Федеральное государственное автономное образовательное учреждение высшего образования «Уральский федеральный университет имени первого Президента России Б.Н. Ельцина»
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На правах рукописи

Ван Ин

НАЛОГОВОЕ СТИМУЛИРОВАНИЕ ТЕХНОЛОГИЧЕСКИХ ИННОВАЦИЙ В СЕКТОРАХ ВОЗОБНОВЛЯЕМОЙ ЭНЕРГЕТИКИ КИТАЯ

5.2.4. Финансы

Диссертация на соискание ученой степени кандидата

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On the rights of the manuscript

Wang Ying

TAX INCENTIVES FOR TECHNOLOGICAL INNOVATION IN CHINA'S RENEWABLE ENERGY POWER GENERATION SECTORS

5.2.4. Finance

Dissertation is Submitted for the degree of Candidate of Economics

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ABSTRACT

The relevance of research theme. The relevance of this research topic stems from a combination of global and national factors associated with the acceleration of the energy transition and the need to develop effective tools to stimulate technological innovation. In the face of the escalating challenges of climate change and the gradual transition away from fossil fuels, governments are actively implementing renewable energy support mechanisms, among which tax incentives play a key role as a tool for correcting market failures and reducing innovation costs.

This issue is particularly significant in China, where the development of the renewable energy sector is accompanied by a large-scale transformation of public policy—from direct administrative regulation to more flexible market mechanisms, including a system of tax incentives and preferences. The adoption in 2013 of a set of tax measures aimed at stimulating corporate innovation marked a turning point in the development of a modern model for supporting green technologies, focused on improving the efficiency and competitiveness of the industry.

Despite the significant proliferation of tax incentives, their actual impact on companies' innovative behavior remains ambiguous. On the one hand, tax incentives reduce the cost of research and development (R&D), increase the availability of financial resources, and promote innovation. On the other hand, given information asymmetries and imperfect control mechanisms, there is a risk of opportunistic behavior, manifested in so-called "fake R&D" practices aimed at obtaining tax advantages without actual technological results.

Modern research in the field of tax policy and innovation development primarily focuses on assessing the overall incentive effect of tax instruments, while the problem of distinguishing between real and simulated innovation remains underdeveloped. The lack of reliable methods for identifying fake innovation activity distorts assessments of the effectiveness of public policy and reduces its impact. Therefore, there is a need to develop new theoretical and methodological approaches that take into account the dual nature of

the impact of tax incentives. The study's relevance is further enhanced by the industry-specific characteristics of renewable energy, including long investment cycles, high capital intensity, significant technological uncertainty, and pronounced dependence on government support. Under these conditions, tax incentives serve not only as a means of compensating for market failures but also as a factor determining companies' strategic behavior and the trajectory of the industry's technological development.

Therefore, the need for a comprehensive assessment of the effectiveness of tax incentives, taking into account their impact on both genuine and distorted forms of innovation, as well as the development of mechanisms to improve their targeting and effectiveness, underscore the high scientific and practical significance of this study. The results of this study can be used to improve tax policy in stimulating green technologies and enhance government regulation of innovative development.

Research questions. Faced with the current challenge of promoting green transformation while maintaining innovation-driven growth, besides long-term institutional arrangements such as industrial upgrading and structural reform, can tax incentives serve as a relatively flexible and effective policy instrument to stimulate technological innovation in China’s renewable energy power generation sector? More importantly, under conditions of information asymmetry, do tax incentives only generate positive innovation effects, or can they also induce strategic and opportunistic behaviors such as fake R&D, thereby weakening the real effectiveness of policy support? Against the background of China’s post-2013 renewable-energy-oriented tax support regime, this dissertation theoretically explains and empirically tests the dual effects of tax incentives on firm behavior, namely, their role in promoting genuine green innovation and their potential to distort R&D decisions through regulatory arbitrage. Existing studies have largely confirmed that tax incentives can reduce innovation costs, ease financing constraints, and improve firms’ innovation performance, yet the identification of fictitious R&D and the institutional conditions under which tax incentives can produce sustained and genuine innovation effects remain insufficiently explored. Therefore, this dissertation goes beyond the conventional question of whether tax incentives work, and further asks whether tax incentives improve firms' profitability and green innovation output, whether such effects exhibit significant heterogeneity across regions and firm types, and whether a coordinated policy configuration integrating incentives, quotas, and penalties can more effectively promote the diffusion of genuine green R&D while restraining fake R&D behavior. In this sense, the dissertation not only evaluates the incentive effect of tax policy, but also extends the analysis toward the governance of distortion risks and the optimization of green innovation policy.

The degree of scientific development of the problem

The issue of tax incentives for innovation is one of the most developed in modern economic science and is based on the fundamental tenets of neoclassical investment theory, public finance theory, and endogenous economic growth theory. Classical approaches to the analysis of tax policy and its impact on economic behavior were developed in the works of researchers such as R. Rolph, S. Surrey, V. Thuronyi, P. McDaniel, and N. Kaldor. They were also further developed in the works of I. A. Mayburov, who views tax incentives as a tool for correcting market failures and redistributing resources in favor of socially significant activities. The development of theoretical concepts regarding the impact of taxes on firms' investment decisions is linked to the research of D.W. Jorgenson and R.E. Hall, who substantiated the dependence of investment activity on the tax burden through the cost of capital mechanism. These ideas were subsequently expanded within the framework of endogenous growth theory (P. Romer and R. Lucas), which views innovation as a key factor in long-term economic development and public policy as the most important incentive for the accumulation of knowledge and technology.

Significant contributions to the empirical study of the effectiveness of tax incentives were made by N. Bloom, R. Griffith, J. Van Reenen, E. Zwick, and J. Mahon, who demonstrated the positive impact of tax incentives on R&D intensity and corporate innovation. Their research has shown that tax incentives are a relatively effective instrument of government support compared to direct subsidies, as they involve lower administrative costs and are more flexible.

A separate line of research is devoted to the analysis of tax incentives in the context of the development of a green economy and renewable energy. The work of H. Breetz, M. Mildenberger, and Chinese researchers Zhong Zhe, S. Wu, J. Hu, L. Fang, and K. Li, among others, demonstrates that tax incentives help reduce the costs of implementing environmental technologies, increase investment activity, and accelerate technological innovation in the industry. Important contributions to the theory of innovative corporate behavior were made by F. Fazzari, B. Petersen, B. Holmström, and J. Stiglitz, who demonstrated that under conditions of capital market imperfections and information asymmetries, companies may deviate from optimal investment strategies. These ideas were further developed in the works of B. Byiers, L. Guceri, R. Yagan, C. Chen, and Tian K., who substantiated the possibility of opportunistic behavior, including the manipulation of R&D indicators for the purpose of obtaining tax advantages. M.E. Porter, J.H. Dunning, A. Gambardella, and A. Fosfuri have made significant contributions to the study of institutional and industry-specific aspects of innovation development, examining innovation as the result of the interaction between the competitive environment, government policy, and firm strategies. The works of B. Van Leeuwen, L. Xiang, D. Feng, D. Castellani, and A. Zanfei emphasize the importance of international and interregional differences in the effectiveness of innovation policy.

However, despite the significant volume of scientific research, a number of aspects remain insufficiently explored. In particular, the existing literature lacks a unified approach to identifying "bogus R&D," the number of empirical studies that take into account the dual nature of tax incentives is limited, and models that simultaneously analyze the incentive and distortionary effects of tax policy at the industry and regional level are insufficiently developed.

Thus, while the current scientific literature provides a theoretical and methodological basis for studying tax incentives for innovation, there remains a need for an in-depth analysis of the mechanisms by which tax incentives influence corporate behavior, the development of methods for identifying opportunistic practices, and improving the effectiveness of public policy in the development of green technologies.

The purpose is to develop a theoretical and methodological approach to assessing and optimizing the effectiveness of tax incentives for technological innovation in China's renewable energy sector, taking into account the distinction between real and fictitious R&D.

Study Objectives

1. To summarize theoretical approaches to tax incentives for innovation and elucidate the mechanism by which they influence the innovative behavior of companies in the renewable energy sector.

2. To assess the impact of tax incentives on the innovative performance and financial performance of renewable energy companies.

3. To develop a method for identifying fictitious R&D and empirically detecting its presence under tax incentives.

4. To formulate a tax policy optimization model, including incentives, quotas, and sanctions, aimed at improving the effectiveness of innovative development.

The object of the study is enterprises in China's renewable energy sector and the technological innovation development processes shaped within them by state tax incentive policies.

The subject of the study is economic relations and mechanisms of influence of tax incentives on the technologically innovative behavior of renewable energy enterprises, including the formation of both real and fictitious R&D.

The temporal and geographical scope (period) of the thesis research.

This research covers China’s renewable energy power sector across 2009–2023, a period characterized by significant national policy reforms in R&D tax incentives, renewable energy subsidy structure, and carbon governance mechanisms. The study incorporates a geographical comparison across three major economic regions: eastern, central, and western China, reflecting diverse industrial foundations, resource endowment, and innovation capabilities.

The theoretical and methodological basis of the research.

The theoretical basis of the study is based on neoclassical investment theory, endogenous growth theory, public finance theory, as well as concepts of information asymmetry and behavioral economics.

The methodological framework is formed by general scientific and specialized research methods, including systems and comparative analysis, econometric modeling methods (DID and DDD), regression analysis, statistical data processing methods, and simulation modeling based on evolutionary game theory.

Research hypothesis:

Hypothesis 1: Tax incentives can significantly improve the profitability (ROE) of renewable energy companies.

Hypothesis 2: Tax incentives have a positive promoting effect on the green technology innovation output of renewable energy companies.

Hypothesis 3: The impact of tax incentives on the green technology innovation output of renewable energy companies exhibits significant heterogeneity.

Hypothesis 3a: Significant regional heterogeneity exists

Hypothesis 3b: Tax incentives have a stronger promoting effect on the green innovation output of non-state-owned renewable energy enterprises.

Hypothesis 3c: High current expensed R&D investment will have a positive impact on green innovation output.

Hypothesis 4: R&D intensity as a mediating mechanism affecting green innovation output.

Hypothesis 5: Tax incentives may lead to “Fake R&D” behaviour.

Hypothesis 6: Compared with single-policy intervention, a coordinated policy configuration integrating tax incentives and penalty constraints is more effective in promoting the diffusion of genuine green R&D, because it can reduce firms’ innovation costs, curb fake R&D behaviour, and enhance the regional adaptability of policy implementation.

Information and empirical base of dissertation research. The study's data base consists of financial statements from publicly traded companies in China's renewable energy sector, as well as official regulatory documents on tax and energy policy.

The empirical base is based on panel data from companies for 2009–2023, including indicators of financial performance, tax incentives, R&D expenditures, and innovation activity. Data from international and national statistical and analytical databases (Wind, CSMAR, Eastmoney, and China's national statistical resources), as well as materials from international organizations (OECD, IEA, and IRENA), ensures the representativeness and reliability of the study's results.

The field of study corresponds to the passport of the scientific specialty 5.2.4. Finance: p. 8 "Behavioral finance" and p. 13 "Taxes and taxation. Tax policy. Tax administration. Ensuring Fiscal Sustainability".

The validity of the research findings is ensured by a combination of theoretical, methodological, and empirical foundations.

First, the study draws on established theoretical concepts in economics—neoclassical investment theory, endogenous growth theory, public finance theory, and the concept of information asymmetry. This ensures the logical consistency and scientific validity of the proposed propositions.

Second, this validity is confirmed by the use of modern econometric tools, including difference-in-differences (DID) and triple-difference (DDD) models, which allow us to identify causal relationships between tax incentives and innovation.

Third, the reliability of the results is ensured by a high-quality empirical base. The study is based on panel data from companies in the Chinese renewable energy sector over a long period (2009–2023), including financial indicators, R&D, and innovation data. The use of authoritative sources (Wind, CSMAR, Eastmoney, and international databases) guarantees the representativeness and reliability of the information.

Fourth, robustness tests were conducted, including placebo tests and randomization, confirming that the observed effects are not due to chance.

Fifth, the reliability of the results is enhanced by the use of multivariate analysis methods, in particular, the principal component analysis (PCA) to construct an integrated "fictitious R&D" indicator, which allows for a more accurate accounting of the latent behavioral characteristics of companies.

Finally, the reliability of the results is confirmed by the validation of the results at international and national scientific conferences, as well as publication in peer-reviewed scientific journals indexed in Web of Science and Scopus.

The scientific novelty lies in its development of theoretical and methodological approaches to analyzing tax incentives for innovation in the renewable energy sector. The study clarifies the mechanisms by which tax incentives influence companies' innovative behavior, taking into account information asymmetries and opportunistic strategies. A new approach to distinguishing real from fictitious R&D has been developed, expanding the toolkit for assessing the effectiveness of tax policy. The developed models and methods deepen understanding of the dual nature of tax incentives and contribute to the development of theory on government regulation of innovation.

Provisions for defense:

1. A theoretical model of tax incentives for innovation is developed by substantiating the effects of incentives under conditions of information asymmetry and regulatory arbitrage mechanisms. This model demonstrates that, while tax incentives promote genuine green innovation through the compensatory effect, they also induce firms to exploit the "opportunistic behavior effect" to imitate R&D in order to obtain tax incentives. It provides a new theoretical basis for understanding the dual effects of tax incentive policies, assisting policymakers in designing incentive instruments that simultaneously promote genuine innovation and discourage economic agents from using regulatory arbitrage mechanisms.

2. The specific features of China's discrete tax policy for stimulating renewable energy production are substantiated. Compared with the incentive policies of developed countries, China's renewable energy sector relies more heavily on structural policy instruments such as tax incentives, demonstrating a unique pattern where leading renewable energy scales coexist with regional differences in innovation potential. This finding highlights the practical need for systematically assessing and optimizing the effectiveness of tax incentive policies. This approach not only provides empirical support for improving China's green tax policy but also offers insights for other countries

considering regional heterogeneity when designing tax incentives for green innovation.

3. A methodological approach to identifying "fake R&D" in renewable energy generation companies has been developed. It is based on the triple-difference (DDD) model, which uses a unique variable called "fake R&D." This approach overcomes the limitations of the traditional difference-in-differences (DID) method, which could not simultaneously distinguish between the increase in fake R&D and the inflated R&D expenditures to obtain tax incentives. This approach expands the tools for causal identification of tax policy effects, enriches theoretical tools for evaluating green innovation policies, and provides policymakers with more precise means of distinguishing between genuine innovation enhancement under incentive policies and strategic behavior toward fictitious R&D.

4. A simulation model of the dynamic adoption and diffusion of green innovative technologies by firms under various combinations of tax incentives and penalties has been developed, based on evolutionary game theory. This model is unique in that it dynamically integrates three mechanisms, including tax incentives, quotas, and penalties, into a single system of influence. The model enables quantitative modeling of the diffusion of green innovative technologies and forecasting their diffusion pathways under various policy combinations.

The theoretical significance of the study lies in its advancement of scientific understanding of the role of tax policy in stimulating technological innovation in the context of economic structural transformation. This work advances the theory of public finance and innovation economics by integrating approaches from neoclassical investment theory, endogenous growth theory, and the concept of information asymmetry.

A theoretical interpretation of the dual impact of tax incentives is proposed, taking into account both their stimulating effect and the potential for shaping opportunistic behavior among enterprises. This allows for the expansion of existing models for analyzing innovative activity by incorporating behavioral and institutional aspects.

Furthermore, the developed approach to distinguishing between real and fictitious R&D contributes to the development of methodology for assessing the effectiveness of public policy, forming the basis for further research in the area of tax incentives for innovation and improving the quality of economic regulatory models.

The practical significance of the study lies in the potential use of the obtained results in developing and improving tax policies to stimulate technological innovation and renewable energy development.

The proposed approaches and models will enable government agencies to more accurately assess the effectiveness of tax incentives, identify the risks of fraudulent R&D, and improve the targeting of support measures. The developed mechanism for combining tax incentives, quotas, and sanctions can be applied in the development of a comprehensive regulatory system aimed at stimulating genuine innovation activity by enterprises.

The study's results can also be used in analytical and expert assessments of government programs, as well as in educational training for specialists in tax policy, government regulation, and the innovative economy.

Recognition of the research findings of the dissertation. The main results of the dissertation research were presented, discussed and positively evaluated at the following conferences: Spring Days of Science International Conference for Students and Young Researchers (April 2024, School of Economics and Management, Ural Federal University); IX All-Russian School on Institutional and Evolutionary Economics for Young Researchers (October 2024, Russian Federation, Institute of Economics, Ural Branch of the Russian Academy of Sciences, Yekaterinburg); XIX International Conference "Russian Regions in the Focus of Change" (November 2024, Yekaterinburg); IX International Conference "Spring Days of Science" (April 2025, School of Economics and Management, Ural Federal University) XX International Conference "Russian Regions in the Focus of Change"(November 2025, Yekaterinburg)

Publications on the topic of dissertation research.

The main provisions and conclusions of the dissertation research were reflected in 12 scientific publications, of which 1 article was published in peer-reviewed scientific journals determined by the Higher Attestation Commission of the Russian Federation and the Attestation Council of UrFU and 7 indexed in the Web of Science or Scopus databases, and 4 are other publications in the form of collections of reports. The total publication length was 14.6 printed pages, including 7.3 printed pages by the author.

Author's personal contribution consists of developing a theoretical and methodological approach to assessing the effectiveness of tax incentives for technological innovation in China's renewable energy sector.

The author substantiates the concept of the dual impact of tax incentives, considering information asymmetry, which helps explain the formation of both real and fictitious R&D. An original empirical approach based on a combination of the DID and DDD models has been developed and implemented, enabling the identification of cause-and-effect relationships between tax policy and enterprise innovation.

The author has developed a method for identifying fictitious R&D based on the integration of financial and behavioral indicators and proposed a model for optimizing tax regulation that combines incentives, quotas, and sanctions. All key results, conclusions, and recommendations were obtained independently by the author and reflect his scientific contribution to the development of the theory and practice of tax incentives for innovation.

The Volume and structure of the dissertation research. The work consists of an abstract, three chapters, a conclusion, a list of references, and appendices. The study is presented on 206 typewritten pages, including 29 tables. The appendix contains 12 tables, and the main text contains 32 figures. The list of references includes 181 titles.

The dissertation is logically structured and includes three interconnected chapters that sequentially explore the theoretical, methodological, and empirical aspects of the topic.

The first chapter examines the theoretical foundations of tax incentives for innovation. It systematizes scientific approaches within the framework of neoclassical investment theory, endogenous growth theory, and public finance theory. The mechanism by which tax incentives influence the innovative behavior of enterprises is revealed, and the dual nature of their impact is substantiated, taking into account information asymmetry and opportunistic behavior.

The second chapter formulates the methodological framework for the study. The sample and key variables are determined, the choice of econometric methods is justified, research hypotheses are formulated, and an analytical model for assessing the impact of tax incentives on the innovation activity of renewable energy companies is constructed.

The third chapter presents the results of the empirical analysis. Using a quasi-experimental approach, the impact of tax policy on innovation is assessed, the presence of fictitious R&D is identified, and the heterogeneity of the effects is analyzed. Additionally, a simulation model is developed and tested to evaluate the effectiveness of various combinations of public policy instruments.

The conclusion This study shows that tax incentives can encourage green innovation in China's renewable energy power generation enterprises, but the response is not the same for all firms and may also create space for opportunistic R&D reporting. Future research can include more types of enterprises and use more detailed R&D records or audit data to judge more accurately whether tax incentives lead to real technological innovation.

CHAPTER 1. THEORETICAL FOUNDATIONS OF TAX INCENTIVES FOR TECHNOLOGICAL INNOVATION

1.1. Economic Foundation of Tax Incentive Policies

Tax policy is a process by which a country or region allocates and redistributes necessary resources primarily through tax revenue. In the theoretical landscape of modern public finance, the role of taxation has undergone a fundamental shift. It is no longer merely a tool for "fiscal extraction" to raise national revenue, as viewed in classical economics, but has evolved into a core lever for regulating the macroeconomy, correcting market failures, and reshaping microeconomic incentive structures [56]. Similarly, as an important means of government intervention, tax incentives typically refer to preferential treatment offered by the government to specific economic activities through the tax system, guiding resources towards areas with social benefits. Buchanan [18] argues that public finance has undergone a major transformation since World War II, shifting from a mechanistic approach focused on revenue extraction toward a public-choice perspective that recognises the political and institutional dimensions of fiscal decisions. Within this framework, government actors are not benevolent optimisers but self-interested agents, making the design of tax institutions critical for shaping collective outcomes. For the analysis of tax incentives, this perspective implies that policy effectiveness depends not only on theoretical market-failure corrections but also on the institutional constraints and incentive structures embedded within the tax system.

This section, "Economic Foundation of Tax Incentive Policies," will explore two theoretical dimensions: (1) the efficiency view, based on neoclassical and endogenous growth theories, demonstrating how tax incentives provide "positive incentives" by correcting externalities and reducing marginal costs; and (2) based on information asymmetry, revealing the "strategic behavior" of firms utilizing policy arbitrage and engaging in pseudo-innovation. this section will also discuss how to identify and suppress pseudo-innovation through refined classification and governance, laying the foundation for the empirical analysis that follows.

(1) Based on neoclassical economics and endogenous growth theory, positive incentives can be provided by correcting externalities and reducing marginal costs.

Tax incentives have a long history and are not a modern invention. In his classic work, Rolph [122] pointed out that government fiscal activity should not be mechanically understood as a simple cycle of "taking from the people and giving back to the people," but rather as a complex process of resource reallocation.

Hall R E and Jorgenson D W [68] extended the investment theory framework based on classical economic theory, arguing that firms do not respond directly to taxes, but rather adjust their optimal capital stock based on changes in the "user cost of capital."

$$C = \frac{q(r + \delta)(1 - k - uz)}{1 - u} \quad (1)$$

As formula (1), C represents the cost of using capital, q represents asset prices, r represents the discount rate, u represents corporate income tax rate, z represents value of depreciation deductions, k represents investment tax credits

The theoretical innovation derived from this formula is that tax incentives are not vague "subsidies," but rather function through a precise parameter transmission mechanism. Parameter k: When the government implements investment tax credits, the value of k increases, directly lowering the cost of capital C. Parameter z: Accelerated depreciation policies, which allow companies to claim more depreciation in the early years of an asset's life, increase the value of z.

Zwick E and Mahon J [181], through their empirical study of millions of U.S. corporate tax returns, investigated the direct impact of the "bonus depreciation" policy on the variable z in the formula. Their research found that investment is extremely sensitive to tax incentives, with an elasticity of -3.7. This directly validates the result of the (1-uz) term in the formula. Wang and Igor A. Mayburov [155] used a panel of 30,483 firm-year observations from Chinese A-share non-financial listed firms spanning 2009–2023(Table 1.1.1). They localized and extended the Hall-Jorgenson formula, categorizing tax incentives into three types: Cost-side: Value-added tax refunds, which directly reduce q in the formula. Profit-side: "Three-year exemption and three-year 50% reduction" income tax preferential treatment, which reduces u. Innovation-side: R&D expense super deduction, which increases z. Bolinger M [15] pointed out that because many new energy developers do not have sufficient profits to utilize the tax credits in 1-k-uz, they must introduce "tax equity investors." This results in the effective u in the formula being 0 for developers, and k and z must be monetized through complex transaction structures, which actually increases the transaction cost r.

Table 1.1.1 Original classification of Chinese tax incentives

Functional Classification	Core Policies	Main Effects
Cost side	Value-added tax refund, import-related tax reductions and exemptions, and accelerated depreciation.	Tax incentives have a significant long-term impact on cost reduction, but there is a time lag in the short term. Large enterprises in the eastern region are more responsive to these policies.
Profit side	Corporate income tax reduction rate (15% for high-tech enterprises, etc.), tax credit and exemption	Tax incentives have a significant impact on long-term financial performance, but exhibit a time lag in the short term.
Innovation-oriented end	Additional deduction for R&D expenses, accelerated amortization of intangible assets, and one-time expense treatment of R&D equipment.	It mainly promotes green and sustainable development of enterprises through innovation and R&D as an intermediary, thereby enhancing the profitability of enterprises.

Source: Compiled by the author

Unlike direct fiscal subsidies, tax incentives are "tax expenditures," meaning they achieve policy objectives by reducing tax revenue. S. S. Surrey [141]; V. Thuronyi and K. Brooks [144]; S. S. Surrey and P. R. McDaniel [142]; Surrey S S [140]do not require direct cash payments from the government; the government can utilize the existing tax collection system, and businesses or individuals automatically enjoy the benefits in their tax returns, without the need for additional special appropriations. This gives tax incentives the advantages of low implementation costs and minimal political resistance.

