show that upstream and midstream enterprises exhibit statistically significant differences in sensitivity for the vast majority of variables, with 95% confidence intervals excluding zero. Although the confidence intervals for individual SHAP values (e.g., *Subsidies*–*CGI_bub*, *GFP*–*Peer_ESG*, *Peer_ESG*–*CGI_bub*) may slightly include zero or approach the boundary, the absolute coefficient values are extremely small and the deviation is near zero, which does not affect the overall results. Therefore, the sensitivity analysis confirms a significant difference in sensitivity between upstream and midstream enterprises to policy combinations, providing reliable statistical evidence for the heterogeneous mechanisms through which energy-saving policies and green finance policies affect the green innovation bubble in the industrial chain.

Table 8. Sensitivity analysis results.

<i>SHAP Values of Variables</i>	<i>Coefficient</i>	<i>Bias</i>	<i>95% Bootstrap CI</i>
<i>ESP</i> – <i>CGI_bub</i>	0.00045	-1.17×10^{-6}	[0.0002 0.0006]
<i>GFP</i> – <i>CGI_bub</i>	0.00248	-3.01×10^{-6}	[0.0017 0.0032]
<i>ESP</i> – <i>Subsidies</i>	0.00415	3.15×10^{-6}	[0.0035 0.0048]
<i>GFP</i> – <i>Subsidies</i>	−0.00521	8.61×10^{-6}	[−0.0060 −0.0043]
<i>Subsidies</i> – <i>CGI_bub</i>	−0.00115	-8.34×10^{-6}	[−0.0023 0.0000]
<i>ESP</i> – <i>Finance</i>	0.00492	2.00×10^{-6}	[0.0031 0.0067]
<i>GFP</i> – <i>Finance</i>	−0.00143	0.0000381	[−0.0027 −0.0001]
<i>Finance</i> – <i>CGI_bub</i>	0.00063	2.86×10^{-6}	[0.0001 0.0012]
<i>ESP</i> – <i>Peer_Carbon</i>	0.00003	-3.20×10^{-7}	[0.0001 0.0004]
<i>GFP</i> – <i>Peer_Carbon</i>	−0.00021	-3.98×10^{-7}	[−0.0002 −0.0001]
<i>Peer_Carbon</i> – <i>CGI_bub</i>	0.00016	2.75×10^{-6}	[0.0001 0.0004]
<i>ESP</i> – <i>Peer_ESG</i>	−0.01093	−0.0000302	[−0.0132 −0.0085]
<i>GFP</i> – <i>Peer_ESG</i>	−0.00164	-4.57×10^{-6}	[−0.0041 0.0007]
<i>Peer_ESG</i> – <i>CGI_bub</i>	−0.00035	6.05×10^{-6}	[−0.0012 0.0005]
<i>ESP</i> – <i>F_Spill</i>	0.00318	−0.000017	[0.0015 0.0048]
<i>GFP</i> – <i>F_Spill</i>	0.00451	3.53×10^{-6}	[0.0031 0.0058]
<i>F_Spill</i> – <i>CGI_bub</i>	0.00057	−0.0000123	[0.0001 0.0009]
<i>ESP</i> – <i>B_Spill</i>	0.00167	-1.96×10^{-6}	[0.0015 0.0018]
<i>GFP</i> – <i>B_Spill</i>	0.00331	-4.07×10^{-6}	[0.0029 0.0037]
<i>B_Spill</i> – <i>CGI_bub</i>	−0.00167	−0.0000144	[−0.0025 −0.0008]

5. Conclusions

5.1. Research Finding

This paper combines the AMO framework with interpretable machine learning analysis to systematically identify the causal chain through which policy combinations deflate green innovation bubbles in power industry chain enterprises, as well as the heterogeneity across industry chain segments and policies. The inhibition of policy combinations on enterprises' green innovation bubbles operates mainly through three paths, innovation incentives, peer effects, and industrial chain dividends, with pronounced heterogeneity across industry chain segments and policies. The main conclusions are as follows:

(1) From the perspective of ability (A), the expansion of government innovation subsidies and regional green finance creates a "fat cat effect" and leads to a green innovation bubble. Energy-saving policies and green finance policies restrain the accumulation of the green innovation bubble by strengthening the regulation of policy subsidies and financial supply, thereby forming an innovation incentive management mechanism. The heterogeneity analysis shows that upstream enterprises are more sensitive to changes in government innovation subsidies, whereas midstream enterprises respond more strongly to regional green finance, confirming the differences in resource contraction effects induced by policy combinations at different stages of the industrial chain.

(2) From the perspective of motivation (M), high peer carbon emissions and peer ESG scores trigger enterprises' free-riding behavior. Peer carbon emissions serve as an important transmission mechanism through which policy combinations weaken the innovation bubble. Policy combinations weaken enterprises' imitative pollution behavior and inhibit bubble accumulation by reducing the industry's overall emission level, thus forming a peer imitation convergence mechanism. Although peer ESG positively promotes the bubble, it does not serve as a significant policy transmission path. This indicates that peer carbon emission reduction pressure in the power industry chain is more policy-sensitive and more conducive to policy effects than the demonstration effect of ESG. The direct constraints of policies on upstream enterprises are more significant, while the changes in the green innovation bubble of midstream enterprises rely more on the amplification of peer effect.