Earl R. Rolph [122] in his treatise on public finance, further points out that this "price effect" makes taxation a "visible hand." Companies must first make substantial capital investments to enjoy tax benefits. This mechanism is theoretically more efficient than direct grants because it screens out speculators who lack genuine investment capabilities [154].

Dale W. Jorgenson and Robert E. Hall [68] explained "how" businesses respond to taxation by reducing costs, endogenous growth theory answers "why" the government must intervene. The academic circle generally such as Khan S [81]; Fligstein et al [52]; Kaldor N [79] Supporting tax intervention in market failure. The functions of national taxes to raise fiscal revenue when market mechanisms fail to effectively allocate resources, taxes should actively intervene to guide the process.

Tilleman S.G, Russo M.V, Nelson A.J [145] think that this policy logic aligns with the target mechanism reducing costs through technological progress and scale expansion to achieve the replacement of traditional fossil fuels with clean energy.

In Romer, Paul M [123] endogenous growth model, think that as a "non-rival" and "partially excludable" good. The research and development (R&D) of renewable energy technologies exhibits typical characteristics of double externalities. In this case of market failure, scholars such as Andreassen G L, Kallbekken S, Rosendahl K E [7] point out that tax incentives are essentially a "Pigouvian subsidy." By granting high-tech companies lower tax rates or additional deductions for R&D expenses, the government is effectively "paying" for the positive externalities generated by these companies.

Liu, et al [100] analyse the pattern of patent-based renewable energy technology innovation in China, revealing that innovation activity is highly concentrated in specific regions and technology fields, with solar and wind energy dominating patent outputs . Their findings indicate that China's renewable energy innovation follows a distinct trajectory shaped by policy incentives rather than purely market forces, and that patent counts have increased rapidly alongside government support programmes.

Based on this, Wang et al [158] develop a method to measure abnormal booking tax differences using data from U.S. quoted firms. By isolating the unexplained component of the gap between financial and taxable income, their approach provides a refined indicator for detecting tax avoidance and aggressive tax planning, offering valuable implications for tax enforcement and the assessment of corporate tax behavior. Using this theory, the government must assess the marginal benefits and marginal costs when introducing tax incentives: on the one hand, tax incentives enhance economic vitality and output by reducing the tax burden on related activities (incentive effect); on the other hand, tax cuts lead to a reduction in fiscal revenue and potential efficiency losses. The optimal tax system requires the government to choose preferential measures that have significant incentive effects and small efficiency losses, thereby achieving a balance between incentive objectives and tax efficiency. Välilä T believes [149] that efficiency and incentives are mutually restraining, and tax incentives are only adopted as a suboptimal option when market failures or externalities in a specific area make government intervention necessary, in order to achieve a corrective effect in a more flexible way than direct subsidies or regulation.

In December 2023, 26 EU member states and 300 companies signed the European Wind Energy Charter, pledging to support the development of the wind energy industry through the EU Innovation Fund [29]. Mason [105] contends that such incentives are a step toward revitalizing nuclear energy, but a broader commitment is needed to fully realize the promise of the peaceful atom. These policies have reduced the production costs of renewable energy and helped companies conduct green research and development.

Yuan [174] systematically review China’s progress in energy conservation and emissions reduction, emphasizing that fiscal support and policy coordination have played an important role in promoting low-carbon transition and improving the effectiveness of clean energy development. Building on this, Zhang L, Chen Y, He Z [176] conduct a cost-benefit analysis of photovoltaic poverty alleviation, proposing optimal subsidy reduction strategies that balance fiscal sustainability with continued emissions reductions. Together, they emphasize that well-calibrated subsidy policies are critical to maintaining momentum in energy conservation and low-carbon transitions. Therefore, its conclusions fully demonstrate the effectiveness of fiscal subsidy policies in the new energy field, further promoting the development of tax incentives [167,170].

With the continuous improvement of tax incentives, the academic community generally believes that tax incentives have both long-term and short-term effects. Bloom N, Griffith R, Van Reenen J [14], using panel data from nine OECD countries between 1979 and 1997 and employing a fixed-effects model, conducted an empirical study. Their findings showed that tax incentives effectively increased firms' R&D intensity, a finding that held true even after incorporating macroeconomic shocks and other policy influences into the empirical analysis. Their estimates indicated that if R&D costs decreased by 10% due to tax incentives, firms' R&D investment would increase by approximately 1% in the short term and nearly 10% in the long term. This demonstrates that tax incentives have a sustained pulling effect on firm R&D, guiding firms to increase innovation investment over a longer timescale.

Base on, Ying W, Leontyeva Y V [169] using Chinese renewable energy companies as case studies, found that the impact of tax incentives on businesses differs in the long and short term. The full effect of the policy is subject to a time lag, but over the long term, its influence on reshaping companies' willingness to innovate is fundamental.

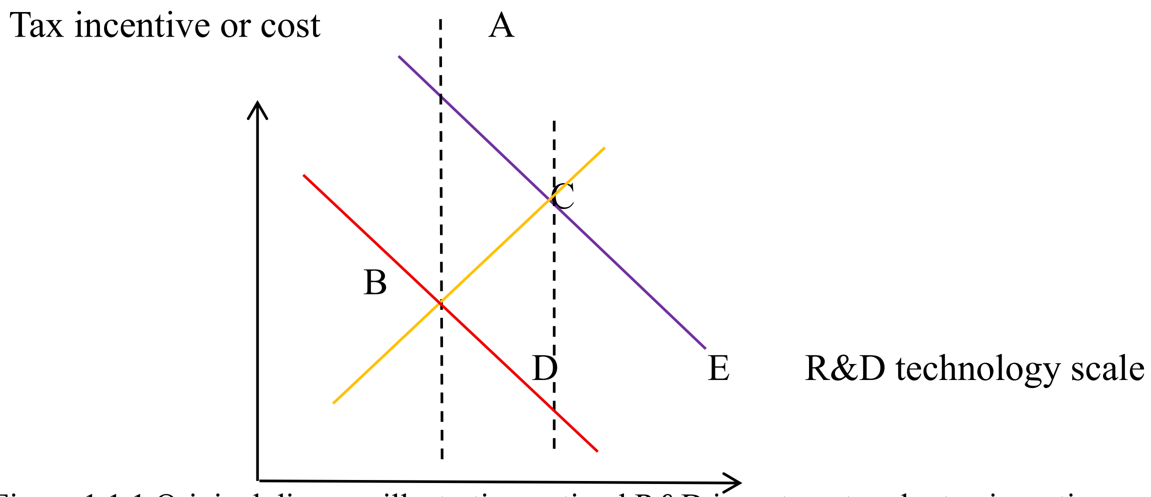


Figure 1.1.1 Original diagram illustrating optimal R&D investment under tax incentives

Source: Compiled by the author

In the Figure 1.1.1, A, B, and C represent the relationship between marginal revenue and marginal cost under different R&D intensities, respectively. B and C are the critical points where marginal revenue equals marginal cost, corresponding to the upper and lower bounds of the optimal R&D investment range. D and E represent the lower and upper limits of the optimal R&D investment, respectively. Together, they depict the reasonable R&D decision range for enterprises under the marginal analysis framework. This figure confirms tax incentives will put R&D technology scale larger.

Based on this, the "positive promotional effect" of tax incentives has received widespread theoretical support and empirical verification in academia. Brown J.R, Fazzari S.M, Petersen B.C [17]; Zhong Z et al[179]; Feng X [51]

Based on this innovation theory and the framework of neoclassical investment theory, Schumpeter argued that technology-innovative companies should be the primary targets for government tax incentives [130].

Schumpeter's innovation theory also indicates that economic development is driven by innovation, which requires the combination of entrepreneurial spirit and policy incentives [58]. Base on, O. S. Isaiah, R. K. Dickson [75]; Komlos J [86]; Diamond Jr A M [41], Scholars believe that the fundamental driving force of economic development comes from "creative destruction," where new technologies and new products constantly disrupt existing market equilibrium through innovation. As the Schumpeter's innovation theory development, Xiong R et al [165] think that tax incentives encourage enterprises to engage in technological research and development and equipment upgrades by increasing innovation returns and reducing innovation costs, thereby driving technological breakthroughs in fields such as wind power, photovoltaics, and hydrogen energy, this has achieved "creative development" at the industry level.

(2) Companies exploit information asymmetry for strategic arbitrage and faked innovation and research.

This section mainly explains the conceptual boundaries and manifestations of fake research and development. Although tax incentives can help businesses grow, there is a significant information asymmetry between the government and businesses. Due to the high uncertainty and difficulty in measuring the output of R&D activities, businesses have a strong incentive to exploit tax incentives for tax arbitrage and engage in faked R&D.

The term "fake R&D" first appeared in the 1980s. China's State Taxation Administration defined "fake R&D" as fabricating, exaggerating, or improperly categorizing R&D activities and expenses in order to fraudulently obtain the qualification of high-tech enterprises, illegally enjoy tax incentives such as additional deductions for R&D expenses, or other policy support. According to “fake R&D”. Byiers B., Dalleau M [21] that from the perspective of fiscal transparency and efficiency, over-reliance on tax incentives can also bring problems. On the one hand, embedding policy objectives into tax law increases the complexity of the tax system, hindering its simplicity and transparency; on the other hand, since tax reductions are not directly reflected in budget expenditures, assessing their effects and beneficiaries is more difficult, making them susceptible to lobbying by special interest groups and posing a risk of policy abuse [19]. During the implementation of tax incentive policies, enterprises often misclassify expenditures that lack an R&D nature as R&D expenditures in order to maximize incentive amounts. This practice is referred to as “re-labeling”. Guceri I and Liu L [61] against the backdrop of the UK's R&D Tax Relief policy, it has been observed that small and medium-sized enterprises (SMEs) exhibit a pronounced tendency to reclassify expenditures under the tax incentive scheme, converting routine expenses into “research and development” activities to secure fiscal rebates. Chen et al [24] Analysis of Chinese enterprises indicate a tendency to classify marketing expenses and administrative expenditures under research and development accounts. This strategy significantly distorts the authenticity of financial data and leads to misallocation of policy resources. He J and Tian X [70] this further indicates that in subsidy-intensive industries, “faked innovation” practices are widespread, undermining the incentive policies' ability to guide genuine technological progress.

The threshold values set by tax policies can easily lead enterprises to engage in “bundling” behavior in their financial data, manipulating financial indicators to just exceed the threshold and obtain preferential treatment. Kleven H.J and Waseem M [83] Taking Pakistan's personal income tax system as an example, it demonstrates how a large number of taxpayers manipulate their income near the threshold, highlighting the microeconomic behavioral responses triggered by tax system design [73]. In the Chinese context, H Liu et al [96] It has been discovered that the certification threshold for high-tech enterprises has prompted some companies to manipulate their R&D expenditure ratios in order to qualify for the 15% corporate income tax incentive, resulting in artificially inflated incentive effects.

To maximize the benefits of incentive policies, enterprises may proactively adjust their spending schedules to achieve intertemporal tax arbitrage. Yagan D [166] An analysis of the 2003 US. dividend tax credit policy revealed that companies employed front-loading dividend strategies, concentrating distributions within the tax-reduction window. This resulted in volatile behavior characterized by short-term surges followed by subsequent declines. Green R.C [60] think that the analysis examined the impact of accelerated depreciation incentives on corporate investment timing, revealing that firms adjusted expenditures to take advantage of the policy window, thereby undermining long-term investment efficiency. Hall B., Van Reenen J [63] as noted in its authoritative review, intertemporal adjustments may undermine the stability and long-term guidance capabilities of incentive policies, leading to policy distortion.

Tax incentives, if poorly designed or inadequately monitored, can easily be exploited by businesses for non-productive activities to generate excess profits, thereby creating systemic rent-seeking. J Lerner [91] think that it is pointed out that subsidy dependency can cause enterprises to focus more on arbitraging the system rather than innovation itself, thereby diminishing the marginal effects of policies. Busso, Gregory and Busso M, Gregory J, Kline P [20] and Kline P [84] analysis of the U.S. "Empowerment Zone" policy reveals that businesses primarily participate through geographic registration rather than actual investment, creating a "shell company effect".

Wang Y, Mayburov I.A [156] used the NW small-world model to study and found that there are different problems in the field of new energy technology and core technologies that are difficult to overcome. They found that the lack of innovation in new energy technology is mainly due to the reality of high cost and low subsidies, as well as the existence of false research and development, which leads to the loss of national funds [43]. At the same time, the government's support for the new energy industry through relevant fiscal and tax policies is lagging behind, such as electricity subsidies and financial stability [55]. Moreover, they believe that if the above problems are to be solved, various fiscal subsidy policies or tax incentive policies need to be formulated. Cordes provides a comprehensive review of empirical studies examining whether tax incentives effectively stimulate private R&D investment. He finds that the estimated price elasticity of R&D spending is relatively modest, suggesting that tax credits often lead to substantial revenue losses for only marginal increases in genuine research activity. To observed increases in reported R&D may partly reflect firms merely relabeling existing expenditures rather than undertaking new, additional research [28].

Yang Guochao et al [62], through empirical research based on data from Chinese listed companies, also confirmed the existence of R&D investment manipulation. This indicates that some companies barely meet the requirements by increasing or falsifying R&D expenditures, thereby obtaining high-tech enterprise status and corresponding tax breaks. Further analysis shows that these companies engaging in R&D fraud often receive more tax breaks and government subsidies, but the correlation between their R&D investment and subsequent innovation output is significantly weak. The fabricated R&D investment does not bring about genuine technological innovation but instead leads to a decline in corporate R&D performance.

As we can see Table 1.1.2, We can clearly understand the logical development of tax incentives and the contributions of representative scholars in this field.

Table 1.1.2 An original classification of how companies utilize tax incentives for arbitrage purposes

Type of Distortion	Mechanism	Key Literature	Economic Consequence
Relabeling	Classifying non-R&D expenses (marketing, administrative) as R&D expenses in accounting records to obtain tax benefits.	Chen, Liu, Suárez Serrato & Xu (2021) Guceri, I. & Liu, L.(2019) He, C. & Tian, X.(2018)	This leads to a loss of government revenue and inflated statistical data, which misleads macroeconomic decision-making.
Threshold clustering	Manipulating financial ratios (such as R&D/Sales) to just barely exceed the threshold for policy incentives.	Yang Guochao et al. (2017);Kleven & Waseem (2013) Zwick, E. & Mahon, J.(2017)	This has led to the emergence of a large number of "pseudo-high-tech" companies, resulting in a decline in the quality of innovation (measured by citation rates and commercialization

			rates).
Intertemporal transfer	Adjust the timing of R&D expenditures to concentrate them in years with tax incentives.	Yagan, D(2015)Hall & Van Reenen (2000) Hall, B. H. & Van Reenen, J.(2000)	This causes dramatic fluctuations in R&D investment, rather than being driven by technological cycles, thus disrupting the continuity of research and development.
Rent-seeking and arbitrage	The focus is on meeting policy requirements rather than addressing market pain points.	Lerner (2009);Igor A. Mayburov (2025)	This leads to a "subsidy dependency syndrome," and once the subsidies are reduced, the companies fall into difficulties.

Source: Compiled by the author

1.2. Analysis of the driving mechanisms and influencing factors of technological innovation

The Eurostat [48] definition of "technological innovation" first appeared in the Oslo Manual, which primarily delineates technological innovation into two forms: product innovation and process innovation. Damanpour F think that product innovation refers to the commercialization of products that have undergone technological changes, whereas process innovation denotes the actual adoption of significantly improved production methods [34,35,36]. The core essence lies not in the innovative concept itself, but rather in the realization that technological changes have entered the market or production process. Tracing the intellectual origins, the theoretical foundation can be traced back to the "new combination" theory of innovation proposed by Schumpeter [128]in his 1911 work The Theory of Economic Development.

（1）The economic driving mechanism of genuine technological innovation

According to Schumpeter [130], innovation is the engine of economic growth, and the innovative activities of entrepreneurs require sufficient incentives. And then Makeeva

E [103], Dechezleprêtre A [40] think that tax incentives, by reducing the costs of research and development and investment, enhance the expected returns from corporate innovation, thus strengthening the motivation for innovation, which aligns with the innovation incentive mechanism emphasized by Schumpeter. Kauffman R.J. think that technological innovation in renewable energy companies is not a "natural upgrade" process determined solely by technological opportunities, but rather a typical intertemporal investment decision [80]. Compared to general productive investments, R&D activities are characterized by high uncertainty, delayed returns, strong asset specificity, and weak collateral capacity. Therefore, whether a company engages in innovation and the level of innovation it achieves depends not only on technological capabilities or market demand, but also on after-tax returns, capital costs, financing availability, and risk-sharing mechanisms. Hall [66] pointed out that innovative enterprises generally face a funding gap in R&D, especially small and medium-sized enterprises and startups, which often face higher capital costs. Hsu, Tian and Xu [74] further found that the development of financial markets significantly affects technological innovation, and a more mature equity market is particularly important for innovation in high-tech industries. This means that for renewable energy companies, technological innovation is first and foremost a matter of financial resource allocation, rather than a matter of technology management. Under this framework, the core mechanism by which tax incentives can affect technological innovation is that they change the revenue-cost structure of corporate innovation investment. Hall and Van Reenen [63][64] pointed out in their review of the literature on R&D tax incentives that the tax system affects corporate innovation behavior by influencing the user cost of R&D. Under the existing evidence, a $1 R&D tax credit can roughly bring about $1 of new R&D expenditure. For renewable energy companies, tools such as additional deductions for R&D expenses, income tax incentives, VAT refunds and accelerated depreciation are essentially aimed at increasing after-tax retained earnings, alleviating cash flow pressure and reducing the marginal capital cost of innovation projects.

Furthermore, research from Chinese enterprises also indicates that tax breaks can significantly improve corporate green innovation output, with this effect being even stronger in the renewable energy industry. However, the impact of tax rebates and fiscal incentives on corporate market value may exhibit an inverted U-shape, suggesting that higher incentive strength is not necessarily better, and there is a risk of diminishing marginal returns or even distorting resource allocation [160]. As shown in the following formula:

$$\max_{R_r,R_f}\Pi=V(R_r,\theta)-\underbrace{(1-A)\rho(R_r+R_f)}_{\text{User Cost of R\&D}}+\Phi(S)-\underbrace{\Gamma(R_f,A)}_{\text{Distortion Cost}} \quad (2)$$

$\max_{R_r,R_f}\Pi$: Π for the company's expected profits; R_r,R_f Real R&D vs. fake R&D; $V(R_r,\theta)$ R&D revenue function, Where θ represents industry heterogeneity (such as the high marginal returns of the renewable energy industry).; $(1-A)\rho$: represent R&D user costs; $\Phi(S)$ Cash flow mitigation effect, S represents the after-tax retained earnings resulting from tax incentives, reflecting the policy's effect on easing financing constraints. $\Gamma(R_f, A)$: Resource misallocation costs. This section describes R&D manipulation caused by excessive incentives or lack of regulation, explaining why policy effects may exhibit an inverted U-shaped curve and the risk of diminishing marginal returns.

（2）The economic driving mechanism of fake technological innovation

This section primarily studies the formation mechanism and economic drivers of fake R&D activities. The occurrence of fake R&D is not solely due to the short-term profit-seeking impulses of individual companies; the deeper reason lies in a systemic incentive mismatch between tax incentives, information asymmetry, and governance constraints. The concept of "fake technological innovation" has its early intellectual antecedents in the notion of 'fake-innovation' proposed by Haustein H.-D., Maier H [69], which refers to activities that appear to align with socio-economic objectives on the surface but, in the long run, fail to enhance—or even undermine—system efficiency. In the subsequent empirical analysis of this dissertation, "fake technological innovation" is operationalized as "fake R&D."

On the one hand, Hall et al [67] document the “patent paradox” in the US semiconductor industry: despite no significant increase in R&D intensity, patent applications surged dramatically after the 1980s, largely driven by firms' strategic use of patents to secure bargaining power and block competitors . This finding suggests that patent counts alone are an unreliable measure of genuine innovation, as firms may engage in strategic patenting without corresponding increases in substantive R&D. For the analysis of tax incentives, this implies that innovation output indicators need to be interpreted with caution, as policy-induced patent growth may partly reflect strategic responses rather than real technological progress. Li [95] examines the dramatic surge in Chinese patenting since the 1980s from an institutional perspective, arguing that it is largely driven by government policies that reward patent quantity rather than quality . These institutional incentives, including tax benefits, subsidies, and preferential treatment for high-tech enterprise certification, encourage firms to file large numbers of low-quality patents strategically, without corresponding technological breakthroughs. This finding provides direct evidence that policy-induced patent growth in China may reflect strategic compliance rather than genuine innovation, further supporting the need to distinguish fake R&D from substantive R&D.

On the other hand, based on Creech B [30] analysis of how the phenomenon of "fake" innovation is constructed within broader social and institutional discourse, fake technological innovation is not merely a matter of damaged corporate reputation. It can also be viewed as a strategic behavior formed under institutional constraints, in which companies weigh potential benefits against compliance costs and regulatory risks. Given that firms seek to obtain greater tax subsidies, and under conditions where innovation incentives are substantial while the costs of verifying authenticity remain high, certain enterprises engage in "fake-innovation" to capture policy rents, capital premiums, and reputational gains by Myers S.C [109].

However, whether tax incentives can truly be transformed into substantial innovation depends on the degree of financing constraints faced by enterprises. Myers and Majluf’s [109] information asymmetry theory suggests that when external investors cannot accurately identify the true value of an enterprise and the quality of investment projects, enterprises may abandon investment opportunities with positive net present value for fear of being undervalued, thus forming a dependence on internal funds. Brown, Fazzari and Petersen [17] further found that the R&D expenditures of young high-tech enterprises are highly sensitive to cash flow and external equity financing, indicating that innovation activities are more susceptible to fluctuations in financing conditions compared to ordinary investments. For renewable energy enterprises, Tang L [143] think that this financing constraint is often more prominent: on the one hand, the R&D cycle of green technology is long and the innovation returns have high uncertainty; on the other hand, the specificity of equipment and knowledge capital makes it difficult to use as high-quality collateral, thereby weakening debt financing capabilities. In the context of green innovation in China, Yu [173] also confirmed that financing constraints significantly inhibit green innovation, while green finance policies can generally alleviate this inhibitory effect. It can be seen that tax incentives do not automatically produce innovative results; they often need to alleviate financing constraints, release internal funds and improve external financing expectations in order to truly be transformed into R&D investment and innovation output. In addition to financing conditions, the policy effects of tax incentives are also significantly affected by corporate governance and oversight mechanisms. Jensen and Meckling [76] argued that when ownership is separated from control, managers' objectives may diverge from shareholders' long-term value maximization. Such agency problems can induce managers to favor short-term and less risky projects over R&D activities, which are typically characterized by long return horizons and substantial uncertainty. Aghion, Van Reenen and Zingales [3] further found that higher institutional investor shareholding is usually associated with stronger corporate innovation, and one of the important mechanisms is to alleviate the professional risks faced by management due to short-term performance fluctuations.

The academic circle generally such as Fagerberg J [49], Oughton C [114], Cheng L.K [26] argue that tax incentives are linked to performance indicators such as R&D expenditure, R&D intensity or high-tech qualifications, well-governed companies are more likely to convert tax benefits into real R&D investment; while companies with weak governance and insufficient oversight may respond strategically through expense reclassification, R&D capitalization or threshold manipulation, exchanging lower real innovation for higher policy benefits. Barbaroux P [11] think that tax incentives may promote real innovation, but they may also induce policy arbitrage under conditions of agency problems and information asymmetry. Although tax incentives provide cash flow and reduce the cost of capital, they also induce serious principal-agent problems. As Holmstrom B. [72] demonstrated in his pioneering study on "Agency Costs and Innovation," the high risk and unobservable nature of innovation activities can easily lead management to deviate from the long-term goals of shareholders or policymakers.

In the implementation of incentive policies, Stiglitz J.E [139] point out that a significant information asymmetry exists between the government and enterprises. When incentives are strong enough to cover R&D costs and regulation is effective, companies will choose to increase substantial R&D investment. However, if policy design has loopholes, some companies may engage in "fake R&D" to obtain subsidies, i.e., packaging routine expenditures as R&D expenditures through financial means such as earnings management, creating a so-called "inducement effect." This is particularly true of Real Earnings Management (REM) and Accrued Earnings Management (AEM), which artificially inflate R&D data [124]. This is the financial root of "fake R&D." Oswald D.R., Zarowin P [112] point out that fraudulently obtain tax breaks without actually consuming valuable operating funds, companies often manipulate accounting choices to abnormally inflate the R&D capitalization rate and manipulate the discrepancy between earnings before interest and taxes (EBIT) and operating cash flow. With the widespread adoption of R&D tax incentives globally, defining and preventing "fake R&D" has become a key institutional focus in fiscal policy design and implementation. From an international perspective, Frascati Manual [53] clearly outlines five basic criteria for defining genuine R&D activities: innovativeness, creativity, uncertainty, systematicity, and commercial applicability. Activities lacking these attributes, even if technical aspects are involved, cannot be considered R&D activities eligible for fiscal incentives.

In China, Wang et al [152] exploit China’s value-added tax reform to investigate the causal impact of tax incentives on corporate innovation. Their findings show that the reform significantly increased firms' R&D investment and patent output, with particularly pronounced effects for financially constrained and private firms, providing robust evidence that well-targeted tax policies can effectively stimulate innovation. Furthermore, Jia et al [77] examine the effectiveness of R&D tax incentives using firm level panel data from China, exploiting a policy change that raised the super deduction rate for R&D expenditures. Their results show that tax incentives significantly increase corporate R&D spending, with the impact particularly pronounced among private firms and those facing tighter financing constraints. The study concludes that such fiscal instruments help correct underinvestment in innovation when credit market imperfections exist, and highlights the importance of institutional context in shaping policy outcomes.

In contrast, regulatory agencies in countries such as the UK, Canada, and Australia have established dedicated R&D compliance audit units, controlling risks through a "post-audit and technical verification" mechanism. Data from the UK tax authorities shows that approximately 11.4% of R&D Tax Credit applications in 2021 involved non-compliance or fraudulent activities (HMRC, 2022). In the Moreton Resources case, Australia ruled that software integration and IT upgrades do not constitute R&D, recovering all tax refunds and imposing a 25% late payment penalty.

In summary, China and OECD countries are largely aligned in principle, but at the implementation level, Popp [116] point out that they need to strengthen substantive technical review, cross-departmental coordination mechanisms, and post-project risk assessment systems to prevent the allocation of fiscal resources from being eroded by non-genuine R&D activities masked by a "compliance facade." Based on the above analysis, this paper argues that the formation of technological innovation in renewable energy enterprises should be understood within a fiscal and financial analysis framework: tax incentives improve corporate cash flow and expected returns by reducing the after-tax costs of R&D and capital investment by Nam C.W [110], thereby influencing innovation investment decisions by Chittenden F., Derregia M [27]; financing constraints determine whether tax incentives can be converted into actual R&D investment by

Klassen K.J et al [82]; corporate governance and external supervision determine whether policy benefits are used for genuine innovation or transformed into strategic financial operations, and D. Acemoglu, J. A. Robinson [1] emphasize that long-term economic development is shaped by institutions that structure incentives, constrain opportunistic behavior, and determine whether economic actors are guided toward productive or extractive activities. Therefore, R&D intensity can be considered an important mediating variable influencing green innovation through tax incentives, while "Fake R&D" can be seen as a strategic response by enterprises under conditions of policy incentives and information asymmetry. This article defines Fake R&D as "disguising research and development, falsely listing testing and maintenance costs" as R&D expenditures to obtain fiscal tax reduction resources.

（3）The reasons why technological innovation drives long-term economic growth

Building upon the foregoing discussion, technological innovation serves as the fundamental driver of sustained economic growth precisely because it transcends the mere accumulation of existing production factors. Instead, it continuously enhances total factor productivity (TFP) by Van Leeuwen B [150], thereby reshaping the production frontier and altering the return structure of the economic system. To more rigorously explain how technological innovation and tax policies jointly drive long-term economic growth, we need to introduce the neoclassical growth model, specifically the Solow-Swan Model [136].

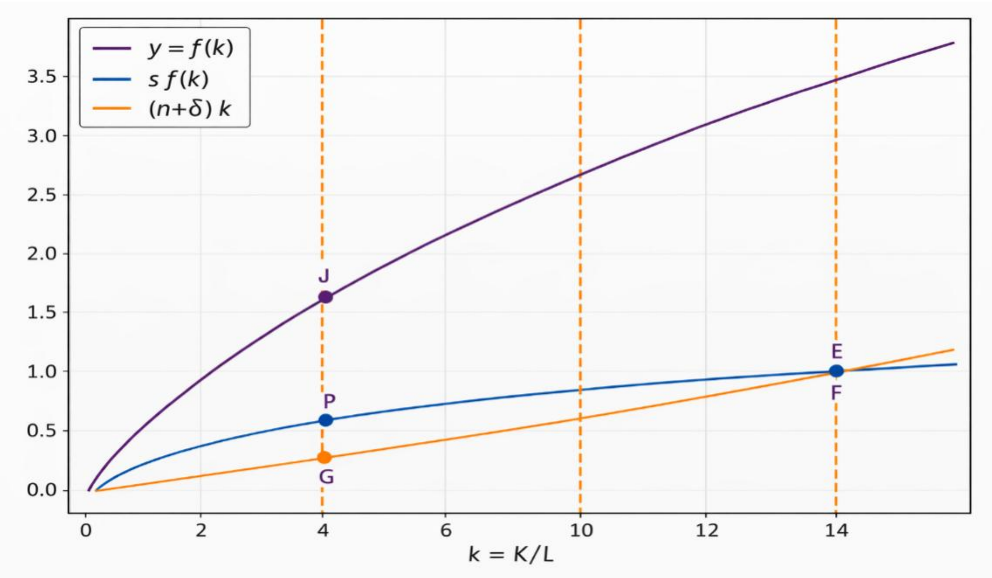


Figure 1.2.1 Tax incentive mechanism diagram under the Solow framework

Source: The author compiled this based on the Solow per capita framework.

Within the Solow per-capita framework Figure 1.2.1, the horizontal axis is capital per worker (k = K/L) and the vertical axis is output per worker (y = Y/L). The production function y = f(k) is increasing and concave (diminishing returns). The investment schedule s·f(k) equals the share of output devoted to investment, while (n + δ)·k is the break-even investment required to keep k constant given labor growth n and depreciation δ. Their intersection determines the steady state k with y = f(k). If, at some k, s·f(k) > (n + δ)·k, net investment is positive and k rises along the transition path; if s·f(k) < (n + δ)·k, capital declines and k falls. This model provides a standard structural framework for understanding the quantitative relationship between capital accumulation, technological progress, and economic output. Within this framework, we will derive in detail how tax incentives influence the steady state and transition path of the economy by altering the user cost of capital and the savings rate (s). Technological innovation is closely linked to national tax policies.

The increase in total factor productivity brought about by technological innovation is known as the Solow residual [135]. The Solow residual explains a large portion of long-term economic growth. Schumpeter also pointed out that there is no capitalist development without innovation; innovation is the driving force behind capitalist economic growth and development [129]. Through continuous technological innovation,a country can achieve industrial upgrading and enhanced international competitiveness: the application of new technologies leads to increased production efficiency and reduced costs, thereby increasing a country's potential output.

Xiang L, Feng D [163] argue with the economic growth and industrial upgrading brought about by technological innovation directly expand the tax base and increase fiscal revenue, providing support for the sustainable development of national finances. Therefore, the government has an incentive to encourage more innovation activities through policy measures.

Srivastava M, Franklin A and Martinette L [137] think that companies can consolidate their market position and form long-term competitive advantages by taking the lead in developing related supporting services and standards. In summary, at the micro level, technological innovation can both improve internal efficiency and give companies market pricing power and excess profits, thereby achieving a leap in their competitive position.

Gale W.G, Samwick A.A [54] think that this is not only reflected in GDP growth rates, but also in comprehensive effects such as increased employment, expanded national tax bases, and improved social welfare. Globally, countries have made technological innovation a strategic pillar for improving total factor productivity and achieving long-term sustainable growth. Therefore, from a macro perspective, technological innovation plays the role of driving economic growth and is a key factor in maintaining long-term prosperity.

At the macro level, Voyvoda E, Yeldan E [151] think that endogenous growth theory emphasizes the importance of knowledge capital and human capital accumulation for long-term growth, thereby driving government and societal attention and incentives toward innovation activities.

Additionally, Castellani D [22] think that international factors have become an important driver of corporate innovation. When multinational firms allocate R&D resources globally, they often consider the host country's tax rates and innovation environment. Technological innovation is widely recognized as the primary driver of long-term economic growth and improvements in total factor productivity [4].

Solow's neoclassical growth model, through growth accounting, found that the main source of long-term economic growth is not capital accumulation, but technological progress. In other words, the increase in total factor productivity brought about by technological innovation. Explains most of the source of long-term economic growth. Yun [175] addresses the inherent growth limits of capitalism by proposing a schumpeterian dynamics of open innovation. He argues that embracing openness and continuous creative destruction can fuel sustained total factor productivity gains, thereby conquering the constraints that closed innovation systems impose on growth.

Momaya K [108] think thatthrough continuous technological innovation, a country can achieve industrial upgrading and enhanced international competitiveness: the application of new technologies leads to improved production efficiency and reduced costs, thereby increasing a country's potential output; at the same time, the emergence of new industries and new markets creates new growth points for the economy.

Dunning J.H and Lundan S.M [47] found that when the corporate income tax rate in the host country is low, Chinese multinational enterprises have an incentive to relocate their R&D activities overseas. However, A. De Vito, F. Grossetti [37] employ bibliometric and network analysis to map the global academic landscape of tax avoidance research. By tracing co-authorship patterns, institutional linkages, and thematic clusters, they reveal how the field’s collaborative structures have evolved.

In other words, De Waegenaere A, Sansing R.C, Wielhouwer J.L [38] think that multinational R&D is not only driven by market and profit considerations but also influenced by international tax competition and capital allocation. To address this challenge, the literature suggests designing tax policies that balance international competitiveness, such as improving the patent box system, to attract and retain high-end R&D activities.

Duncombe R.A [45] think that at the micro-enterprise level, technological innovation has a direct and far-reaching impact on improving enterprise efficiency andobtaining excess returns. Li F et al [92] think that Through technological innovation, enterprises can improve production processes, enhance resource utilization efficiency, and optimize product performance, thereby reducing unit costs, improving product quality, and increasing productivity. Acquaah M [2] think that This efficiency improvement is further converted into enhanced enterprise competitiveness, enabling enterprises to maintain a leading position in intense market competition.

Yu C., Zhang Z., Lin C., Wu Y.J [172] think that research indicates that technological innovation provides enterprises with a sustainable competitive advantage and has become a cornerstone of enterprise development.

A. Arora, A. Fosfuri [8] argue that especially in the era of globalization, enterprises that pioneer technological innovation often gain a head start in capturing markets and establishing technological barriers, thereby reaping monopoly profits from innovation for a certain period.

Porter M.E [118] think that companies can consolidate their market position and form long-term competitive advantages by taking the lead in developing related supporting services and standards. In summary, at the micro level, technological innovation can both improve internal efficiency and give companies market pricing power and excess profits, thereby achieving a leap in their competitive position.

In summary, Lai X et al [87] research on the driving force of low-carbon technology innovation in the construction industry, thinking the driving forces behind corporate technological innovation stem from multiple factors: on the one hand, profit motives, market structure, and competition incentivize firms to innovate in pursuit of growth and excess returns; on the other hand, institutional incentives reduce innovation costs and risks, thereby guiding firms to increase R&D investment.

Additionally, global economic integration and international capital flows have made the innovation decisions of multinational enterprises closely related to the tax systems and industrial policies of multiple countries [46].

（4）Technological innovation drives renewable energy transition

Technological innovation in renewable energy power generation (photovoltaics, wind power, hydrogen energy, biomass energy, etc.) has distinct industry characteristics

[44].

First, renewable energy power generation projects require massive capital investment, making them highly capital-intensive industries [57]. Large-scale wind farms and photovoltaic power plants require huge investments in equipment and system integration, with long project lifespans and payback periods [113]. This slows down technological upgrades and cost reductions, making them reliant on economies of scale[131]. Second, there is strong path dependence [134].

Once early investments establish a certain technological system (such as an energy structure dominated by coal power or traditional power grids), emerging technologies face obstacles in acceptance and deployment speed, making it difficult to quickly replace the existing system [13]. This path dependency constraint indicates that innovation policies cannot deviate from existing development trajectories and local economic structures. Therefore, Lange et al [89] explore the spatial dimensions of post-growth economies, illustrating how alternative economic practices are deeply interwoven with existing institutional and historical contexts. They argue that transformative change does not occur in a vacuum but evolves from path-dependent spatial relations. Therefore, when promoting green innovation, policy design should emphasize the continuity of historical paths, while utilizing demonstration projects, institutional coordination, and gradual reforms to mitigate resistance during the transition process. Third, renewable energy technological innovation exhibits a typical diffusion curve pattern [147]. The development of many renewable energy technologies follows an S-shaped curve: early growth is slow due to immature technology and high costs [126]; with breakthroughs in R&D and large-scale application, costs decrease rapidly and adoption increases; eventually, it enters the stage of grid parity and marketization. According to policy reports, China's wind power and photovoltaic technologies have reached a historic turning point towards grid parity, and will fully enter a new era of market-oriented development without subsidies or even at low prices [148]. This signifies that technological innovation has entered a phase of accelerated application and iteration.

Breetz [16] argue that politics is the hidden dimension of technology experience curves, affecting both costs and deployment. This institutional perspective complements the economic mechanisms discussed above by emphasizing that the efficiency of tax incentives depends critically on the underlying political conditions.

Köhler C and Laredo P found that innovation in the renewable energy sector is primarily driven by R&D incentives, with targeted R&D incentives outperforming broad tax cuts [85]. R&D is the main channel for policy transmission. Including intermediaries such as R&D intensity significantly reduces the direct term of tax variables, and mechanism regression and fit improve simultaneously[39]. Innovation output is highly heterogeneous. Grouped by enterprise size and governance structure, large enterprises and samples with high ownership concentration show stronger and more concentrated marginal effects, while small and medium-sized enterprises and samples with decentralized governance exhibit greater volatility and weaker effects [98].

Along this positive path, corporate R&D intensity and innovation output increase with the enhancement of tax incentives, and the policy effect manifests as the generation of more green invention patents and technological breakthroughs, aligning with the original intention of the policy. The second is the "opportunism" path. Chen Z, He Y and Kwan Y.K [25] point out that under conditions of information asymmetry, enterprises may also adopt regulatory arbitrage tactics to "cater" to policy requirements for benefits: management, considering their own interests, strategically embellish and package R&D activities by exploiting regulatory gaps or audit loopholes. Under this path, the increase in corporate R&D expenditure is more motivated by obtaining incentives rather than pursuing actual technological progress, and thus may not yield corresponding high-quality innovation outcomes. Conversely, Görg H, Strobl E [59] point out that opportunistic behavior crowding out resource allocation and diminishing the actual efficiency of R&D funds ultimately leads to a decline in innovation performance. The coexistence of these two transmission mechanisms results in a "dual effect" of tax incentive policies on corporate innovation.

Akerlof G.A [6] point out that based on this theoretical framework, important analytical inferences can be drawn: the net effect of tax incentive policies depends on the equilibrium between the positive and negative paths mentioned above. That is to say, the degree of information asymmetry becomes a key factor determining the effectiveness of tax incentive policies. Hall B.H [65] said that when information is transparent and regulation is strong, the "compensation effect" path prevails, and enterprises are more inclined to convert tax benefits into real R&D investment, leading to increased innovation output and predominantly positive policy effects. Conversely, in situations where information asymmetry is severe and regulation is inadequate, the "opportunism" path may prevail, and enterprises' behavior of falsifying to obtain benefits undermines the substantive effect of policy incentives [120]. In extreme cases, it may even distort and offset the original intention of the policy. Therefore, the key to enhancing the effectiveness of tax incentive policies lies in curbing opportunistic behavior and strengthening real innovation incentives. Theoretically, this provides a basis for subsequently constructing the "Fakei" index to measure the degree of strategic R&D manipulation, as well as designing policy tools combining "incentives-penalties". Scenario simulations in existing research also confirm this point: the simulation analysis by Wang Y and Mayburov I.A [156] shows that relying solely on ex post punishment while eliminating incentives does not improve enterprises' green innovation capabilities. Instead, retaining appropriate tax incentives while supplementing with strict quota constraints and high-intensity penalties can effectively curb enterprises' behaviour of disguising R&D to obtain subsidies, and significantly enhance enterprises' real R&D level. Therefore, an effective policy framework should integrate tax-based incentives with stronger regulatory oversight, so as to stimulate genuine innovation while raising the cost of opportunistic or fraudulent behavior, thereby promoting a better balance between these two policy objectives. This approach provides theoretical support for the "incentive-penalty" mechanism proposed later in this paper, that is, by establishing a more comprehensive system of incentives and constraints, maximizing the compensation effect of tax incentives, curbing opportunistic impulses under information asymmetry, and ultimately improving the net benefits of policies in promoting green innovation.

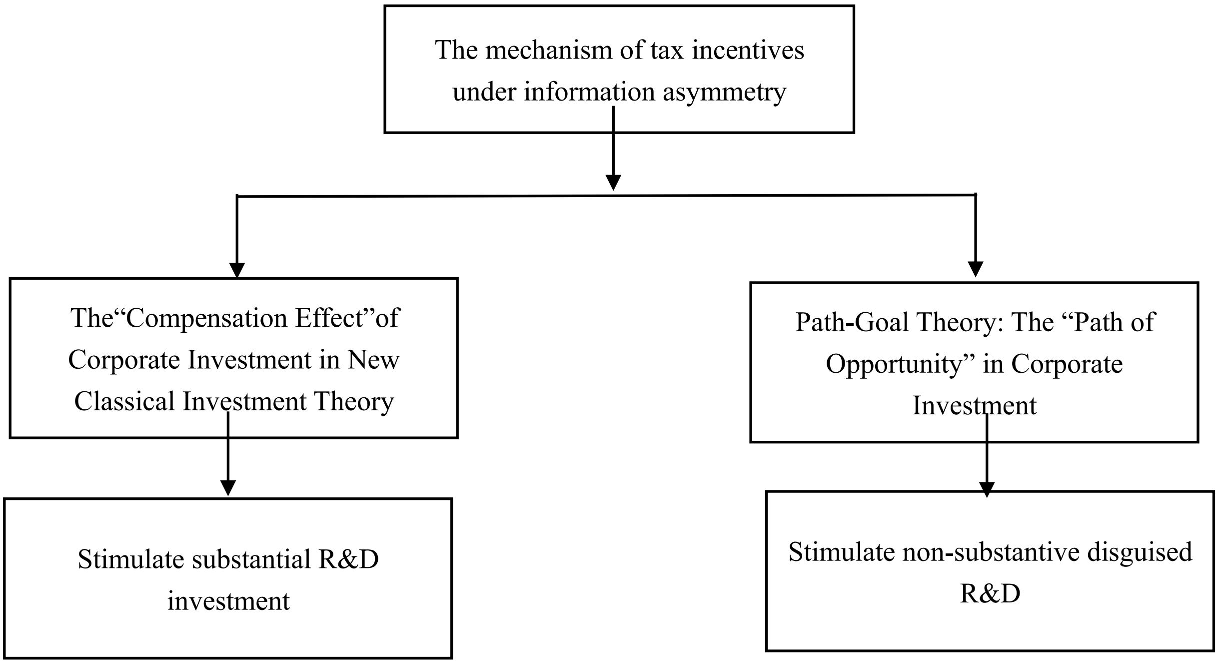


Figure 1.2.2 Innovative theoretical framework of tax incentive mechanism for information asymmetry

Source Author complied

1.3. Specifics of Tax Incentive Policy for Technological Innovation in Renewable Energy Sectors in China

China's tax incentive policies for the renewable energy industry are not a static system that can be established overnight, but rather a complex process that is constantly being optimized dynamically in response to adjustments in national macro-strategies, the evolution of the industry's development stage, and changes in technological maturity. From a historical institutionalist perspective, based on the supervision and coordination between "finance enterprise", with "policy tools enterprise response" as the integration path, and "dual carbon strategy system" as the goal [99], a closed loop green technology innovation mechanism is built [146]. This mechanism not only embeds the national strategic goals, but also effectively fits the marketization of enterprises, reflecting the deep integration of market mechanisms and government intervention [93].

As we shown in Figure 1.3.1, The development of China's renewable energy industry is influenced not only by market dynamics but also by targeted national strategic planning. National goals such as energy security, dual-carbon transformation, environmental modernization, and high-quality growth have been translated into a set of fiscal constraints and tax incentives. Through these mechanisms, the government has reduced innovation costs for enterprises and increased the expected returns on R&D, thereby integrating green strategies into the innovation-driven forces of enterprises.

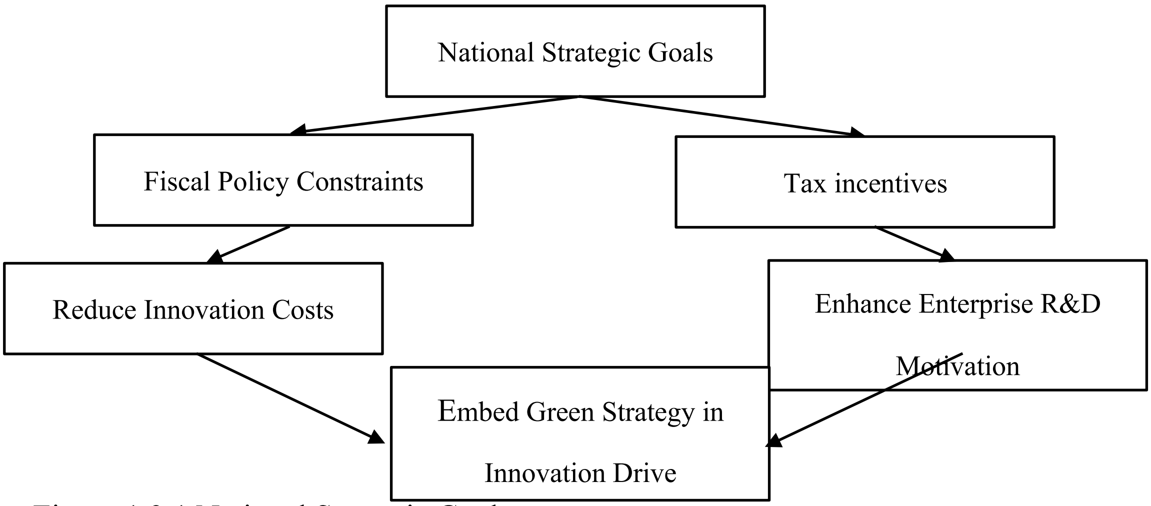


Figure 1.3.1 National Strategic Goals

Source: Compiled by the author

As we shown in Figure 1.3.1, The development of China's renewable energy industry is influenced not only by market dynamics but also by targeted national strategic planning. National goals such as energy security, dual carbon transformation, environmental modernization, and high quality growth have been translated into a set of fiscal constraints and tax incentives. Through these mechanisms, the government has reduced innovation costs for enterprises and increased the expected returns on R&D, thereby integrating green strategies into the innovation-driven forces of enterprises.

(1) The development logic of tax incentive policies for China's renewable energy power generation industry.

The evolution of China's tax incentive policies for renewable energy substantively reflects the state's continuous recalibration of the functional positioning of fiscal instruments. This process aims to rectify energy market failures, reduce the diffusion costs of emerging technologies, and mitigate the initial competitive disadvantages faced by the industry, ultimately steering the sector from policy dependence toward the formation of endogenous competitiveness. The developmental logic of this evolution can be broadly characterized as a sequential transition: from universal subsidies during the incubation phase, to production orient incentives in the expansion phase, followed by structural optimization in the adjustment phase, and culminating in a stage of institutional deepening oriented toward technological innovation and highly quality development. Phase I (circa 2000): Policy Introduction and Technology Import Substitution. The initial phase, emerging around the year 2000, was characterized by policy introduction, with a strategic focus on lowering capital entry barriers through tariff exemptions on imported equipment and preferential corporate income tax rates for foreign-invested enterprises. The overarching objective was to facilitate a trajectory of "importation–absorption–re-innovation" regarding advanced energy technologies. The underlying institutional logic of this phase rested on a strategic trade-off: sacrificing immediate tax bases in exchange for long-term technology spillovers. Luo C and Zhi Y [101], the Chinese government has successively implemented a series of tax incentive measures: initially, preferential policies such as “tax reduction and exemption” were implemented for foreign invested enterprises in special economic zones and coastal open cities, and the corporate income tax rate of foreign invested enterprises was significantly reduced. The corporate income tax rate of 15% was much lower than that of domestic enterprises. China's renewable energy industry is still in its early stages, facing multiple constraints such as a weak technological foundation, high initial investment costs, and insufficient supply of domestically produced equipment. Tax policies during this period primarily served the strategic goal of "introducing, digesting, and absorbing" foreign technologies. Their core characteristic was lowering capital entry barriers and encouraging companies to introduce advanced foreign wind power equipment and photovoltaic manufacturing technologies through tariff reductions and exemptions on import value-added tax.