(3) From the perspective of opportunity (O) dimension, backward technology spillover plays a crucial mediating role in the policy process. Policy combinations strengthen management to curb the spread of false innovation, reduce enterprises' excessive innovation investment impulses, and form a technology spillover mechanism along the industrial chain. Although forward spillovers restrain the bubble, they do not play a significant mediating role, reflecting the selective impact of policy combinations on spillovers in different directions. Upstream enterprises are more sensitive to spillover effects, while the spillover effects received by midstream enterprises have weakened.

5.2. Limitations

This paper reveals the mechanisms through which energy-saving policies and green finance policies restrain the green innovation bubble, enrich the research on green innovation, and provide theoretical support and empirical evidence for policy optimization and strategic adjustment. Nevertheless, several limitations remain. First, the research samples and regions are primarily limited to the Chinese power industry chain. The cross-industry applicability of the findings and their generalizability to other countries and regions require further verification. Second, this paper focuses only on energy-saving policies and green finance policies and does not cover other policy tools that may affect the green innovation bubble, such as carbon trading policies and environmental tax policies. Moreover, the interactions among these policies remain unclear, which may limit the comprehensiveness of the conclusions. Finally, the dynamic micro-mechanisms of internal innovation behavior

within enterprises, the interactive effects between industries, and the time-lag effects of policy implementation have not been fully revealed. Future research could further explore these issues using internal innovation data, case studies, or dynamic models to verify and refine the formation and bursting mechanisms of the green innovation bubble, thereby providing more precise references for policy formulation and corporate green strategy.

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Conflicts of Interest: The authors declare no competing interests.

Appendix A

(1) Gradient Boosted Trees (GBT)

The boosting method emerged from the question posed by Kearns: Can a set of weak learners be equivalent to a strong learner? Compared with strong models, weak models are generally easier to train. Schapire combined many weak learners into a single high-precision model using a boosting algorithm, thereby answering the question in the affirmative.

Boosting employs a forward stagewise approach to fit multiple models, minimizing the loss function (e.g., squared error or absolute error) on the training data and making predictions as close to the true values as possible. The forward stagewise method adds new base models sequentially without altering the parameters or coefficients of previously added models. Boosting solves regression problems using functional gradient descent, which minimizes the loss function by adding a base model at each step. The specific formula is as follows:

$$g_m(x) = \sum_{j=1}^J b_{jm} I(x \in R_{jm}), \quad \text{where} \quad I(x \in R_{jm}) = \begin{cases} 1, & x \in R_{jm} \\ 0, & \text{otherwise} \end{cases} \quad (\text{A1})$$

Use regression tree to replace $g_m(x)$ in the general gradient boosting method, and update the model equation and gradient descent step size:

$$f_m(x) = f_{m-1}(x) + \sum_{j=1}^J \rho_m I(x \in R_{jm}) \quad (\text{A2})$$

$$\rho_m = \operatorname{argmin}_{\rho} \sum_{i=1}^n L \left[y_i, f_{m-1}(x_i) + \sum_{j=1}^J \rho I(x \in R_{jm}) \right] \quad (\text{A3})$$

Gradient boosting regression trees are constructed in a phased manner to update the model by minimizing the expected values of certain loss functions. As more regression trees are added, the fitted model can achieve an arbitrarily small training error. However, fitting the model too closely to the training data can lead to poor generalization. By increasing

the number of iterations, the model becomes more complex and small fluctuations in the data are exaggerated. This leads to poor predictive performance on unseen (test) data. The optimal number of iterations M (or the number of trees) should be determined to minimize future prediction risk. Overfitting can be prevented by controlling the number of gradient boosting iterations, or more effectively, by scaling the contribution of each tree by a factor J . The final formula obtained is

$$f_m(x) = f_{m-1}(x) + J \cdot \sum_{j=1}^J \rho_m I(x \in R_{jm}) \quad (\text{A4})$$

The parameter J is called the learning rate, which controls the contribution of each base model by scaling it by factor J . For a fixed number of iterations, a smaller learning rate tends to yield higher training errors. Under the same number of iterations, a smaller J requires a larger M to achieve the same training error. Therefore, a smaller J with a larger M is typically chosen during parameter selection.

(2) Shapley Additive Explanations (SHAP)

The SHAP method extends the Shapley value concept from game theory, evaluating the importance of each feature by summing its marginal contributions to the model output over all possible feature orderings. The SHAP value X for a specific function in the model is as follows:

$$\Phi(X_i) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \quad (\text{A5})$$

Among them, N is the total number of features, $N \setminus \{i\}$ is the set of all possible feature arrangements except X , S is the feature set in $N \setminus \{i\}$, $f(S)$ is the model trained from S , and $f(S \cup \{i\})$ is the model trained from S and X .

The additivity of SHAP enables local interpretation of individual samples. For each enterprise, the estimated result is equal to the sum of the SHAP value of each feature and the average estimated value of all samples:

$$f(x) = \sum_{i=1}^N \Phi(x_i) + E[f(X)] \quad (\text{A6})$$

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