Tax incentives in the renewable energy sector are rooted in the need to guide technological innovation. Dinica V [42] found that from a fiscal perspective, governments, constrained by revenue and expenditure, use tax incentives to reduce innovation costs for businesses, compensate for externalities in R&D, and market failures, thereby stimulating autonomous innovation.

The State Council's "Notice on Adjusting the Tax Policy for Imported Equipment" (State Council Document No. 37) issued in 1997 established the early policy tone, exempting imported equipment for domestic investment projects and foreign investment projects encouraged by the state from customs duties and import value-added tax within the prescribed scope.

Phase II (2008–2013): Policy Expansion, Deepening, and the Shift to Cash Flow Optimization. The second phase, spanning from 2008 to 2013, marked a period of policy expansion and deepening. During this interval, fiscal incentive instruments underwent a strategic transition: shifting focus from import stage tariffs to core domestic tax regimes, specifically Corporate Income Tax (CIT) and Value-Added Tax (VAT). Wind power has no fuel costs, and the input tax during the operation period is extremely low. By collecting and refunding the input tax immediately, it directly supplemented the operating cash flow of enterprises, and in effect played a role of fiscal "blood transfusion" in addition to electricity price subsidies. Asmundo G [9] think that at the macro level, stimulating product consumption and improving the business environment are crucial. Tax incentives encourage consumers and businesses to purchase and use renewable energy products, which helps promote the green economic transformation. By lowering the price of renewable energy, consumer demand is released, increasing not only the consumption of green goods but also promoting the development of green industries, thereby driving the transformation of the energy structure [104]. Government tax incentives reduce the cost of renewable energy, making it more competitive [107]. This price change not only promotes consumer shifts but also drives energy market reform, especially in the competition between renewable and traditional energy sources, where renewable energy's market share is gradually increasing [127]. With policy support, the marketization process of renewable energy is accelerating, laying the foundation for the future competitive landscape of the energy market [10].

Tax incentives are typically implemented alongside broader industrial policy instruments. In pursuit of sustainability objectives, they interact with fiscal subsidies, public procurement, and related policy tools to create an integrated support framework for the advancement of low carbon technologies [153]. However, this also implies that tax incentives must balance fiscal burdens and effectiveness. In policy design, it is essential to ensure that tax incentives precisely target the innovation chain of renewable energy technologies [180]. It is necessary to control tax base erosion. Overall, tax incentives optimize resource allocation, reduce R&D costs, and align national strategic objectives with corporate profit motives, thereby embedding the strategic intent of green development into the innovative drive of enterprises [90].

The academic circle generally such as Shen X and Lin B [132]; Barbieri E, Di Tommaso M.R, Bonnini S [12]; You J, Zhang W [171] think that these incentive policies based on regions and ownership have effectively promoted the introduction of capital and technology and industrial upgrading. China's tax incentive policy has been further improved, and the scope has been expanded from attracting foreign investment to encouraging independent innovation and regional coordinated development. A preferential tax rate of 15% and additional deduction of R&D expenses are implemented high technological enterprises . Zhang et al [178] exploit China's value-added tax reform as a quasi-experiment to evaluate investment tax incentives. Their findings demonstrate that allowing firms to deduct fixed asset investments significantly stimulated corporate investment, reinforcing the effectiveness of such incentives. This evidence supports the policy evolution from simply attracting foreign investment toward fostering independent innovation and coordinated regional development.

Income tax and value-added tax are reduced or exempted for small and micro enterprises. Tax reduction and exemption are introduced for underdeveloped areas such as the west to promote regional balance [78]. Through continuous evolution, China has formed a tax incentive policy framework covering multiple tax types and multilevel objectives, including corporate income tax and value-added tax, Saeed et al [125] critically assess the validity of the value-added tax in the SAARC region, identifying constraints in tax compliance and revenue mobilization. From a broader policy perspective, Ahmad [5] investigates governance models and policy frameworks through

Chinese experiences, illuminating how institutional design and adaptive governance can support effective policy implementation. Together, they emphasize that the success of fiscal measures like VAT is deeply intertwined with the quality of underlying governance structures. Xin-gang Z, Ling W and Ying Z[164]; Liu J [97] think that tax incentive policies for renewable energy power generation lack specificity, resulting in limited marginal effects on green technology innovation.

Phase III (2016–Present): Institutional Leap toward Strategic Embedding and Structural Incentives. The third stage marks the embedding of the green development strategy into the core design logic of the tax system. Tax incentives have expanded to areas such as green manufacturing, clean energy operation and maintenance, and energy storage. This reflects the institutional transition from "general subsidies" to "structural incentives". Wang Y, Mayburov I.A, Chenghao Y [157]; research found that while tax incentives significantly increased corporate R&D investment and patent output, the benefits varied across different ownership types, sizes, and regions due to the adoption of a universally applicable strategy, reflecting a lack of targeted policy design. Think that economic research can be used difference-in-differences (DID) model. Foreign studies based on difference-in-differences (DID) also indicate that incentives require precise design to be effective: Wu Z, Zeng N, Song J [161] found that accelerated depreciation tax incentives reduced carbon emission intensity and encouraged companies to increase R&D investment in emission reduction technologies. Therefore, to accurately assess policy effects and optimize design, identification methods such as difference-in-differences (DID) can be used to identify the causal effects of policies by using the timing of policy implementation and group differences as a "quasi-natural experiment," providing a basis for improving China's green tax policies.

Relevant literature further underscores that the relationship between tax incentives and corporate green innovation is not characterized by unidirectional causality. Rather, this relationship is embedded within corporate behavior through multiple pathways, including: Reducing innovation costs; Unlocking consumer green preferences; Restructuring corporate financial architectures [117]. These mechanisms collectively foster a positive feedback loop that reinforces sustainable innovation trajectories. Consequently, China's tax policy transcends its conventional fiscal function of merely promoting corporate green development. At the institutional level, it accomplishes the deeper objective of "embedding green logic" into the economic system, thereby completing a paradigmatic transition from subsidy-based instruments to a structural fiscal and tax regime.

(2) The design logic of the core tax incentives for renewable energy in China

According to the first section of Chapter One, Wang Ying and Igor A. Mayburov [154,155] innovatively classified China's tax incentives into three categories: cost end, profit end, and innovation end. This section will study the design logic of China's core tax items for renewable energy based on this classification method.

The cost end mainly functions by reducing capital formation and operating costs. The profit end mainly works by improving the expected after-tax income. The innovation end promotes technological accumulation by increasing the deductible value of R&D expenditures and reducing the cost for R&D users.

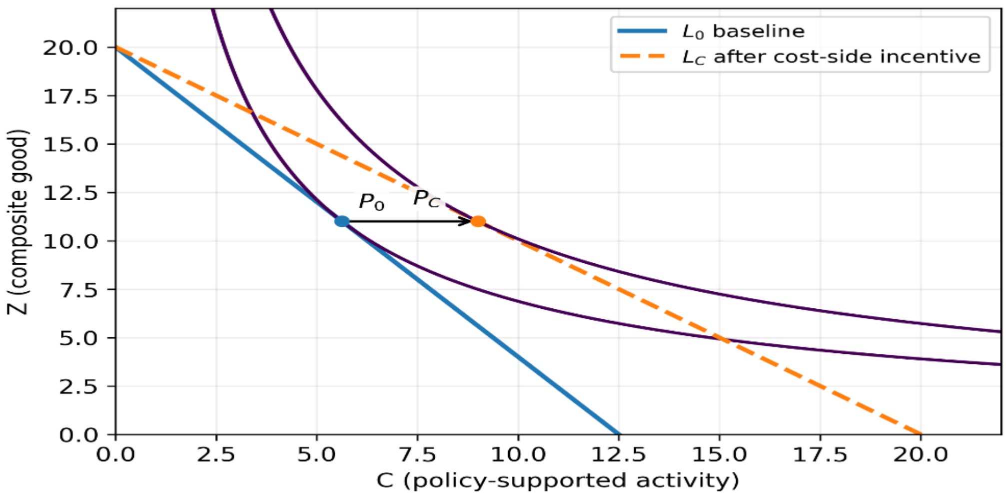


Figure 1.3.2 policy-supported activity

Source: Compiled by the author

From the cost end perspective, value-added tax, import related taxes, and fixed asset depreciation deductions apply. Renewable energy projects generally have the characteristics of large upfront investment, high fixed costs, and long recovery periods. If the same turnover taxes and import taxes as those for fossil energy are fully borne in the early stage of the industry, it will further amplify their cost disadvantages and inhibit the entry of social capital. Therefore, direct deductions such as immediate tax refund, carryover tax refund, import tariff reduction, and accelerated depreciation are implemented at the cost end to alleviate the cash flow pressure during the operation period, reduce capital formation costs, and improve the initial feasibility of the project. Zwick and Mahon's research on accelerated depreciation also indicates that such tax incentives can significantly increase enterprise investment, and have a more obvious effect on enterprises with stronger financing constraints.(Figure 1.3.2)

Cost Sideshows that the tax incentives on the cost side cause the budget line to rotate from L0 to LC by lowering the relative price of policy supported activity C. The optimal point moves from P0 to PC. This indicates that policies such as VAT refunds, import tax exemptions, and accelerated depreciation mainly guide enterprises to increase their investment in the target activities by reducing the cost of capital formation and alleviating cash flow constraints.

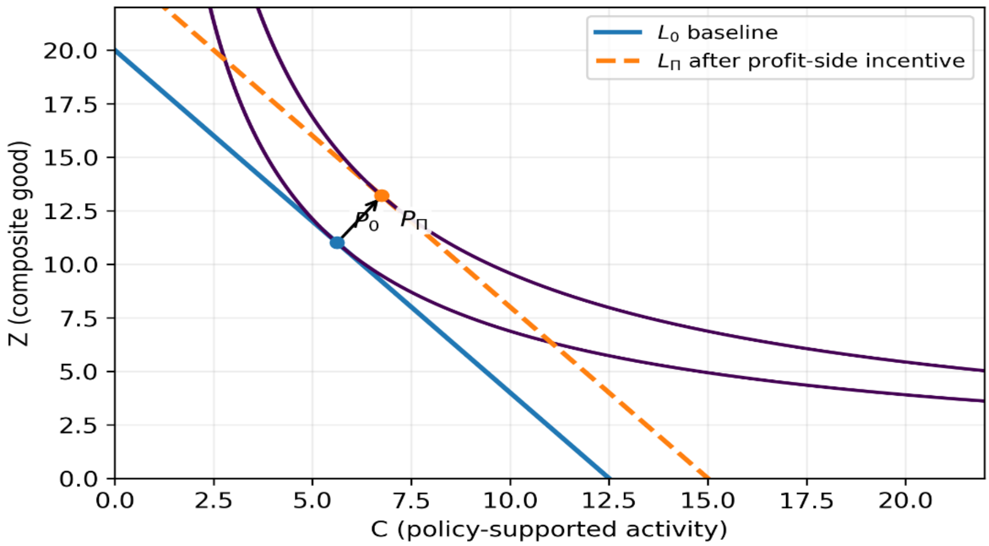


Figure 1.3.3 Profit-side incentive

Source: Compiled by the author

As we shown in Figure 1.3.3, profit Side shows that the tax incentives on the profit side cause the budget line to shift outward parallelly from L0 to Ln, and the optimal point to rise from P0 to Pn. This indicates that the preferential corporate income tax rate and tax reduction mainly enhance the enterprises' willingness to continuously allocate capital by increasing after-tax profits and improving the expected return on investment.

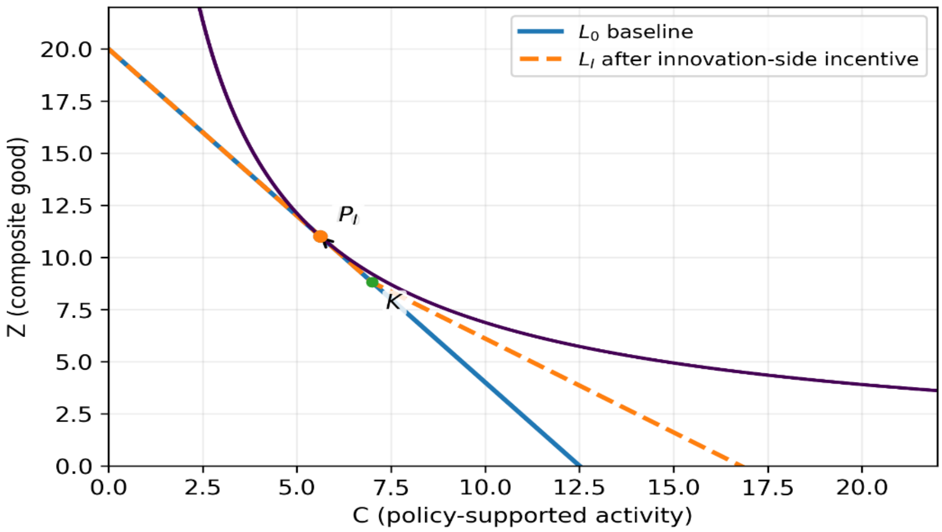


Figure 1.3.4 innovation-side incentive

Source: Compiled by the author

From the innovation side, Hall [64] and Van Reenen [63] finds that the stock market assigned a notably high valuation to corporate R&D investment during the 1980s, signaling strong anticipated returns. Extending this inquiry, they provide a comprehensive review of fiscal incentives for R&D, concluding that tax credits generally stimulate additional research spending. However, their effectiveness varies considerably depending on policy design, firm characteristics, and the economic environment, as well as by Bloom and Griffith [14], all demonstrate that tax incentives can significantly increase corporate R&D investment, with the long-term effect being particularly prominent. At the same time, Guceri's [61] research also found that the true effect of research tax incentives must be distinguished from strategic behaviors such as "cost classification", meaning that the design of the tax system in the innovation sector not only needs to enhance the intensity of incentives but also improve the ability to identify the authenticity. For the renewable energy industry, the true significance of this sector lies in promoting the competitive logic of enterprises to shift from general capacity expansion to key technology accumulation and efficiency improvement.

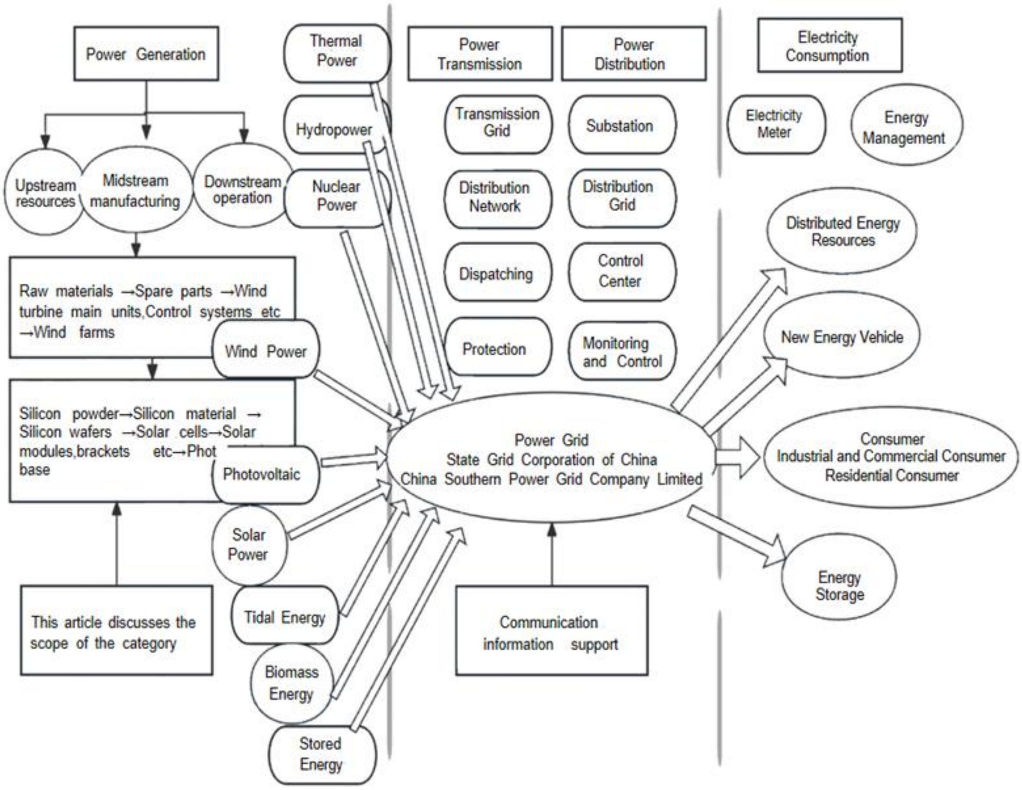


Figure 1.3.5 Original panoramic view of new power industry chain

Source: Compiled by the author

This dissertation examines the entire renewable energy industry chain in China to better understand the key aspects of tax the onset of the post year policy period. Currently, China's new power system is essentially a multi-linked collaborative system with the power grid as a platform, clean energy as a foundation, and energy storage and information systems as support. Based on this, within the context of the overall industry chain, this paper further focuses on the tax incentives and technological innovation issues of renewable energy power generation enterprises. In China's current tax system, turnover tax (mainly value-added tax) and income tax constitute the two main tax categories (Table 1.3.1, Appendix A). As we can show in Table 1.3.2, Appendix B tax incentives for the renewable energy industry also primarily rely on these two taxes, supplemented by auxiliary taxes such as customs duties.

The first chapter analyzes the tax incentive policy's classification, scope of use, operating mechanism, relationship with the market, and its impact on the economy. Concluded as follow:

1. The role of tax incentives in promoting technological innovation in renewable energy, grounded in neoclassical economics, endogenous growth theory, innovation economics, and institutional economics.

2. Tax incentives encourage companies to increase investment in technology to help them grow by reducing R&D costs, increasing returns on innovation, and mitigating risks.

3. The author pioneered the "three-side" tax classification and developed policy tools such as tax credits, value-added tax refunds, and preferential tax rates for high technology enterprises, which have played a significant role in supporting the development of green technologies.

4. Due to information asymmetry between the government and enterprises, some companies engage in "pseudo-innovation" behavior, falsely inflating R&D expenditures to fraudulently obtain tax benefits.

5. China's tax incentive policies have gone through three stages: introduction, expansion, and innovation driven, gradually forming a systematic incentive framework oriented towards green development.

CHAPTER 2. RESEARCH METHODOLOGY FOR TAX INCENTIVE POLICIES IN CHINA'S RENEWABLE ENERGY SECTOR

2.1. Current Status of Tax incentives Policy for the Renewable Energy Sector in Major Countries Worldwide

Driven by multiple destabilizing factors such as the global energy transition, climate change, and geopolitical uncertainties, energy systems face intertwined threats. Hoffart et al [71] demonstrate that geopolitical and climate risks jointly undermine financial stability and disrupt energy transitions. Complementing this, Pedraza [115] analyzes renewable energy' s role in advancing green, low carbon power generation in Asia, underscoring its potential to alleviate systemic vulnerabilities while supporting sustainable pathways. China's current renewable energy tax incentive policies have progressively transitioned from "scale expansion" to "structural optimization." The current issuance of tax preferential policies aims to establish an innovation-oriented tax system centred on "R&D investment to equipment upgrading to technology transfer high technology iteration" for renewable energy enterprises.

In December 2009, the United Nations Climate Change Conference held in Copenhagen represented an unprecedented global environmental conference in terms of scale, attracting participation from 192 countries and regions. The conference focused on addressing global warming and discussing the feasibility of large scales renewable energy adoption. Therefore, this study primarily examines renewable energy tax incentives from 2009 to the present. 2009 to 2013, China's renewable energy support policies remained driven by surcharge levies and fiscal subsidies to facilitate industrial expansion. During this period, fiscal support for renewable energy in China exhibited distinct characteristics of rapid expansion. On one hand, the renewable energy surcharge standard gradually increased from 0.002 yuan per kWh in 2009 to 0.015 yuan/kWh in 2013, representing a

6.5 folds increase over five years. On the other hand, the total subsidy amount rose from 5 billion yuan to 39 billion yuan, indicating that the state's support intensity for renewable energy power generation projects, including wind power and photovoltaics, continued to strengthen. Due to subsidy to driven industrial expansion, the subsidy funding gap expanded from 1 billion yuan to 8.5 billion yuan. Although levy standards continued to increase, fiscal pressure was not alleviated synchronously due to the rapid expansion of renewable energy installed capacity and the continuous increase in subsidy demand.

Changes in data regarding China's renewable energy surcharge standards and subsidy funds indicate that during the initial stage of industrial development, the government primarily expanded subsidy funding sources by increasing renewable energy surcharge levy standards to support large scales construction of renewable energy projects. After 2012, although the surcharge standard remained unchanged at 0.008 yuan/kWh, the subsidy funding gap further expanded from 3.5 billion yuan to 6 billion yuan, indicating that the original levy level had become insufficient to cover rapidly growing subsidy demands, with fiscal pressure beginning to emerge. In 2013, the Chinese government again increased the surcharge standard to 0.015 yuan/kWh, and the total subsidy amount rose to 39 billion yuan, yet the funding gap remained as high as 8.5 billion yuan, reflecting that the renewable energy subsidy mechanism had entered a stage characterized by "larger subsidy scale, stronger financial constraints."This mechanism played a critical role during the initial stage of industrial scale development but also exposed significant institutional limitations. On one hand, the rapid growth in total subsidies effectively promoted the expansion of new energy installed capacity and industrial incubation. On the other hand, the continuous expansion of the subsidy gap indicates that a model relying solely on surcharge standards for support exhibits sustainability issues. After 2013, the Chinese government's renewable energy policies gradually transitioned toward tax incentives, market-oriented trading, and innovation-oriented support instruments.

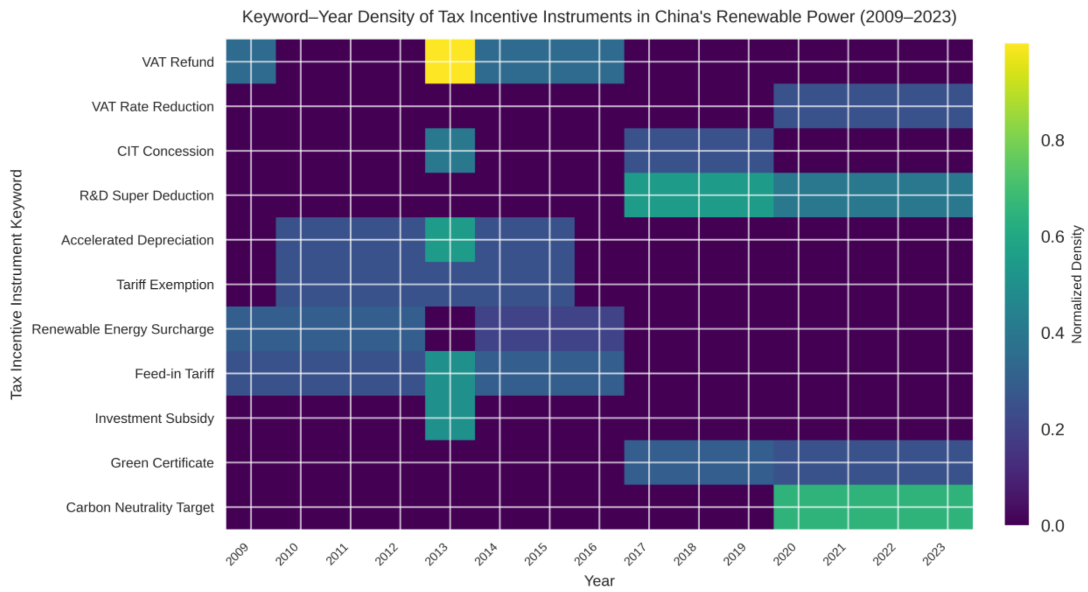


Figure 2.1.1 Keyword-Year Density of Tax Incentive instruments in China's Renewable Power (2009-2023)

Source: Compiled by the author from the State Taxation Administration

2013 was a pivotal year for the transformation of China's renewable energy tax policy system. As illustrated in Figure 2.1.1, the classification follows the original taxonomic framework developed by Wang and Igor Mayburov. Based on the year of policy promulgation, 2013 represents a pivotal year in the transformation of China's renewable energy tax incentive system, which also constitutes the rationale for selecting this year as the policy baseline for subsequent empirical analysis.

As we shown in Table 2.1.1, Appendix C and Table 2.1.5, Appendix D), regarding refund policies, the Ministry of Finance issued Document No. 66 in 2013 (Caishui [2013] No. 66), implementing a 50% value-added tax (VAT) refund policy for photovoltaic product sales, which substantially reduced the tax burden during enterprise operations. In terms of renewable energy surcharge standards, the surcharge rate was increased to 0.015 yuan per kWh, thereby enhancing the financing capacity for fiscal subsidies. Supporting import tariff exemptions, VAT exemptions, and terminal consumption tax exemptions remained unchanged.

In terms of tax support for high-tech enterprises, the scope of the 15% preferential corporate income tax rate was further broadened, providing sustained tax relief and contributing to the expansion of manufacturing and R&D activities in renewable energy projects.

Since 2013, the photovoltaic industry has benefited from the 50% VAT refund policy (Caishui [2013] No. 66), which was subsequently extended to the wind power industry in 2015 (Caishui [2015] No.74). On the consumption side, according to Document No. 16 of 2015, renewable energy equipment products, including solar cells and fuel cells, were explicitly exempted from consumption tax. This measure aimed to promote green consumption by reducing the final market prices of clean energy technologies. As the fiscal support mechanism for renewable energy gradually transitioned from direct subsidies to indirect incentives, indirect tax policies have progressively become a critical pillar of China's green fiscal system.

Between 2013 and 2023, as China's renewable energy industry entered the stage of grid parity and market of oriented development, the government gradually shifted from a direct fiscal expenditure system centered on electricity price subsidies to an indirect incentive framework dominated by tax expenditures. This transformation in fiscal policy logic is reflected in the widespread deployment of multiple tiered tax policy tools and their quantifiable fiscal relief effects. The tax incentive policy for high-tech enterprises has gradually covered the renewable energy industry since 2013. As of 2023, an average of 300 billion yuan in tax reduction has been achieved each year.

For eligible renewable energy projects, the corporate income tax policy providing a three years exemption and a subsequent three-year 50% reduction remains in force, thereby alleviating the tax burden in the initial operational period and improving the financial viability of project start up. On average, each project can save 5-20 million RMB in taxes annually, with an estimated total of approximately 100 billion RMB nationwide. Furthermore, the Ministry of Finance issued documents Cai Shui [2013] No. 66 and Cai Shui [2015] No. 74 in 2013 and 2015 respectively, establishing a policy of immediate VAT refund of 50% on grid-connected photovoltaic and wind power electricity. This reduced the actual VAT burden for enterprises from 13% to 6.5%, with estimated annual tax refunds of 2 billion RMB and 1.5 billion RMB respectively.

Table 2.1.2 Renewable Energy Preferential Policies for 2013

Year	Policy Document Name	Policy Content	Incentive Intensity	Implementation Period/Status
2013	Notice on the Value-Added Tax Policy for Photovoltaic Power Generation (Cai Shui [2013] No. 66)	For electricity products sold that are self-produced using solar energy, a policy of immediate VAT refund of 50% is implemented.	Immediate VAT refund of 50%	2013–2018
2013	Notice on Issues Concerning the Implementation of Feed-in Tariff Subsidies for Distributed Photovoltaic Power Generation (Cai Jian [2013] No. 390)	Provides subsidies for distributed photovoltaic power generation based on the amount of electricity generated.	Electricity Generation Subsidy	Implemented in 2013
2013	Notice on Adjusting the Levy Standard for the Renewable Energy Electricity Price Surcharge (Cai Zong [2013] No. 89)	Increases the levy standard for the renewable energy electricity price surcharge collected from electricity consumption other than residential and agricultural use to RMB 0.015 per kilowatt-hour.	Levy Standard increased to RMB 0.015/kWh	Implemented in 2013
2013	Policy on Exemption from Government Funds for Distributed PV Power Generation	Exempts self-consumed electricity from distributed photovoltaic power generation from four government-managed funds: the Renewable Energy Electricity Price Surcharge, the National Major Water Conservancy Project Construction Fund, the Large and Medium-sized Reservoir Resettlement Support Fund, and the Rural Power Grid Loan Repayment Fund.	Exemption from 4 Government-managed Funds	Implemented in 2013
2013	VAT Immediate Refund Policy for Photovoltaic Power Generation	Implements an immediate 50% VAT refund for photovoltaic power generation.	Immediate VAT Refund of 50%	Implemented in 2013
2013	Preferential VAT Policy for Wind Power Generation	Implements an immediate 50% VAT refund policy for wind power	Immediate VAT Refund of 50%	Implemented in 2013

Year	Policy Document Name	Policy Content	Incentive Intensity	Implementation Period/Status
		generation.		
2013	Catalogue for Corporate Income Tax Preferences on Public Infrastructure Projects	For newly constructed renewable energy projects such as wind power, solar power, and geothermal power, starting from the tax year in which their first production and operating income is generated, they are eligible for a three-year corporate income tax exemption followed by a three-year 50% reduction.	Corporate Income Tax "Three-Year Exemption and Three-Year Half Reduction"	Implemented in 2013
2013	Notice on Exempting Consumption Tax on Recycled Waste Mineral Oil Products	Exempts consumption tax on industrial oils such as lubricant base oils, gasoline, and diesel produced from recycled waste mineral oil.	Consumption Tax Exemption	2013–2023

Source: Compiled by the author, information from the State Council, the Ministry of Finance of the People's Republic of China, the Ministry of Industry and Information Technology of the People's Republic of China, and the State Administration of Taxation.

Overall, the aforementioned policies have established a relatively comprehensive tax support system, playing a significant role in reducing enterprise burdens, incentivizing technology research and development, and facilitating industrial expansion. In terms of tax reduction scale, the 100% super deduction policy for R&D expenses generates the highest annual tax reduction amount, reaching 44 billion RMB. This data indicates that the focus of China's tax incentives has clearly shifted toward the innovation investment stage, namely, enhancing technological advancement capabilities through reducing enterprise R&D costs.

The second largest category is the 15% corporate income tax preferential rate for high-tech enterprises, with an annual tax reduction amount of approximately 30 billion RMB, demonstrating that corporate income tax preferences constitute the core institutional instrument for supporting the development of high technology enterprises. Tax preferences for specific industrial chain segments, such as the 50% immediate VAT refund policy for photovoltaic and wind power industries, have annual tax reduction scales of 2 billion RMB and 1.5 billion RMB, respectively. Although these amounts are relatively modest, these policies exhibit stronger targeted specificity.

Additionally, project based corporate income tax preferences of the "three years exemption followed by three years half reduction" category generate annual tax reductions of approximately 10 billion RMB, reflecting that the state continues to maintain support for key projects during the industrial incubation stage.

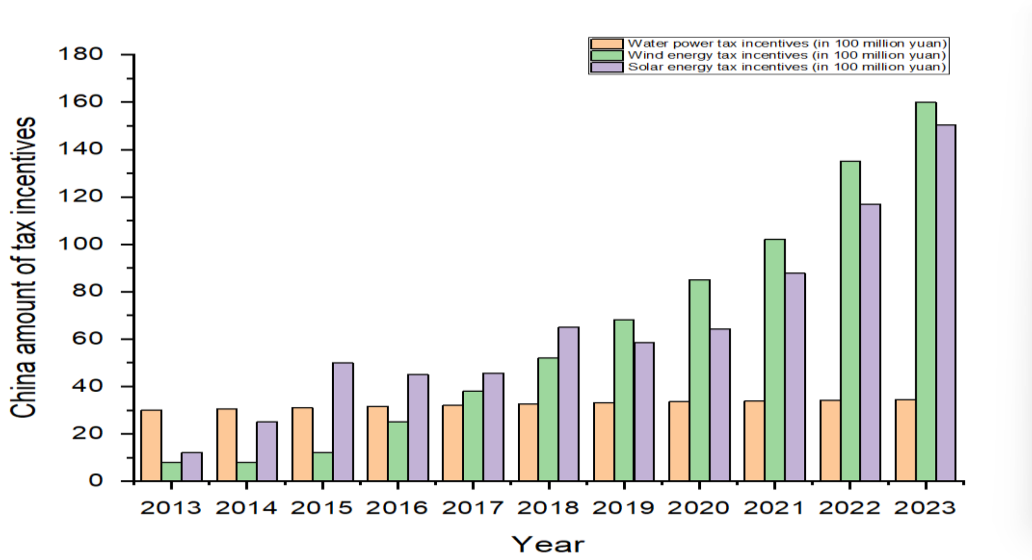


Figure 2.1.2 Change in the scale of China's renewable energy tax incentives from 2013 to 2023

Source: Compiled by the author from Wind database

As shown in Figure 2.1.2, from 2013 to 2023, the scale of tax incentives for the renewable energy sector in China exhibited a significant structural growth pattern. This trend profoundly demonstrates the crucial driving role of the structural tax reduction pattern initiated in 2013 as the "first year of policy", which has laid the foundation for industrial development. In 2013, the policy focus began to shift towards new energy sources such as hydropower, photovoltaic, and wind power, and a series of core policies were released, marking the industry's transition from scattered support to systematic and structured tax incentives. The data clearly reflects the long-term effect of this policy orientation:

Firstly, the distribution structure of industries benefiting from tax incentives profoundly reflects the policy orientation. As the most technologically advanced and largest-scale clean energy at that time, hydropower enjoyed steadily increasing tax incentives over the decade, rising from 2.95 billion yuan in 2013 to 3.75 billion yuan in 2023, with an average annual compound growth rate of approximately 2.4%, demonstrating continuous and stable support for basic renewable energy.

Secondly, strategic emerging industries have become the biggest beneficiaries of structural tax cuts, experiencing explosive growth. This is closely related to the structural preferential policies issued in 2013 and subsequent years for renewable energy sources such as wind power and solar energy. Data shows that the tax rebate amount for the wind power industry increased from 1.05 billion yuan in 2013 to 16.00 billion yuan in 2023, with an average annual compound growth rate of 31.3%; for the solar energy industry, it soared from nearly zero 0.5 billion yuan to 15.00 billion yuan, with an average annual compound growth rate of an astonishing 75.5%. This rapid growth far exceeds that of traditional energy sources, fully demonstrating that the structural tax reduction policies have precisely targeted strategic emerging industries.

Table 2.1.3 The amount of tax subsidies and incentives for major renewable energy sources in China from 2013

Year	Amount of tax preference for hydropower (billion RMB)	Wind power tax reduction amount (billion RMB)	Amount of solar energy tax incentives (billion RMB)
2013	30	5	12
2014	30.5	6	25
2015	31	12	50
2016	31.5	25	45
2017	32	38	45.5
2018	32.5	52	65
2019	33	68	58.5
2020	33.5	85	64.35
2021	33.8	102	87.75
2022	34	135	117

Source: Compiled by the author, information from the State Council, the Ministry of Finance of the People's Republic of China, the Ministry of Industry and Information Technology of the People's Republic of China, and the State Administration of Taxation.

Table 2.1.3 illustrates the phased implementation of China’s renewable energy policies. The impact of policies enacted in 2013 on the renewable energy industry. Hydropower, wind power, and solar power have all benefited from differentiated tax incentive policies. The data corroborate the sustained pro-growth trajectory under the transition from "monolithic tax exemptions" to a "structured development framework."

As the policy inception year (2013), tax incentives for hydropower, wind power, and solar power were CNY 3.0 billion, CNY 0 billion, and CNY 1.2 billion, respectively. By 2023, these figures had risen to CNY 3.43 billion (hydropower), CNY 16.0 billion (wind power), and CNY 15.03 billion (solar power), representing increases of 14.33%, 1,233.33%, and 1,152.5% compared to 2013. This established a foundational framework for collaborative development across multifaceted renewable energy sectors, with subsequent tax incentives exhibiting a "long-term growth and structural optimization" pattern across all three energy types.

Collectively, these measures represent an early transition in government expenditure from direct subsidies to embedded tax incentives, marking a shift in the national fiscal expenditure pattern from direct fiscal transfers to structural tax expenditures. This also indicates that, even prior to the advent of the grid parity era, the fiscal architecture had already begun evolving toward a more sustainable and market-oriented framework.

Concurrently, obtaining preferential treatment through high-tech enterprise certification has become an important tax reduction mechanism for renewable energy enterprises. A combination of preferential tax policies—including value-added tax (VAT) refunds, corporate income tax reductions, super-deduction allowances, and preferential low tax rates—constitutes China's structural policy toolkit for promoting renewable energy development. These policies, implemented in conjunction with contemporaneous fiscal subsidies, have enabled China's renewable energy installed capacity to achieve leapfrog growth (see Appendix A, Appendix B, and Appendix E).

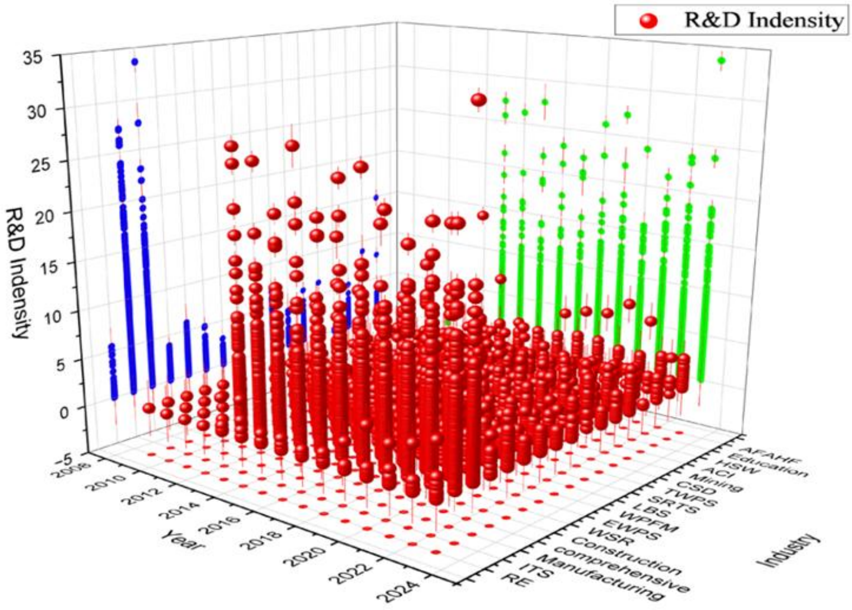


Figure 2.1.3 China's Industry-Specific R&D Intensity (analyze see abbreviations)

Source: compiled by the authors based on data China Statistics Bureau

According to these tax incentive policy, significant "ladder-like" gaps between different industries are shown in Figure 2.1.3, The overall R&D intensity of several industries on the right side of the figure (knowledge and technology intensive sectors) is significantly higher than that of the industries in the middle and left sides, with typical values in the range of 15-30% and peak values close to 35%; traditional and factor-intensive industries are generally in the range of 3-8% and 5-12% respectively.

As shown in Figure 2.1.4, China's total renewable energy power generation increased from 669.2 billion kilowatt-hours in 2009 to 3,190.7 billion kilowatt-hours in 2023. China's renewable energy power generation industry is undergoing a structural transformation from “scale expansion” to “quality-driven growth.” This shift is clearly reflected in the evolution of the energy mix and technological advancements across sub-sectors, as demonstrated by the total output of renewable energy power generation. This article focuses on the three major renewable energy sources—hydropower, wind power, and solar power generation—and, drawing on relevant data, examines and analyzes their current development status globally and in China.

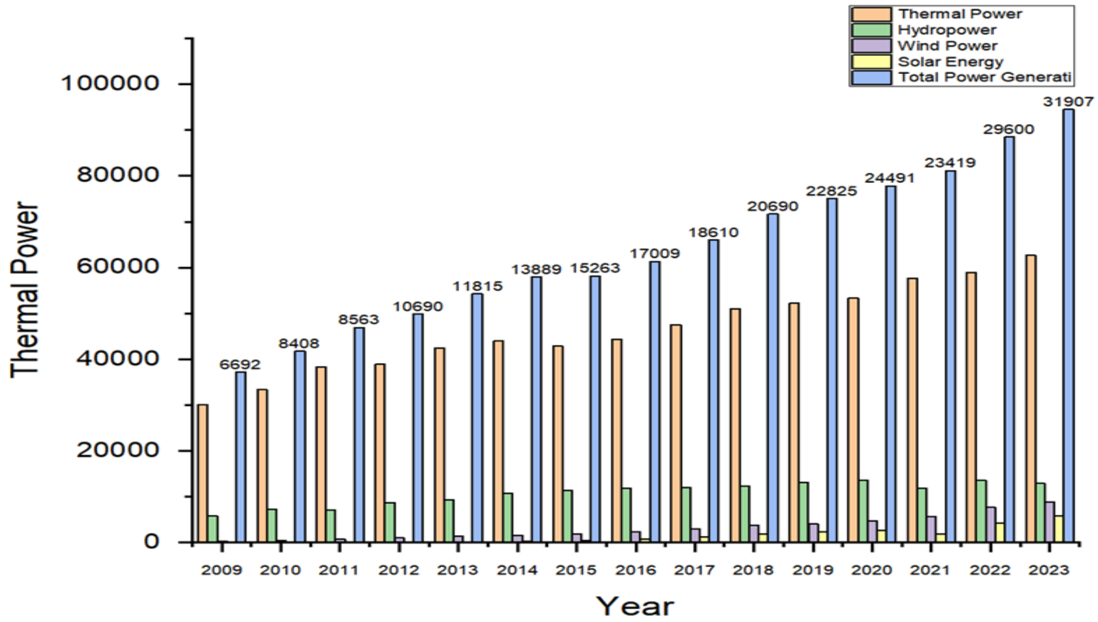


Figure 2.1.4 Overview of Electricity Generation from Various Energy Sources in China from 2009 to 2023（Unit: Billion Kilowatt-hours）

Source: National Bureau of Statistics, BP World Energy Statistical Yearbook

Regarding the energy structure transition, as shown in Figure 2.1.4 and Figure 2.1.5, Table 2.1.6 in Appendix E renewable energy has gradually become the mainstay of electricity supply. By the end of 2023, China's renewable energy power generation capacity reached 318 gigawatts, accounting for 48.8% of the country's total installed power generation capacity. In 2023, renewable energy generation accounted for approximately one-third of total electricity consumption nationwide, with wind and solar power output exceeding the combined residential electricity consumption of urban and rural households across the country. This transformation is driven by clear policy objectives and improvements in technological and economic viability. According to the Chinese government's projections, the share of non-fossil energy consumption is expected to rise to approximately 35% by 2030.

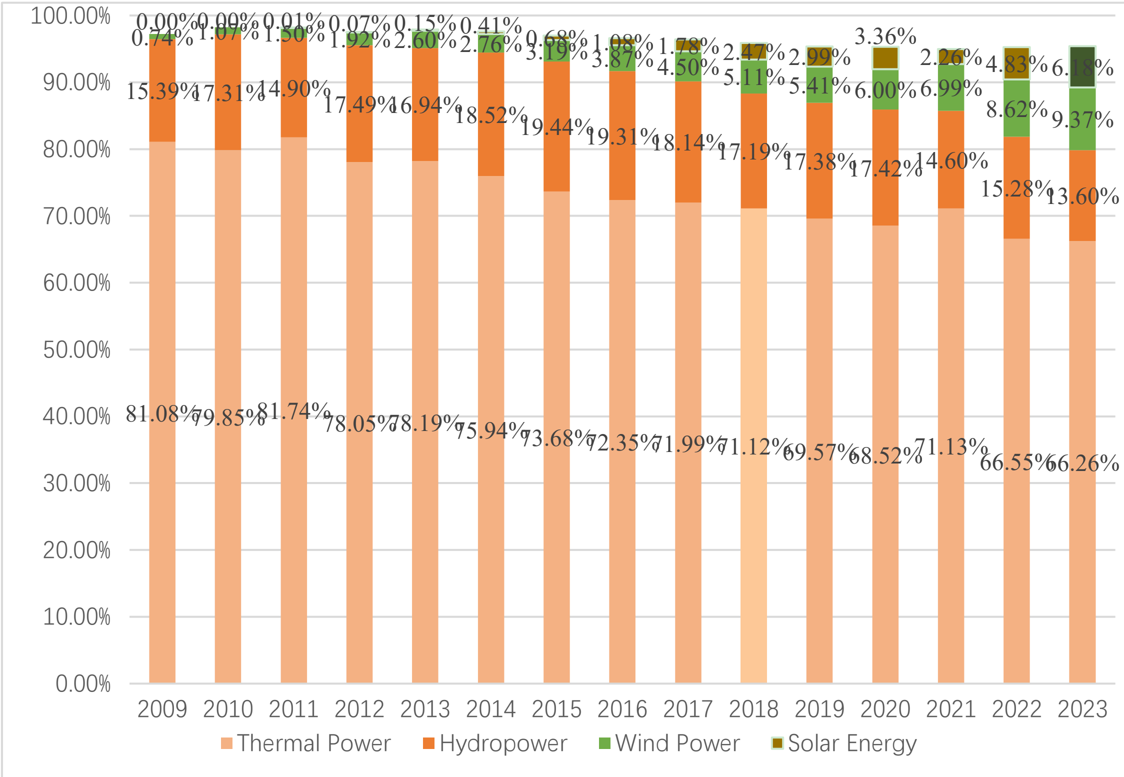


Figure 2.1.5 Proportion of various types of energy generation in China from 2009 to 2023

Source: National Bureau of Statistics, BP World Energy Statistical Yearbook

Against the backdrop of China's long-term planning（Figure 2.1.5）, the share of thermal power generation is declining year by year, while the total volume and proportion of renewable energy generation are increasing annually. The cumulative installed capacity has already ranked first globally.

The corresponding ROA for renewable energy power generation was 1.61%, representing only 15% of the ROA for nuclear power. On the other hand, core equipment for renewable energy still requires imports, resulting in higher initial investment costs for the industry. Furthermore, intelligent operation and maintenance systems have yet to become widespread, limiting the optimization of full-lifecycle returns [12]. (Figure 2.1.6)

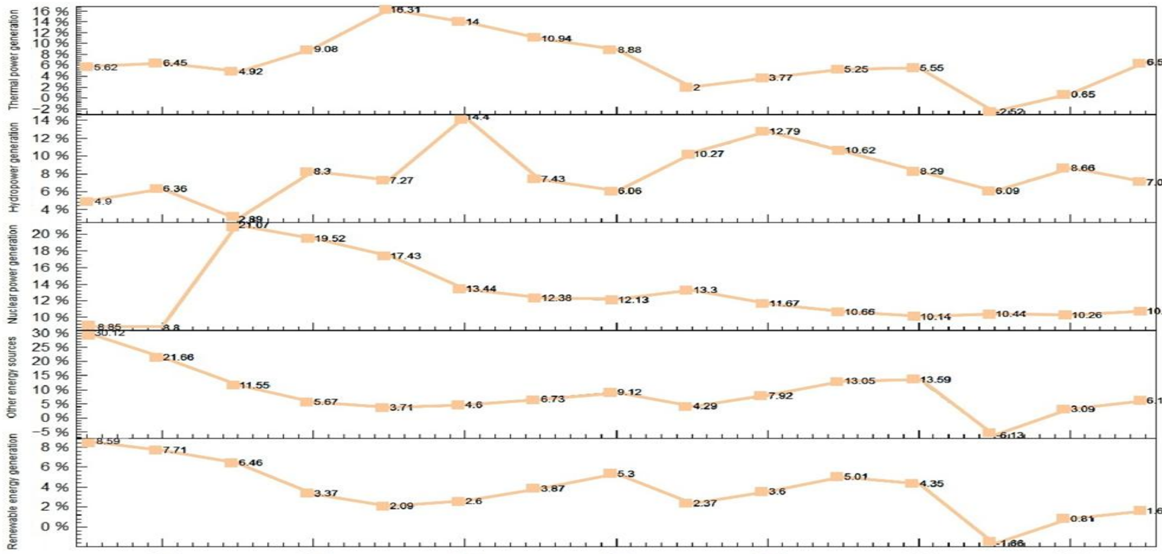


Figure 2.1.6 Return on Asset (ROA) of Different Types of Renewable Energy Enterprises from 2009 to 2023(%)

Source: The author compiled the data based on the Wind database.

Before 2013, China's tax incentives for renewable energy were relatively limited. Since 2013, China has implemented the "structural tax incentives for energy" policy, aiming to promote energy structure adjustment and industrial upgrading. However, during this policy benefit period, some enterprises exploited policy loopholes to conduct false research and development in order to obtain improper benefits.

A typical case is the fraud in the "Golden Sun Project". The Golden Sun Demonstration Project is an important policy implemented by the state to promote the development of the solar energy industry, aiming to support the construction of solar power generation projects through fiscal subsidies. However, the National Audit Office conducted audits on the projects from 2012 to 2013 and found that some enterprises had serious fraud behavior.

The audit results showed that 8 Golden Sun projects illegally used funds amounting to 207 million, accounting for 12.8% of the total illegal funds. These enterprises used methods such as embezzlement, misappropriation, and false reporting to claim state subsidies, seriously disrupting the normal order of the market. For example, some enterprises might not have truly conducted research and construction of solar energy projects, but through means such as forging project materials and overstating project costs, they obtained high subsidies.

This false research and development behavior not only led to the waste of China's fiscal funds but also affected the healthy development of the photovoltaic industry. Therefore, the state subsequently strengthened the supervision and auditing of related projects to ensure that the policy benefits truly benefited those enterprises that truly conducted research and innovation, promoting the healthy development of the industry.

In summary, although the "structural tax incentives for energy" policy in 2013 promoted the development of the renewable energy industry, during its implementation, due to the imperfect regulatory mechanism, some enterprises exploited policy loopholes to claim subsidies, resulting in unstable ROA (Return on Assets) and ROE (Return on Equity), and having a negative impact on the policy effect and the healthy development of the industry.

Owing to substantial regional disparities in economic development and infrastructure endowment in China, remote and mountainous areas still exhibit clear shortcomings in essential supporting facilities, especially with regard to road transportation and electricity grid systems .

Faked R&D activities. Porter et al [117] argue that well-designed environmental regulations can spur innovation and enhance competitiveness. However, when monitoring is weak, firms may engage in faked R&D activities instead of genuine innovation. Due to China's relatively weak development foundation and regulatory gaps in policy implementation, this measure has regrettably failed to effectively enhance corporate innovation performance.

This indicates that R&D incentive policies have not achieved the desired results in China's wind power industry [71]. Research indicates that the primary reason R&D policies have failed to achieve their intended outcomes is due to firms engaging in faked R&D activities. Rena [121] documents the continued decline in renewable power generation costs, strengthening the economic case for clean energy. To sustain this momentum, public subsidies that effectively stimulate corporate R&D are essential. Dai and Cheng [32] apply a generalized propensity score approach to examine this relationship, revealing that the impact of subsidies on private R&D investment is non-linear and varies with subsidy intensity. Therefore, Chavez [23] finds that public R&D subsidies can stimulate R&D, their effectiveness varies significantly across firms. Shi and Lin [133] offer a contrasting market-based approach, demonstrating that China's dual-credit policy can effectively replace direct subsidies by enhancing R&D intensity, thus providing a more self-sustaining pathway to innovation.

According to the original tax incentive classification table from wang and igov, globally, a comparison shows that China's intervention on the cost side is the most comprehensive, being the only country among the sampled countries to simultaneously and extensively apply both "VAT refund" and "direct corporate income tax reduction." This reflects the strong "front-end compensation" character of Chinese policy, ensuring the viability of projects in the early stages of achieving "grid parity" by directly increasing the operating cash flow of enterprises. The evolution of renewable energy tax incentives has shifted from internalizing externalities (such as carbon pricing and pollution control) to actively promoting industrial upgrading and innovation-driven growth. The United States and Germany have long used tax credits and accelerated depreciation as counter-cyclical fiscal tools to stimulate private investment in green infrastructure and explicitly emphasize job creation and energy independence. In contrast, China's early tax incentive policies (such as VAT refunds and import tax exemptions) were closely related to industrial policy and the urgent need for technological catch-up. In terms of investment and output in renewable energy, Western countries adopt a governance approach that is "output-oriented".

As we shown in Table 2.1.4. The United States exhibits a more comprehensive approach: cost deductions (accelerated depreciation), profit incentives (investment tax credits/production tax credits), and R&D excess deductions coexist, providing multi-layered support for the enterprise life-cycle. Germany and Denmark also employ similar multi-layered tools, but place greater emphasis on differentiated environmental taxes and consumer-side incentives (such as VAT and land tax refunds).

China and Russia have significant gaps in ITC, PTC, and personal income tax credits for green investments. Currently, China focuses on the "compliance investment" of small and medium-sized enterprises rather than their "actual output". The difference between China and Western countries in terms of investment and output in renewable energy lies in the integration of innovation goals. The key difference lies in the integration of innovation objectives. The United States provides specific tax support for green patents and emerging clean technology industries through clear definitions and dynamic assessments, while China's innovation-side tools often rely on general high-tech enterprise classifications, lacking specificity for green industries. This structural characteristic may weaken the behavioral targeting of incentive measures. This situation also easily leads to cases of faking R&D to defraud taxes, which is the core of this study. Russia has only applied property/land tax reductions out of 11 core tools, and is currently in a critical transitional period of actively attracting and deeply integrating foreign companies (especially those from "friendly countries"). To offset the impact of Western sanctions, Russia has introduced a series of substantial measures in legal protection, fiscal and tax incentives, and industrial zone construction. Decree No. 436, "Additional Protections for the Rights of Foreign Investors," allows foreign investors, including those from unfriendly jurisdictions, to purchase Russian securities without prior regulatory approval.

On the innovation front, countries have shown a high degree of consensus, all using tax measures to compensate for the "double externalities" of green technologies. China has been extremely generous in its R&D expense super deduction, increasing it to 100% or even higher after 2023. While this threshold incentive based on "input intensity" has greatly boosted total R&D investment, it has also created an incentive for companies to strategically declare R&D expenditures to cross specific "notch" thresholds. (Table 2.1.1).

Table 2.1.4 Renewable energy power generation sector of major Countries tax incentive tool

Policy Category	Tax Incentive Tool	Russia	China	USA	Germany	Denmark	Japan
Cost side	VAT refund for renewable energy	×	√	×	×	×	×
	Accelerated depreciation / one-time deduction for green	×	√	√	√	√	√

	equipment						
	Corporate income tax reductions	×	√	×	×	×	×
	Property/Land use tax reductions for green projects	√	√	√	√	√	√
Profit side	Investment Tax Credit (ITC)	×	×	√	√	√	√
	Production Tax Credit (PTC)	×	×	√	×	×	×
	Personal income tax deduction for green investment	×	×	√	√	√	√
	Environmental/Carbon tax reduction mechanisms	×	×	√	√	√	√
Innovation oriented side	Super deduction of R&D expenses for green technologies	×	√	√	√	√	√
	Preferential tax rate for high-tech/green enterprises	×	√	×	√	√	√
	Tax support for green patents	×	√	√	√	√	√

Source: The author has compiled based on the tax policies of various countries

Figure 2.1.7 illustrates the total renewable energy generation of the United States, Germany, Denmark, Japan, and Russia and their relative share of global renewable energy generation. This figure reveals how tax incentive policies interact with generation capacity, determining a country's role and weight in the global energy landscape.The United States leads by a wide margin in absolute generation (>4000 TWh) and contributes approximately 14.5% of global renewable energy generation, reflecting the synergistic effect of its systematic tax incentives (such as ITC and PTC) and large-scale technology deployment strategies. In contrast, while Germany, Russia, and Japan each possess policy advantages, their share in the global system is significantly lower, demonstrating a structural gap between green incentives and industry scale. Denmark, though known for its cutting-edge technology, has limited global influence due to its relatively small size.

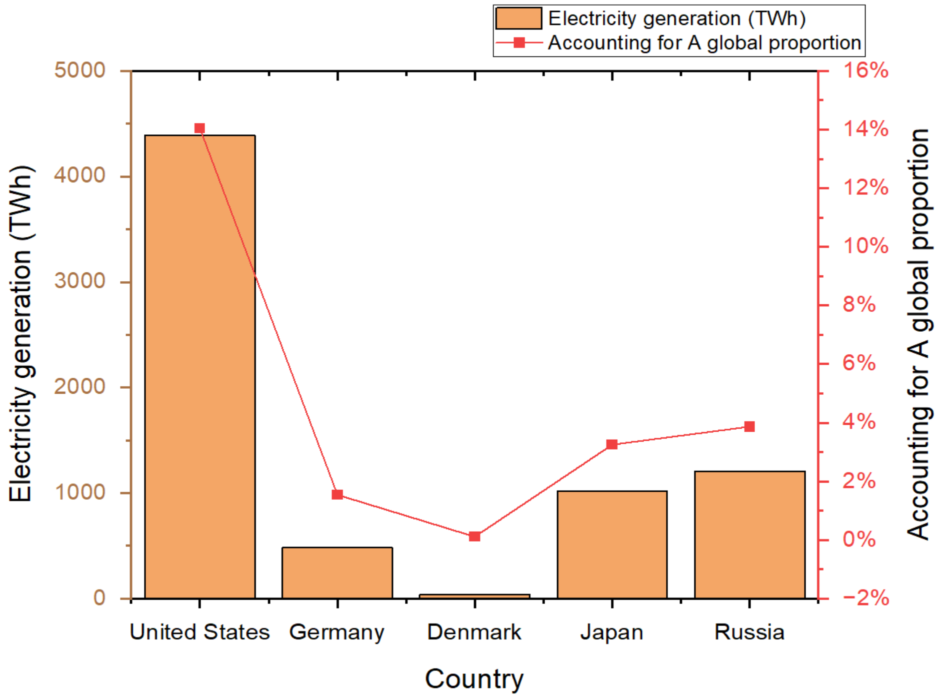


Figure 2.1.7 Overview of Renewable Energy Generation in Major Developed Countries

Source: Electricity generation of significant country

Tax incentives have significantly driven the scale expansion and technological innovation of renewable energy in the United States (Figure 2.1.8). Supported by the Production Tax Credit (PTC) and Investment Tax Credit (ITC) [33], U.S. wind power capacity surged from less than 10 GW in 2005 to approximately 120 GW by 2020, establishing the country as the world's second-largest wind power market. Over the same decade, solar power installation costs plummeted by more than 80%, substantially increasing the share of photovoltaic electricity generation. These policies have also fostered supply chain maturity and job growth, domestic turbine manufacturers and specialized service companies while driving improvements in turbine capacity and efficiency. Local wind power employment has surged significantly, spurring numerous technological advancements such as longer blades and taller towers.

Wiser and colleagues [159] report highlights that federal tax incentives, particularly the Production Tax Credit (PTC), have been the primary driver of wind power deployment, although policy uncertainty and supply chain constraints pose ongoing challenges. This evidence reaffirms the critical role of stable, long-term tax incentives in sustaining renewable energy innovation and market growth.

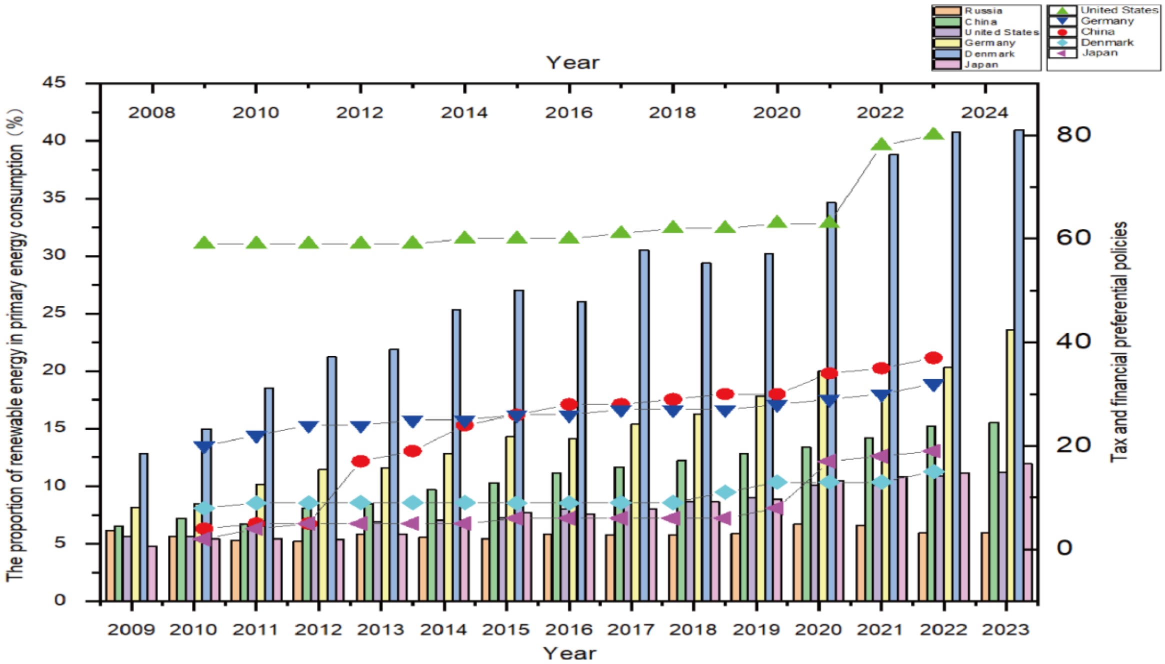


Figure 2.1.8: The Relationship Between the Proportion of Primary Energy Consumption and Fiscal and Tax Policies in Major Countries Worldwide (2009-2023)

Source: Compiled by the author from the EWA official website

As demonstrated by the above analysis, the United States has consistently employed tax policies as a stabilizing force, enacting numerous policies and legislation to facilitate the transition to renewable energy systems and advance its renewable energy strategy.

McCoy [106] provide a comprehensive assessment of the global offshore wind market, documenting record-high annual installations, declining levelised costs, and expanding geographic deployment. Their report highlights that tax incentives, particularly the Investment Tax Credit (ITC) and Production Tax Credit (PTC) in the United States, remain critical drivers of offshore wind investment and innovation, although supply chain bottlenecks and inflation pose emerging challenges. This evidence underscores the continued relevance of well-designed tax incentives in sustaining renewable energy technology diffusion.

As one of the world's most developed countries, Russia's economy is primarily based on fossil fuels. According to the IEA's energy strategy for the Russian region, the goal is to maximize domestic energy use and leverage the potential of the energy sector to sustain economic growth. Therefore, it will not be studied further here. From an overall trend perspective, the major countries can be broadly categorized into three types. The first type is characterized by continuous structural improvement, with China and Japan serving as typical examples [115]. The second type exhibits a substantial policy stock accumulation pattern, with the United States as the representative case. The third type demonstrates high efficiency in structural transformation, with Germany and Denmark being the most representative. In contrast, Russia presents distinctly different characteristics from the aforementioned countries. For instance, during the sample period, the proportion of renewable energy in its energy consumption remained basically at a low-level fluctuation range, showing no significant upward trend.

The first type: Continuous Structural Improvement. During the sample period, China's expansion of fiscal and financial support policies exhibited the most prominent "late-mover catch-up" characteristics. In 2009, China had accumulated only 4 relevant policies. By 2022, this number had increased to 35, representing a net increase of 31 policies, with a growth rate of 775%. Correspondingly, China's proportion of renewable energy in energy consumption rose from 6.56% in 2009 to 15.51% in 2023, achieving a cumulative increase of 8.95 percentage points.

2013 marked a significant turning point: in this year, the cumulative number of China's fiscal and financial policies rapidly jumped from 5 items in the previous year to 17 items, further reaching 24 items in 2014, and rising to 28 items in 2016. This concentrated intensification within a short period indicates that China's renewable energy policy system construction possesses distinctive characteristics of administrative promotion and centralized allocation, namely, providing institutional guarantees for industrial expansion and project investment through the rapid increase in the number of policy instruments.

As a result, China's renewable energy proportion entered a sustained upward channel after 2012, indicating that China's policies manifest more of a progressive structure of "scaling up first, optimizing structure later." On the other hand, China's development data also highlight an important issue: the expansion of policy quantity and the improvement of energy structure do not correspond proportionally. Based on data from 2009 to 2022, for each additional fiscal and tax policy in China, the corresponding increase in renewable energy proportion was not substantial. This implies that although China's policy system expanded rapidly in terms of quantity, the structural transformation efficiency per unit of policy still has ability for further improvement.

The reasons for this outcome are not difficult to understand: China's total energy consumption is large, and the proportion of coal is high. Even with rapid growth in renewable energy installed capacity and power generation capacity, the improvement of its proportion in the energy consumption structure will be significantly affected by the large volume of traditional energy. Therefore, China's fiscal and tax policies more accurately promoted the scale expansion of the renewable energy industry, while structural improvement exhibited significant lag.

The second type: High Policy Stock Pattern. The situation in the United States differs from that of China. In 2009, the cumulative number of fiscal support policies in the United States had already reached 59, increasing to 78 by 2022, with a net increase of 19 items. This indicates that its policy system was already quite mature before the beginning of the sample period. During the same period, the proportion of renewable energy in U.S. energy consumption increased from 5.60% to 11.21%, with a cumulative increase of 5.61 percentage points.

Superficially, the United States has a large number of policies, but the magnitude of energy structure improvement is not particularly prominent. This suggests that the problem in the United States is not insufficient policy supply, but rather a strong lock-in effect of the traditional energy system. As a major global oil and gas producer and consumer, the United States' energy structure transformation must advance on the basis of a massive fossil energy foundation. Therefore, even with continuous expansion of renewable energy, the improvement in renewable energy proportion in energy consumption remains relatively slow.

In other words, the United States exemplifies a typical "high policy stock–low structural elasticity" model, namely, abundant policy instruments, but structural adjustment is strongly constrained by the existing energy system and market inertia.

The third type: High Efficiency in Structural Transformation. In sharp contrast to the United States is Germany. In 2009, Germany had accumulated 20 fiscal support policies, increasing to 30 by 2022, with a net increase of only 10 items. However, its proportion of renewable energy in energy consumption rose from 8.15% to 23.60%, with a cumulative increase of 15.45 percentage points.

In other words, Germany did not promote transformation through a large increase in policy quantity, but rather achieved effective conversion of structural improvement through policy continuity and institutional implementation efficiency. The key issue revealed by the data is that policy quantity itself does not determine transformation effectiveness; what truly plays a decisive role is the stability of the policy system, the degree of coordination with market mechanisms, and the coupling efficiency between policy and industry.

Germany's fiscal support policy scale is not large, but its energy structure improvement degree is significantly higher than that of China and the United States, indicating that its structural transformation efficiency per unit of policy is relatively high.

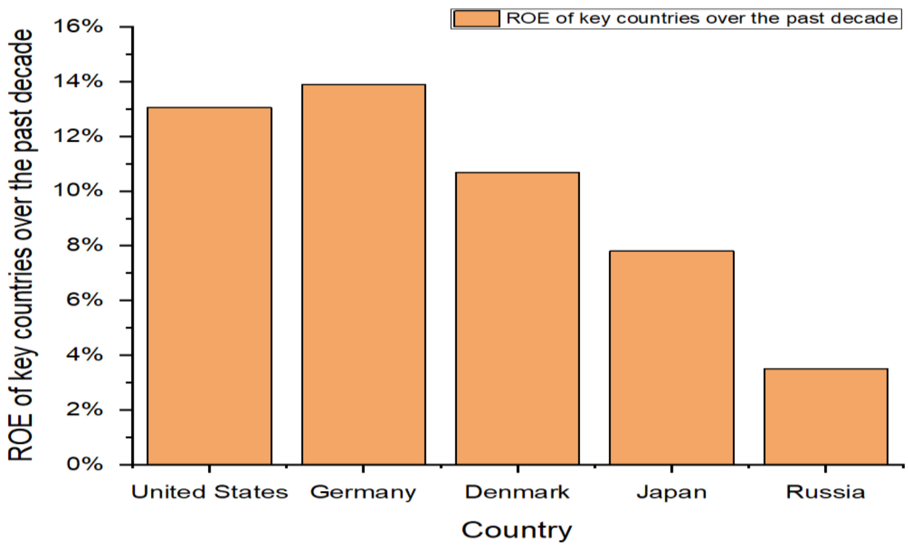


Figure 2.1.9. Average ROE of renewable energy in major countries worldwide, 2009-2023

Source: IEA Official Website

As shown in Figures 2.1.6, 2.1.7 and 2.1.9, the ROE of renewable energy companies in major developed countries such as Russia and the United States is generally higher than that of the Chinese sample companies, with Germany, the United States, and Denmark showing particularly strong performance. In contrast, the average ROE of Chinese companies is only about 3%, indicating a significant gap between strong innovation and expansion capabilities and relatively limited capital returns. In other words, China's renewable energy industry has already established an advantage in the scale of innovation output, but this "quantitative innovation" has not yet been fully transformed into "profit-generating innovation." Therefore, it is necessary to further examine at the micro-enterprise level whether tax incentive policies have truly improved corporate profitability, effectively promoted green technology innovation output, and whether this promotional effect is sustainable and heterogeneous. Therefore, this paper further constructs a DID model to systematically identify the economic and innovation effects of tax incentive policies.

Stepanov and Makarov [138] argue that while global pressures create significant transition risks for economies heavily dependent on hydrocarbon revenues, they also open windows for diversification into renewable energy. For Russia, this implies a need to carefully balance international climate commitments with domestic economic stability, making the design of effective fiscal instruments, including tax incentives for green innovation, a critical policy priority.

2.2 Methodology for Studying the Development and Tax Incentives in China's Renewable Energy Power Generation Sector

As evidenced by the aforementioned research, policies enacted by the Chinese government play a decisive role in the development of enterprises within its jurisdiction. Therefore, to identify the causal effect of tax incentive policies on green technological innovation among enterprises in China's renewable energy power generation sector, this paper constructs an econometric identification strategy treating the policy as an exogenous shock. In terms of model specification, this study innovatively builds upon the traditional Difference-in-Differences (DID) framework [102], creatively extending it into a dynamic triple difference (DDD) structure incorporating the time dimension to identify potential "faked R&D" activities. By innovatively constructing the index of "$fake_i$" within the triple interaction term and cross-multiplying these grouping variables with post-2013 policy regime dummy variables to generate triple difference terms, we can more precisely measure the differential impact of tax incentive policies on green technology innovation outputs across different types of enterprises.

This research innovatively applies the DDD method for the first time to China's renewable energy power generation sector, identifying heterogeneous response pathways of green innovation outputs under tax incentive policies. The constructed model employs a dynamic estimation strategy using the event study approach, enabling the depiction of policy effects' evolutionary trajectory over time. This captures the distinction between the lagged effects of post-2013 policy regime and firms' short-term strategic responses. Within the research framework of this paper, although China's energy industry as a whole is undergoing decarbonization, the special tax incentive policy introduced in 2013 exhibits significant 'exclusivity' in terms of incentive intensity. Based on the identification logic of Intensity Difference-in-Differences (DID), even if the control group is affected by macroeconomic policies, as long as the experimental group receives significantly higher marginal incentives from the policies, the model can identify the net effect of the policies.

The concept was first proposed by economists Orley Ashenfelter and David Card in 1985 in a paper evaluating the impact of a vocational training program (CETA program) on trainees' income. Differences-in-Differences Model (DID). Due to relatively stable differences among enterprises in terms of scale, management characteristics, and regional environments, these features are difficult to fully control through observed variables. Directly comparing changes in average levels before and after the onset of the post-year policy period risks conflating policy effects with these long-term factors. Therefore, when identifying policy effects, this paper employs the Difference-in-Differences (DID) method. By simultaneously utilizing changes over time and across groups, DID can isolate these non-time-varying characteristics from the estimation process, thereby enhancing the reliability of the identification results. DID measures the difference in the magnitude of change in outcome variables between the treatment group and the control group before and after the onset of the post-year 2013 period. As can be seen from Chapter 2.1, 2013 was an important year for the "structural" reform of China's tax incentive policy. Therefore, 2013 was chosen as the average relative effect of the post-2013 policy system on renewable energy companies relative to traditional energy companies under the common macroeconomic policy background. As long as the trends in both groups were relatively consistent prior to the policy introduction, the difference in post-policy changes can reasonably be attributed to the policy effect. This paper constructs the following regression model.

Xia, Huang and Zhang [162] employ a staggered Difference-in-Differences (DID) design to evaluate the impact of China's intellectual property rights city policy on firm green innovation. Their quasi-experimental evidence shows that strengthening intellectual property protection significantly promotes green patent output, with the effect being more pronounced in regions with stronger enforcement and among firms with higher R&D intensity. This study validates the applicability of DID identification strategies in evaluating innovation-oriented policies and supports the use of similar methods in the context of tax incentives for renewable energy.

Each firm faces two potential outcomes under the policy: $Y_{it}(1)$ represents the green innovation output of firm i if it is subject to the policy in period t, and $Y_{it}(0)$ represents the output without the policy. The true individual treatment effect is $Y_{it}(1)-Y_{it}(0)$, and its overall objective parameter is the treatment group mean treatment effect ATT, defined as $E[Y_{it}(1)-Y_{it}(0) \mid Treat_i=1]$. Since it is impossible to observe both potential outcomes for the same firm simultaneously in the observational data, we indirectly estimate ATT by using the change in the control group as a counterfactual through a difference-in-differences (DID) design.

Under a standard DID design with two groups (treatment group $Treat_i=1$ and control group $Treat_i=0$)) and two periods (before the onset of the post-year policy period $Post_t=0$ and after implementation $Post_t=1$), ATT can be represented as a four-term difference:

$$ATT=[E(Y| Treat=1,Post=1)-E(Y| Treat=1,Post=0)] - [E(Y| Treat=0,Post=1)-E(Y| Treat=0,Post=0)] \quad (3)$$

The first set of parentheses represents the time-varying changes in the treatment group, and the second set represents the time-varying changes in the control group. The difference between the two eliminates the common part of the time trend, thus identifying the average effect of the policy. According to the potential outcome framework, without policy intervention, the green innovation output of the treatment group and the control group should evolve along similar trends; this is the parallel trend assumption of the DID method. Although the Enterprise Income Tax Law that came into effect on January 1, 2008 provided the general institutional basis for tax preferences in China, it is not treated in this study as the direct post-2013 policy regime for causal identification. The quasi-natural experiment used in the DID design is instead based on the targeted package of renewable-energy-related tax incentive measures that began to be implemented in 2013.The basic form of the constructed DID model is as follows:

$$Y_{it}=\alpha+\beta\,(Treat_i\times Post_t)+\gamma X_{it}+\mu_i+\lambda_t+\epsilon_{it} \quad (4)$$

Where in, Y_{it} represents the green technology innovation output of the i-th enterprise in year t (measured by the number of green invention patent applications), $Treat_i$ is a dummy variable for the treatment group $Treat_i$ if the enterprise belongs to the renewable energy industry; otherwise, $Treat_i=0$), $Post_t$ is a time dummy variable after the onset of the post-2013 policy period (Post=1;if $t \geq 2013$;otherwise,Post=0), and the interaction term $Treat_i\times Post_t$ is the DID term of the post-2013 policy regime, whose coefficient β measures the additional change in green innovation output of the treatment group relative to the control group after policy implementation. 2013 was not the only single policy shock, but rather a year of policy breakpoint and the starting point of the post-policy institutional phase. DID identifies the average relative effect of the post-2013 policy environment, rather than the pure effect of a single policy document in 2013.A control variable X_{it}, as well as enterprise fixed effects μ_i and time fixed effects λ_t, are added to the model to control for the impact of unobserved heterogeneity factors and macroeconomic trends on innovation, thereby improving the accuracy and reliability of the estimation. To control for the impact of unobserved heterogeneity and macroeconomic trends on innovation, the accuracy and reliability of the estimation are improved.

If the estimated β is significantly greater than zero, it indicates that, controlling for other conditions, tax incentives significantly improve the green innovation output of renewable energy companies relative to the control group. It is important to note that the β estimated by the DID method can only be interpreted as a causal effect of the policy if the parallel trend assumption is met. That is, the innovation performance of the no-policy-intervention group and the control group should show similar trends. Once this key assumption holds, the policy effect estimates obtained by the DID method is rigorous and reliable. This study empirically ensures the validity of this assumption through ex-ante trend testing, thus supporting the DID identification results.

Triple Difference Model (DDD) to Identify fake R&D behaviour. Although the DID model can identify the average effect of tax incentive policies, different companies may react differently to policy incentives. Some companies may engage in "faked R&D" in order to obtain tax relief, nominally increasing R&D investment or patent applications to meet the preferential eligibility, but without generating corresponding real technological innovation. If such behaviour exists, it may lead to an overestimation or distortion of the policy effect estimated by DID. According to 1. Lamberova N [88], the government's intention to encourage innovation may lead to the proliferation of low-quality patents. Therefore, it is necessary to introduce a triple difference strategy in this paper. On the basis of the original differences between the treatment group and the control group, and the differences before and after the implementation of the policy, a third difference is added to distinguish the R&D behaviour patterns of enterprises. Specifically, we construct a dummy variable $Fake_i$ of potential faked R&D capability based on PCA.

$$Y_{it} = \alpha + \beta_1(Treat_i \times Post_t) + \beta_2(Treat_i \times Post_t \times Fake_i) + \beta_3(Post_t \times Fake_i) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

β_1 reflects the average impact of the policy on firms that "do not have a tendency to fake R&D" (when P_i=0), while β_2 corresponds to the triple interaction term $Treat_i \times Post_t \times Fake_i$, which characterizes the difference in additional policy effects between firms with fake R&D characteristics and normal firms. By focusing on the sign and significance of β_2 we can determine the direction of the impact of faked R&D behaviour on policy effectiveness: if the estimation result shows that β_2 is significantly negative, it indicates that the policy effect on enterprises with high R&D expenditure is significantly smaller than that on other enterprises, suggesting that a considerable portion of the innovation output increased by these enterprises through the policy may be "faked" non-genuine technological progress; conversely, if β_2 is positive and significant, it means that enterprises with this characteristic obtain greater innovation improvement from the policy, possibly indicating that high-tech enterprises have achieved a stronger innovation response due to more sufficient R&D investment. It should be noted that applying the triple difference strategy is also based on a similar parallel trend assumption: in addition to requiring that the treatment group and the control group have similar trends before the policy, we further assume that the difference in innovation trends between enterprises with and without the "faked R&D" characteristic is constant in the absence of policy influence. In other words, without tax incentives, the gap in innovation output between enterprises of type P_i=1 and type P_i=0 should remain relatively stable. Only when this additional assumption holds can the difference effect estimated by the DDD model have a reliable causal meaning. By introducing a third difference, this paper can more deeply analyze the effectiveness of tax incentive policies under different corporate behaviour patterns, thereby identifying what proportion of the innovative growth induced by policy incentives comes from genuine technological innovation.

Dynamic Effect Model (Event Study Methodology). To further investigate the temporal lag characteristics and dynamic evolution path of the policy impact, this study, drawing on the approach of Fama, Fisher, Jensen, and Roll[50], incorporates the event study methodology within the aforementioned difference framework to estimate the dynamic effects. To analyze the time-varying dynamic characteristics of the policy effect and test the parallel trends assumption, we further introduce the event time dummy variable $Fake_i$, defined as $Fake_i$=1 if and only if it is the k-th year relative to the onset of the post-2013 policy period year for firm i (k can be negative, indicating pre-common policy cutoff year), with the baseline period typically set at k = -1. The two-period DID model is thus extended into a multi-period specification as follows:

$$Y_{it}=\alpha+\sum_{k\neq-1}\theta_k\left(Treat_i\times D_{k,t}\right)+\mu_i+\lambda_t+\epsilon_{it} \quad (6)$$

When incorporating the triple difference (DDD) structure, the model expands to:

$$Y_{it}=\alpha+\sum_{k\neq-1}\delta_k\left(Treat_i\times D_{k,t}\times Fake_i\right)+\mu_i+\lambda_t+\epsilon_{it}. \quad (7)$$

Here, I split $Post_t$ into several relative-year dummies $D_{k,t}$.$Treat_i\times D_{k,t}$ shows the policy effect in each year before and after the policy. the coefficient θ_k represents the marginal effect in the k-the onset of the post-2013 policy period (if k < 0, it tests the pre-trend). The sequence of θ_k coefficients across k is used to plot the event study curve. Specifically, the parallel trends hypothesis is supported if θ_k for k < 0 is not statistically different from zero. The coefficients for K ≥ 0 describe the accumulation and dissipation process of the policy effect over time.

The design of this dynamic effect analysis serves to test the validity of the parallel trends hypothesis and reveal the time-evolving pattern of the policy impact. If the parallel trends assumption holds, the difference in innovation outcomes between the treatment and control groups (δ_k) in the pre-policy periods (k < 0) is expected not to deviate significantly from zero, indicating no systematic differential trends between the groups before the policy intervention. For post-implementation periods (k ≥ 0), a statistically significant deviation of δ_k can be attributed to the post-2013 policy regime. Secondly, by observing the evolution of δ_k and θ_k over time, we can infer the dynamic characteristics of how the tax incentive policy affects innovation output. If the tax incentives genuinely promote substantive technological innovation, a certain time lag is often anticipated: increasing R&D investment, conducting R&D activities, yielding results, and filing patent applications usually do not happen instantaneously.

Therefore, the full policy effect is not expected to materialize immediately in the implementation year (k=0). Instead, it may gradually intensify after a gestation period of n years and subsequently sustain a positive influence for some time. This dynamic path characterized by an "initial lag followed by gradual strengthening" would suggest that the observed increase in innovation primarily stems from the accumulated outcomes of solid R&D activities. Conversely, if the results show a sharp spike in δ_0 in the implementation year, followed by a rapid decline or disappearance in subsequent years, it might indicate that some firms engaged in short-term, rushed patent applications to meet policy requirements or reclassified routine expenditures as R&D spending, implying a certain degree of "window dressing" in R&D reporting. In this scenario, the dynamic curve of the policy effect would exhibit a pattern of "short-term surge followed by attenuation," hinting that the initially observed innovation boost may not represent fully sustainable technological progress. Through the analysis using the dynamic DDD model, this study can link the temporal pattern of the policy effect to the cycle of firms' genuine innovation activities, thereby providing a more comprehensive assessment of the actual promoting effect and lasting impact of the tax preference policy on green technology innovation.

The core identification condition for the difference-in-differences (DID) or triple-differences (DDD) design is the Parallel Trends Assumption. This assumption requires that, in the absence of the policy intervention, the outcome variable of the treatment group and the control group would have followed similar development trends over time. Formally, this assumption can be expressed for all time periods t as follows:

$$E[\,Y_{it}(0) \mid Treat_i=1\,] = E[\,Y_{it}(0) \mid Treat_i=0\,] \quad \forall t. \quad (8)$$

This condition implies that there should be no systematic differences in the expected outcome levels between the treatment and control groups prior to the implementation of the policy. If this assumption is satisfied, the coefficient estimated from the aforementioned DID or DDD design can be interpreted as the causal effect of the policy. To test the validity of this assumption, one can examine whether the coefficients for the periods preceding the onset of the post-2013 policy period (when the event time k< 0) in a dynamic event study model are statistically indistinguishable from zero.

Principal Component Analysis (PCA) ,to identify potential "window-dressing in R&D" activities by firms, this study employs Principal Component Analysis (PCA) for indicator construction. According to Li T [94]; Zhang H[177] research, PCA method is a multivariate statistical technique used for dimensionality reduction and variable synthesis. It transforms multiple correlated variables into a smaller set of uncorrelated principal components through linear transformation, with these components capturing the maximum variance in the data. Multiple indicators can be merged into a new composite indicator the first principal component--- via PCA, thereby simplifying the analysis and reducing information redundancy. The core concept of PCA is that the first principal component is a linear combination of the original variables and possesses the largest variance; each subsequent principal component is orthogonal (uncorrelated) to the preceding one and accounts for a decreasing proportion of the variance. In empirical analysis, if the variance contribution rate of the first principal component is sufficiently high (e.g. exceeding 70%), it can serve as an effective composite indicator. As the original indicators may have different units and variances, standardization is first necessary to ensure each indicator has a mean of 0 and a standard deviation of 1. This guarantees the comparability of all indicators in the analysis. With the original indicators be $X_1,X_2,X_3......X_n, X_j=[x_{1j},x_{2j},...,x_{nj}]^T$

$$\bar{X}_j=\frac{1}{n}\sum_{i=1}^{n} x_{ij}, s_j=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_{ij}-\bar{X}_j)^2} \quad (9)$$

The standardized indicator Z_j is:

$$Z_{ij}=\frac{x_{ij}-\bar{X}_j}{s_j}, i=1,2,...,n;\ j=1,2,3 \quad (10)$$

After standardization, Z_j has a mean of 0 and a standard deviation of 1.

Since the data have been standardized, the covariance matrix is equivalent to the correlation matrix. The covariance matrix reflects the linear relationships between the indicators .The covariance matrix Σ is a 3x3 symmetric matrix, where the element σ_{jk} is the covariance between Z_j and Z_k:

$$\Sigma=\begin{bmatrix}\sigma_{11} & \cdots & \sigma_{1n}\\ \vdots & \ddots & \vdots\\ \sigma_{1n} & \cdots & \sigma_{nn}\end{bmatrix} \quad (11)$$

where

$$\sigma_{jk}=\frac{1}{n-1}\sum_{i=1}^{n} Z_{ij}Z_{ik} \quad (12)$$

Perform composition on the covariance matrix Σ to obtain eigenvalues and eigenvectors. The eigenvalues represent the magnitude of variance explained by each principal component, and the eigenvectors indicate the direction of the components.

Solve the characteristic equation:

$$\Sigma v=\lambda v \quad (13)$$

where λ is the eigenvalue, and $v=[v_1,v_2,v_3]^T$ is the corresponding eigenvector.

Typically, the eigenvalues are sorted in descending order: $\lambda_1 \geq \lambda_2 \geq \ldots\ldots \geq \lambda_n$, with corresponding eigenvectors $v_1,v_2,\ldots\ldots v_n$. The eigenvectors are unit vectors, satisfying $v_k^T v_k=1$. To consolidate into a single new indicator, the first principal component (PC1) is selected as it captures the maximum variance. The variance contribution rate of the first principal component is:

$$\text{Contribution Rate}=\frac{\lambda_1}{\lambda_1+\lambda_2+\ldots\ldots+\lambda_n} \quad (14)$$

If the contribution rate is sufficiently high (e.g. >60%), PC1 is adequate to represent the majority of the information from the original indicators. The cumulative variance contribution rate can assess multiple principal components, but the focus here is on PC1 for constructing a single new indicator. Constructing the New Indicator.

The new indicator is the score of the first principal component, which is a linear combination of the standardized indicators, with weights derived from the first eigenvector. The formula for calculating the first principal component PC1 is:

$$PC1_i=v_{11}Z_{i1}+v_{12}Z_{i2}+\ldots\ldots+v_{in}Z_{in}, i=1,2,\ldots,n \quad (15)$$

Where $v_1=[v_{11},v_{12},\ldots.v_{in}]^T$ is the first eigenvector.

The new indicator Yis the vector of PC1 scores:

$$Y=[PC1_1,PC1_2,\ldots,PC1_n]^T \quad (16)$$

Thus, the new variable can be constructed.

Error Structure and Robust Estimation. In panel data regressions, the error term ϵ_{it} may exhibit heteroskedasticity or within-group correlation. Therefore, cluster-robust standard errors are commonly employed. As noted by Croux C [31], who included industry, region, and year fixed effects in their model and applied cluster-robust standard errors adjusted for clustering at the regional level, this approach helps obtain reliable inference.

Due to the asymmetry of information between the regulator and firms, the regulator may not be able to fully recognise whether a firm is engaging in green R&D or not. It is assumed that the regulator is a relatively permanent body that monitors the R&D activities of firms to reduce non-compliance.

Denoted by φ, represents the likelihood of a successful innovation. there is a (1 − φ) chance that R&D will not succeed, meaning the firm will continue to produce its standard product. Success in green R&D lessens the environmental impact of manufacturing without altering the performance or quality of the original product.

Firms will use to predict the number of firms x_{i1}^{t} that will undertake green R&D in period t. The expected number of firms with successful R&D is φx_{i1}^{t}. Assume that the price of an individual product is p and the cost is c. Yang [62] argues that in the absence of significant heterogeneity among firms, a firm's expected profit can be expressed as:

$$R_i=(p-c)\frac{w-\eta w}{N} \quad (17)$$

where: w represents the market demand for green power, N is the total number of firms, and η is the green quota in the green R&D quota system.

The market allocation for successful R&D companies is denoted as R_{GQ}:

$$R_{GQ}=(p-c)\frac{\eta w}{\varphi x_{i1}^{t}} \quad (18)$$

Firm i is 'green-listed' after a successful R&D endeavour and is inaccessible after a failure. Therefore, the expectation of market returns when choosing strategy 1 can be expressed as:

$$R_{i1}=\varphi(R_i+R_{GQ})+(1-\varphi)R_i \quad (19)$$

Adjusted as follows:

$$R_{i1}=(p-c)\left(\frac{w-nw}{N}+\frac{\varphi\eta w}{\varphi x_{i1}^{t}}\right) \quad (20)$$

Equation (20) suggests that market returns may become optimal as the number of R&D firms reaches a certain level, and that market competition will drive the expansion of the emergence of new R&D firms to a halt once firms no longer flock to R&D competition.

Therefore, the market gains for firms in these two scenarios are:

$$R_{i2}=R_{i3}=(p-c)\frac{w-nw}{N} \quad (21)$$

For firms counterfeiting green R&D, all R&D activities are examined and analysed according to the equation $\gamma \cdot P_i^g$,γ is the penalty coefficient.

Therefore, the expectation of the tax benefit when choosing strategy 2 can be expressed as follows:

$$\gamma \cdot P_i^g \quad (22)$$

Referring to the network effect function the firm's expected return function can be expressed as follows:

$$\Pi_i^g = R_i^g - C_i^g + \iota \cdot S_i^g - \gamma \cdot P_i^g + \beta \cdot NE_i^g \quad (23)$$

where R_i^g— is the return from strategy g, C_i^g— is the R&D expenditure, ι— is the tax incentive parameter, γ— is the penalty coefficient, P_i^g— is the probability of sanctions, β— is the network effect coefficient, NE_i^g— is the network externality.

In the payoff function, C_i^g denotes the specific cost associated with strategy g. According to the strategy cost matrix C_{ig} defined in formula (28), we specify: Where C_i^g includes the basic R&D costs C_1 and camouflage costs C_2 defined in formula (28)

Choosing Strategy 1 (Real green R&D): The firm commits to substantive technological innovation. The expected return Π_1 is an expected value that incorporates the innovation success probability φ and the resulting market premium. It can be expressed as:

$$\Pi_1 = R_i + \varphi R_{GQ} - C_1 + \iota \cdot S_i^1 + \beta \cdot NE_{i1}^t \quad (24)$$

Where R_i is the baseline profit, R_{GQ} is the additional market allocation from the green quota system, and C_1 is the actual R&D expenditure (equivalent to c(φ)). $\iota \cdot S_i^1$ represents the legitimate tax incentives received for successful or ongoing green R&D activities.

Choosing Strategy 2 (fake R&D/Camouflage): The firm does not engage in real innovation but develops "camouflage" products to defraud the government of tax incentives. The expected return Π_2 accounts for the lower cost of deception and the risk of being sanctioned by regulators:

$$\Pi_2 = Z_i - C_2 + \iota \cdot S_i^2 - \gamma \cdot P_i^g + \beta \cdot NE_{i2}^t \quad (25)$$

Where$b_2$is the cost of camouflage ($C_2 < C_1$). $\iota \cdot S_i^2$ denotes the illicit tax benefits gained through misreporting, while $\gamma \cdot P_i^g$ represents the expected penalty, with γ being the penalty coefficient and P_i^g being the probability of the regulator detecting the non-compliance.

Choosing Strategy 3 (Conventional production): The firm maintains its existing traditional manufacturing processes without engaging in any form of green R&D or misreporting. The expected return Π_3 is purely derived from the baseline market profit and the network externalities associated with the traditional production cluster:

$$\Pi_3 = R_i + \beta \cdot NE_{i3}^t \quad (26)$$

Where $R_i = (p - c)\frac{w - \eta w}{N}$ represents the baseline market profit in the absence of green innovation (as derived in formula 17). Since the firm does not undertake green R&D, it incurs no additional costs ($C_i^3 = 0$) and is ineligible for tax incentives ($\iota \cdot S = 0$). The term$\beta \cdot NE_{i3}^t$ captures the network externality benefits gained from the existing industrial scale and traditional market synergy.

In the process of switching between the two strategies, there is a cost associated with the difference in strategies, whereas there is no additional cost associated with continuing the strategy from the previous stage. As follow:

$$C_{ig}=C_{jk}=\begin{bmatrix} 0 & C_2 & 0 \\ C_1 & 0 & 0 \\ C_1 & C_2 & 0 \end{bmatrix}. \quad (27)$$

Among them: C_1 – for research and development costs c(φ), C_2 – the cost of camouflage developed for camouflage green ($C_2 < C_1$).

Evolutionary mechanisms of corporate R&D strategies

The Experience Weighted Attraction model combines the properties of belief learning and reinforcement learning to enable the prediction accuracy of behaviours by assigning dynamic weights to choices during the learning process. In this paper, the EWA model is applied to portray the evolutionary strategies and learning behaviours of individuals in R&D decision-making.

The EWA model is as follows:

$$NE_i^g = \sum_{j \neq i} \omega_{ij} \cdot I(g_i = g_j) \quad (28)$$

Where ω_{ij} — is the degree of interaction between companies, the indicator function reflects the convergence of strategies:

$$I(g_i = g_j) \quad (29)$$

is an indicator that company i has chosen strategy j. This allows us to take into account the clustering effect of innovative behavior, which is characteristic of the renewable energy industry.

$$\text{If } g_i = g_j = 1 \quad (30)$$

They have connection.

The higher the attractiveness index, the higher the probability of being selected. The probability that individual i chooses strategy g at moment t is:

$$P_i^g(t) = \frac{\exp(\lambda A_i^g(t))}{\sum_k \exp(\lambda A_i^k(t))} \quad (31)$$

where $A_i^g(t)$— attractiveness of the strategy, λ— s the strategy's attractiveness, and λ is its sensitivity to choice.

Attractiveness is updated based on accumulated experience:

$$A_i^g(t) = \rho \cdot A_i^g(t-1) + \delta \cdot \Pi_i^g(t) \quad (32)$$

Its inverse denotes the noise effect due to disturbances. The noise effect implies that individuals may not always rationally choose the highest payoff strategy, i.e., a low payoff strategy may also be chosen by a high payoff with a lower probability.

In this paper, noise indicates that individuals have limited rationality and do not have access to all information when making decisions. In addition, some uncontrollable factors in the external environment can interfere with the manufacturer's decision.

According to the previous research, we set the noise level as λ At time t, individuals update their strategies in a synchronized manner. The simulation outcomes are derived as the average of 50 experiments conducted under consistent parameter configurations.

To investigate the strategic dynamics between low-carbon enterprises and the government during subsidy applications, the study integrates the network effect function and employs the EWA model to compute the probabilities of different strategic choices. Considering the specific traits of renewable energy power companies as low-carbon enterprises, the parameters of the network effect function and the EWA model are informed by prior studies.

Table 2.2.1 Parameters of the model

Name	Explain	Data
β	Index of network effects	1.5
ρ	Past experience discount rate	0.25
δ	Anticipated adjustment multiplier	0.5
λ	Responsiveness of the attractiveness parameter	0.1

In summary, this study constructs a unified and coherent identification strategy through a progressive sequence from the Difference-in-Differences (DID) model to the Triple Differences (DDD) model and further to the dynamic effect model (event study approach). The logic is as follows: the post-2013 tax-support regime serves as an exogenous shock to ensure causal identification; the DID model, derived within the potential outcomes framework, is used to estimate the average treatment effect: the DDD extension captures effect heterogeneity across different firm behavioural patterns; and the event study methodology is incorporated to trace the time lag and dynamic evolution of the policy impact. All models adhere to consistent variable definitions (e.g. measuring innovation output by the number of green invention patents) and rigorous econometric specifications, tailored to the context of green technology innovation among renewable energy firms in China. This comprehensive approach underpins the scientific validity and reliability of the study's findings.

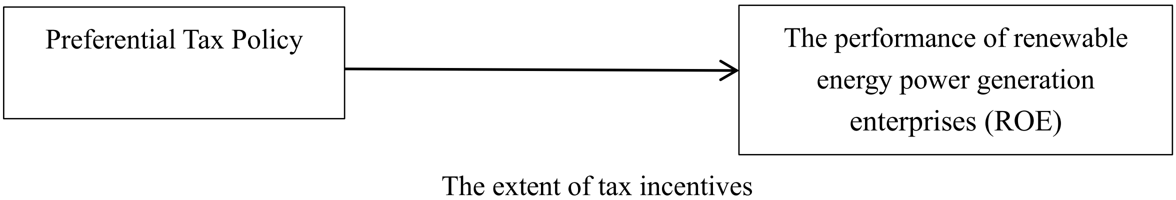
2.3 Empirical Research Logic and Research Hypotheses on the Impact of Tax Incentive Policies on Technological Innovation in China's Renewable Energy Industry

In recent years, the Chinese government has promulgated a series of tax incentive policies to stimulate enterprise development. Based on a suite of green tax preference policies implemented by the Chinese government for the renewable energy power generation industry starting from 2013, this study treats the year 2013 as the starting point of the post-2013 policy regime for a quasi-natural experiment. Notifications such as the "Notice on Continuing the Pre-tax Additional Deduction Policy for Enterprise R&D Expenses" (Finance and Taxation〔2013〕No.60,〔2016〕No. 70) issued by the Ministry of Finance and the State Administration of Taxation further expanded the scope of pre-tax additional deductions for R&D expenses, encouraging enterprises to conduct R&D activities to obtain more tax benefits. The aforementioned measures are supported by the legal basis provided, for instance, by the "Renewable Energy Law of the People's Republic of China" – Article 26 of which explicitly states that the state provides tax incentives for projects listed in the renewable energy industrial development guidance catalogue (Table 2.3.1, Appendix F and Table 2.3.5 Appendix G).

Within this policy context, this paper constructs an empirical research framework comprising three stages, designed to sequentially examine the impact mechanism of tax incentive policies on the financial performance and green innovation of renewable energy enterprises, as well as the heterogeneity of these effects across different firms.

Experiment 1: This experiment aims to investigate the impact of tax incentive policies on corporate Return on Equity (ROE), using a two-way fixed effects model as the foundational research model. Firstly, the primary objective of a firm is to maximize profits, which supports sustainable operation. Given that this study focuses on the impact of tax incentives on the renewable energy power generation industry, Experiment 1 takes listed companies in this sector as the research sample. It employs panel data regression methods to test the correlation between tax incentive policies and corporate financial performance, specifically examining changes in corporate profitability (Return on Equity, ROE) following the onset of the post-2013 policy period. Existing research indicates that the ROE of new energy enterprises, such as those in wind and solar power, increased significantly after enjoying tax incentives. The profit increase resulting from tax reduction not only directly enhances corporate financial performance but also provides financial assurance for technological research and development, thereby laying the foundation for further innovation investment. (Table 2.3.2)

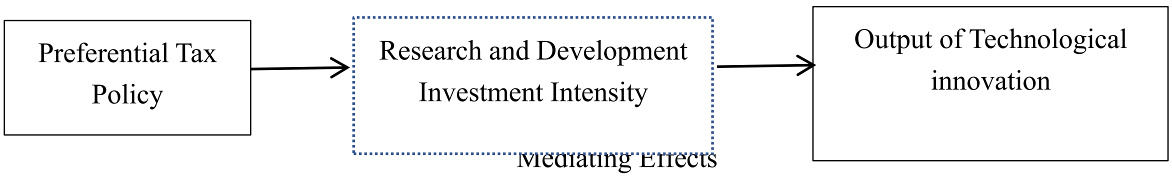
Table 2.3.2 The flame of extent of tax incentive



Source: the author organized the text according to its structure

Experiment 2: This experiment investigates the impact of tax incentive policies on technological innovation in the renewable energy industry, using a Difference-in-Differences (DID) model as the foundational research framework. The sample is expanded to include all enterprises in the power generation sector, constructing a DID model to identify the causal effect of the onset of the post-2013 policy period. Given the multitude of tax incentive policies promulgated in China around 2013, the year 2013 is designated as the experimental cutoff point. Renewable energy enterprises eligible for the tax incentives constitute the treatment group, while traditional energy enterprises not receiving the incentives serve as the control group, comparing the changes before and after the onset of the post-2013 policy period. The model incorporates both firm fixed effects and time fixed effects to control for the influence of unobserved heterogeneity and common trends. Within this framework, the analysis focuses on testing whether tax incentives indirectly drive green technology innovation output (measured by the number of green patents) by enhancing R&D intensity (R&D expenditure as a proportion of operating revenue). Specifically, it examines the policy's effect on corporate R&D investment and the subsequent effect of increased R&D investment on green patent output, thereby verifying the validity of the impact of R&D investment as an intermediary mechanism on green innovation output. If, following the implementation of the tax incentives, the treatment group enterprises show a significant increase in both R&D intensity and green patent output compared to the control group, and if the increase in R&D intensity partially explains the rise in patent output, it would indicate that the tax incentives indirectly promoted green technology innovation by stimulating R&D investment. (Table 2.3.3)

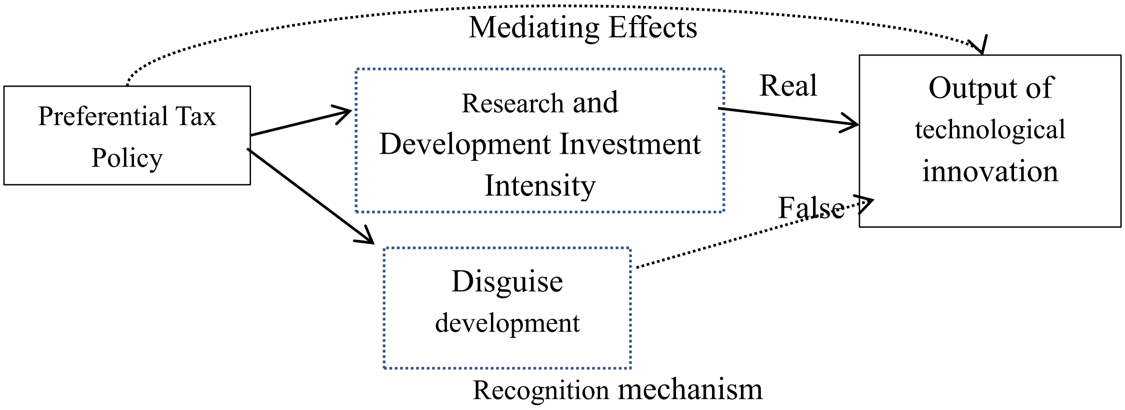
Table 2.3.3 Preferential Tax Policy Mediating Effects



Source: the author organized the text according to its structure

Experiment 3: This experiment aims to identify potential "Fake R&D" by firms, using a Triple Differences (DDD) model as the foundational research framework. Acknowledging the impact of heterogeneity in firms' innovation capabilities on the policy effects, a Principal Component Analysis (PCA) is first employed to integrate indicators such as corporate innovation input, operating cash flow, and patent output, thereby constructing a potential Fake R&D. A triple interaction term—incorporating the onset of the post-2013 policy period, firm classification (based on innovation capability), and time—is then incorporated into the regression model for the DDD analysis. This stage is designed to test whether the tax incentive policy exerts a significant heterogeneous effect across firms with different levels of innovation capability, that is, whether there are systematic differences in the policy response between firms with high innovation capability and those with low innovation capability. (Table 2.3.4)

Table 2.3.4 Research frame of tax incentive



Source: the author organized the text according to its structure.

(1) Research Hypotheses

Hypothesis 1: Tax incentives can significantly improve the profitability (ROE) of renewable energy companies.

China is accelerating the development of renewable energy, actively promoting carbon peaking and carbon neutrality goals, and has introduced a series of tax incentive policies to support the development of the new energy industry. Therefore, to explore whether tax incentives can significantly improve the profitability of renewable energy companies and provide financial security for their innovation and R&D, this paper proposes Hypothesis 1 based on this logic.

Hypothesis 2: Tax incentives have a positive promoting effect on the green technology innovation output of renewable energy companies.

Previous studies have shown that tax incentives can significantly improve companies' R&D investment and innovation capabilities by reducing their tax burden and increasing their disposable funds. Therefore, to explore whether tax incentives in the renewable energy field can encourage companies enjoying tax incentives to invest more funds in green technology R&D, thereby generating more high-value green invention patents, this paper proposes Hypothesis 2.

Hypothesis 3: The impact of tax incentives on the green technology innovation output of renewable energy companies exhibits significant heterogeneity.

Hypothesis 3a: Significant regional heterogeneity exists; tax incentives have a stronger promoting effect on the green innovation output of renewable energy companies in the central and western regions. Non-eastern regions often lag behind in R&D investment, talent reserves, and technology market maturity, making their enterprises more sensitive to external policy incentives and resulting in a more significant marginal effect of tax breaks. Meanwhile, as the central and western regions are key follow-up areas in China's energy strategy, possessing richer renewable energy resources, policy dividends can be more directly translated into internal motivation for enterprises to develop these resources and engage in targeted innovation.

Hypothesis 3b: Tax incentives have a stronger promoting effect on the green innovation output of non-state-owned renewable energy enterprises.

Ownership structure may also affect policy effectiveness. State-owned enterprises are generally considered to have ample financing channels, but their efficiency may be lower, while private enterprises are often more sensitive to fiscal incentives. Tax incentives can reduce the burden on private enterprises, increase their income, and thus help stimulate their R&D and innovation motivation. State-owned enterprises may be less dependent on a single tax incentive due to access to other policy resources. Therefore, the incentive effect of tax incentives on non-state-owned renewable energy enterprises is expected to be stronger than that on state-owned enterprises.

Hypothesis 3c: High Current expensed R&D investment will have a positive impact on green innovation output. Because enterprises invest heavily in the initial R&D exploration phase of green innovation, higher current-performing R&D expenses mean they can support more intensive R&D activities, accommodate more trial-and-error processes, and accelerate the iterative accumulation of knowledge. This directly improves the efficiency of achieving green technology breakthroughs and obtaining patents. Therefore, it is reasonable to infer that current-performing R&D expenses will affect green innovation output.

Hypothesis 4: R&D intensity as a mediating mechanism affecting green innovation output.

To further reveal the intrinsic mechanism by which tax incentives affect corporate green innovation, this paper proposes a fourth research hypothesis: tax incentives indirectly promote green technology innovation output by increasing corporate R&D intensity. Tax incentives can release disposable funds for enterprises, reduce the marginal cost of R&D, and thus increase the proportion of R&D expenditure to operating revenue. Increased R&D intensity not only reflects the strategic orientation of enterprises but also demonstrates their positive attitude towards green technology innovation output.

Hypothesis 5: Tax incentives may lead to fake R&D behaviour. When enjoying tax incentives and other support policies, some enterprises may use accounting techniques to increase the capitalization rate of R&D expenses to obtain higher tax credits, thereby engaging in fake R&D activities. Develop indicators to identify potential fake R&D. Under tax incentives, companies may capitalize R&D expenditures that would otherwise be expensed.

Hypothesis 6: Compared with single-policy intervention, a coordinated policy configuration integrating tax incentives and penalty constraints is more effective in promoting the diffusion of genuine green R&D, because it can reduce firms' innovation costs, curb fake R&D behaviour, and enhance the regional adaptability of policy implementation.

Based on the current policy context and theoretical analysis, the above assumptions explore the potential impact of tax incentives on the performance of renewable energy companies and green innovation output. The second chapter analysis of tax incentive policies, analysis of the driving mechanism and influencing factors of technological innovation, and the mechanism of tax incentive policies on technological innovation in China's new energy power generation industry:

1. Analysis of Industry Status and Structural Contradictions. This chapter systematically reviews the large-scale development path and global positioning of China's renewable energy, highlighting the deep-seated structural problems such as disguised R&D behind the surge in installed capacity, and comparing them with the tax incentive practices of countries such as the developed country.

2. Construction of a Causal Inference Methodology System, A difference-in-differences (DID) baseline model was constructed to identify the average treatment effect

of the policy, and an event study method was introduced to test the parallel trend assumption and the dynamic lagged effects of the policy.

3. Identification of fake R&D and Design of a Triple Difference Model: A novel approach using principal component analysis (PCA) was introduced to construct a "potential fake R&D capability index (*Fakei*)" based on three dimensions: earnings before interest and taxes, R&D capitalization rate, and net operating cash flow. A triple difference (DDD) model was then built based on this index to accurately isolate non-substantive innovation behaviors of enterprises using accounting methods for tax arbitrage.

4. Empirical Logic and Research Hypothesis Derivation: Based on neoclassical investment theory and information asymmetry theory, six core hypotheses were systematically derived, covering profitability (ROE), green innovation output, heterogeneous adjustments (regional and ownership), and mediating transmission mechanisms, laying a rigorous logical foundation for subsequent empirical testing and evolutionary game simulation.

CHAPTER 3. EMPIRICAL ANALYSIS OF TAX INCENTIVES ON TECHNOLOGICAL INNOVATION IN CHINA'S RENEWABLE ENERGY INDUSTRY AND POLICY RECOMMENDATIONS

3.1 An Empirical Analysis of the Effects of Tax Incentives on Corporate Performance and Green Innovation Output

This dissertation utilizes a sample of energy sector listed companies from the Shanghai and Shenzhen A-share markets in China during the period 2009–2023. The sample comprises 67 enterprises, which are divided into two groups based on their primary business activities: renewable energy enterprises and non-renewable energy enterprises. Specifically, 26 are classified as renewable energy enterprises (mainly engaged in green energy businesses such as wind power), and 41 are classified as non-renewable energy enterprises (primarily engaged in traditional fossil fuel power generation). This timeframe, spanning from the post-financial crisis era to the announcement of the "carbon neutrality" goal, facilitates the observation of dynamic changes before and after policy implementation (Table 3.1.4, Appendix J). Given that the Chinese government promulgated multiple tax incentive policies related to renewable energy in 2013, such as Cai Shui [2013] No. 66 and Cai Zong [2013] No. 103. 2013 is designated as the policy intervention year for Experiments 2 and 3.

Regarding data sources, the data for this study are primarily sourced from authoritative domestic financial databases and research-oriented databases: the CSMAR database, the Wind database, and the RESSET database. Specifically, the RESSET Green Patent Database is used to obtain data on the number of green technology patents held by firms. Aligned with Noe’s profile of the World Intellectual Property Organization (WIPO), this database filters patent data from the China National Intellectual Property Administration using WIPO’s International Patent Classification Green List to identify green patents granted or applied for by listed companies [111]. Data on the number of applications and grants for green invention patents and utility model patents for each company are extracted from RESSET and used to construct the green innovation output indicators. The combination of these data sources ensures the authoritativeness and reliability of the sample data used in this study. The pricing method is denominated in RMB, which will not be elaborated further below.

Reasons for variable selection (Table 3.1.1, Appendix H). The first experimental sample: Following the approach of Yeoh W.W [168], the explanatory variable was constructed as return on equity (ROE), which is the ratio of net profit to average shareholders' equity and is an important financial indicator for measuring the profitability of listed companies. The higher the indicator, the higher the rate of return on shareholders' equity and the higher the efficiency of the company in using its own capital. The core explanatory variable is the level of tax support, which is measured by the ratio of tax refunds received by the company to various taxes paid. This indicator can intuitively reflect the actual level of support obtained by the company from the tax system from the perspective of cash flow. At the same time, we performed a 1% tail reduction on the continuous variable to eliminate the influence of extreme values.

Experiment 2 sample: The dependent variable is green innovation output (I), which is represented by the logarithm of the number of green patents. Specifically, the indicator was constructed as follow formula 33:

$$Y_{it} = \ln\left(\text{Number of green independent patents grants} + \text{Number of green independent patents applied} + 1\right) \quad (33)$$

The green patents granted to enterprises in a given year are summed with the number of green patents applied for in that year, and the result is taken as the natural logarithm (adding 1 is to avoid taking the logarithm as zero when there are no patents). This innovation indicator comprehensively considers both the output (granting) and input (application) of green technology achievements, and can more comprehensively reflect the actual output level of enterprises' green technology innovation. To identify the causal effect of the policy, the core explanatory variable is the difference-in-differences variable constructed in this paper: Treat: A dummy variable for the treatment group. If the enterprise belongs to the renewable energy industry (wind power, photovoltaic, etc.), then $Treat_i$=1; otherwise (traditional non-renewable energy enterprises), it is taken as 0. Renewable energy enterprises, as the policy beneficiary group, are expected to receive more policy support because they conform to the industrial direction of green development during the research period. Post: A dummy variable for the policy period. $Post_t$=1 for 2013 and later years, representing the period after the onset of the post-2013 policy period; it is taken as 0 before 2013. According to the policy background, 2013 was selected as the dividing point because the government intensively introduced tax incentives to support renewable energy that year. This marked the full implementation stage of tax incentives for renewable energy. did: A difference-in-differences interaction term, defined as did, $did_{it}=Treat_i \times Post_t$. This term captures the net effect of the policy on the treatment group. When did = 1, it represents the scenario after the implementation of the policy for renewable energy companies. The corresponding coefficient reflects the additional change brought about by the policy to renewable energy companies, assuming other factors remain constant. If the tax incentive policy does indeed increase the innovation output of renewable energy companies, we expect the coefficient of this interaction term to be positive.

Third-stage sample: Based on the second stage, a potential fake R&D indicator is introduced as the third interaction term $Fake_i$. Considering that innovation capability is an endogenous characteristic of enterprises and may significantly affect the actual strength of the tax incentive policy, this paper uses principal component analysis to construct a potential $Fake_i$ indicator. EBIT (Earnings Before Interest and Taxes), capitalized R&D investment, and net cash flow from operating activities are selected as the basis for constructing the indicator. EBIT eliminates the impact of capital structure and taxes, reflecting the accounting profit of core operations. Capitalized R&D investment reflects management's recognition of the future economic benefits of R&D projects, reflecting strategic investment for the future. Net cash flow from operating activities reveals the cash-generating capacity of operating activities and is a touchstone of profit quality. However, these three indicators also have certain drawbacks. EBIT is easily affected by accruals and earnings management, capitalized R&D investment is highly subjective, and operating cash flow may be affected by short-term fluctuations in working capital. If used alone, any one indicator may lead to biased conclusions. Therefore, we use PCA to extract the first principal component score as a representative indicator of a company's potential for faked R&D, reflecting a potential tendency through multiple observable indicators. This is because companies that adopt aggressive capitalization of R&D expenditures, possess strong financial support, but have relatively low green patent output may be more inclined to use R&D as a means to obtain preferential treatment rather than genuinely pursuing technological breakthroughs. We also grouped the sample companies by median year, constructing a binary dummy variable $Fake_i$. Companies above the median were designated as the "high potential faked R&D capability group" (set to 1), and the rest as the "low potential faked R&D group" (set to 0).

To mitigate the bias of omitted variables, the following control variables were introduced into all models across the three phases of the experimental samples, covering key dimensions such as corporate financial condition, capital structure, and R&D investment. Specifically, these include:

Cash Flow: as an important measure of a company's financial condition, reflects the renewable energy power generation industry's ability to generate cash from its main business and the adequacy of its internal funds. A higher value indicates more cash available for reinvestment.

Return on Assets (ROA): ROA is calculated from net profit and average total assets, reflecting the renewable energy power generation industry's ability to generate profit using all its assets. A higher ROA value indicates better overall operational performance. This indicator is widely used to measure a company's basic profitability.

Tobin's Q: Tobin's Q measures the market's evaluation of a company's growth potential. It is generally defined as the ratio of a company's market value to its asset replacement cost. Because it is difficult for the renewable energy power generation industry to directly obtain asset replacement costs, empirical studies often approximate this ratio as the ratio of market capitalization to total book assets. A Tobin's Q > 1 suggests that investors are optimistic about the company's future development, while a Q < 1 suggests the opposite.

Net cash flow from operating activities: This is the absolute value of the net cash inflow generated by a company's operating activities. This indicator directly reflects the cash-generating capacity and operating performance quality of the renewable energy power generation industry's main business. A high net cash flow from operating activities indicates a healthy cash position, including sales revenue collection.

Company Size: Expressed as the natural logarithm of total assets, this reflects the size of the company. Size can affect a company's performance and innovation investment.

Larger size indicates a stronger ability to exclude the interference of size heterogeneity.

Total Assets: Higher total assets mean a larger proportion of long-term capital in the company's assets, indicating a capital-intensive nature. Net fixed assets affect a company's cost structure and investment behaviour.

Net Fixed Assets: This represents a company's capital intensity or tangible asset strength. Companies with high capital intensity, such as those in manufacturing, and companies with low capital intensity, such as those in the software industry, exhibit systematic differences in R&D models, investment decisions, and financing methods. Since the renewable energy power generation industry exhibits both high and low capital intensity, this indicator is chosen as a control variable.

Ending Cash and Cash Equivalents Balance: The cash and cash equivalents held by the company at the end of the year, measuring its liquidity and short-term solvency. A higher cash balance provides a stronger financial buffer and investment flexibility, but excessive idle cash may also indicate underutilization of resources.

R&D Expenditure as a Percentage of Revenue: This indicator represents R&D intensity, expressed as the ratio of R&D expenditure to revenue. It reflects the relative strength of a company's R&D investment, eliminating the influence of scale, and is often used to measure a company's willingness to invest in innovation.

Total R&D Investment: The total amount of R&D expenditure by the company in the current year (logarithmic). Total R&D expenditure controls the absolute scale of a company's R&D investment, capturing the effect that large companies may invest more in absolute R&D.

R&D Capitalization Ratio: The proportion of R&D expenditure capitalized in the current year, i.e., the ratio of R&D expenditure capitalized in the current year to total R&D expenditure. This indicator reflects how much R&D investment a company recognizes as intangible assets in its accounting, rather than current expenses. Different companies may adopt different R&D capitalization policies, which have an impact on financial performance and asset structure, so this is controlled for (CSMAR data).

The selection of the above control variables comprehensively considers aspects such as corporate profitability, operating conditions, growth potential, financial structure, governance characteristics, and innovation investment, basically covering the main factors affecting corporate performance and innovation. By uniformly including these control variables, the net impact of tax incentive policies and the degree of tax incentives on the dependent variable can be identified more accurately.

In the first phase of empirical analysis, since profit is key to business development, this chapter as a whole is based on a broader panel of 67 power generation firms, but the first-stage fixed effects analysis is conducted only on the renewable energy subsample of 26 firms.to verify whether policies can truly promote business growth. following the sample selection method outlined in section 3.1, companies subject to special treatment (ST, *ST) during the study period and observations with missing key financial data were excluded.

Based on this, the following two-way fixed effects model was established formula 34:

$$ROE_{it}=\alpha+\beta\cdot TaxSubsidy_{it}+\gamma Xit+\mu_i+\lambda_t+\epsilon \quad (34)$$

Where in, this model is designed as a preliminary empirical test of the financial-performance effect of tax incentives, providing a mechanism-based foundation for the subsequent identification of innovation effects, rather than serving as the core causal identification strategy of this study. subscript i represents the company, t represents the year; ROE_{it} is the return on equity of company i in year t; $TaxSubsidy_{it}$ is the tax incentive level indicator defined above; X_{it} is a factor of control variables; μ_i represents the company fixed effect, used to control for inherent invariant characteristics of different companies; λ_t represents the year fixed effect, used to control for common factors affecting all companies over time, such as macroeconomic conditions and industry prosperity; ϵ is the random error term. The model uses two-way fixed effects to leverage the advantages of panel data and control for the interference of unobservable heterogeneity on the estimation results. After incorporating individual and time effects, the estimated value of β reflects the differences in ROE resulting from different levels of tax incentives under the same macroeconomic environment. The data standardization process for these three indicators was the same in Experiments 2 and 3, and will not be repeated below.

We can see Figure 3.1.1 descriptive statistics reveal some differences in the financial performance and R&D investment of the sample companies. The mean Return on Equity (ROE) is 0.613, with relatively small fluctuations, indicating that most companies have relatively stable profitability, but a few are on the verge of losses. We can see Table 3.1.3(Appendix I). The mean tax subsidy is only 0.034, suggesting that companies generally receive limited tax benefits, and the relatively large standard deviation indicates significant differences in the extent to which different companies benefit from tax policies. Regarding cash flow, the mean ratio of operating cash flow to total assets is 0.637, reflecting a generally good internal financial situation. The mean ROA (Return on Assets) is 0.662, indicating that most companies perform reasonably well in utilizing their assets to generate profits. The mean Tobin's Q is 1.56, but the highest value is close to 9, suggesting that some companies may be highly recognized by the capital market, while also reflecting significant differences in companies' growth expectations. Among the variables reflecting company size and capital structure, the standard deviations of total assets and net fixed assets are both large, indicating significant heterogeneity in size and capital intensity among the sample companies. Furthermore, the median values of indicators such as ending cash balance and net cash flow from operating activities were both below the mean, suggesting that some companies are experiencing relatively tight short-term cash flow. Regarding R&D, the average ratio of R&D expenditure to operating revenue was 0.075, which, while not high overall, showed that some companies had significantly higher R&D intensity than the average, indicating that some companies have a high willingness and ability to invest in innovation activities. The average capitalization ratio of R&D expenditure was 0.202, suggesting that some companies tend to recognize R&D activities as long-term assets, possibly related to their expectations of the sustainability of R&D results.

Overall, the sample companies exhibited certain differences in profitability, market valuation, financial status, and innovation investment, providing a foundation for subsequent grouped regression and policy effect identification.

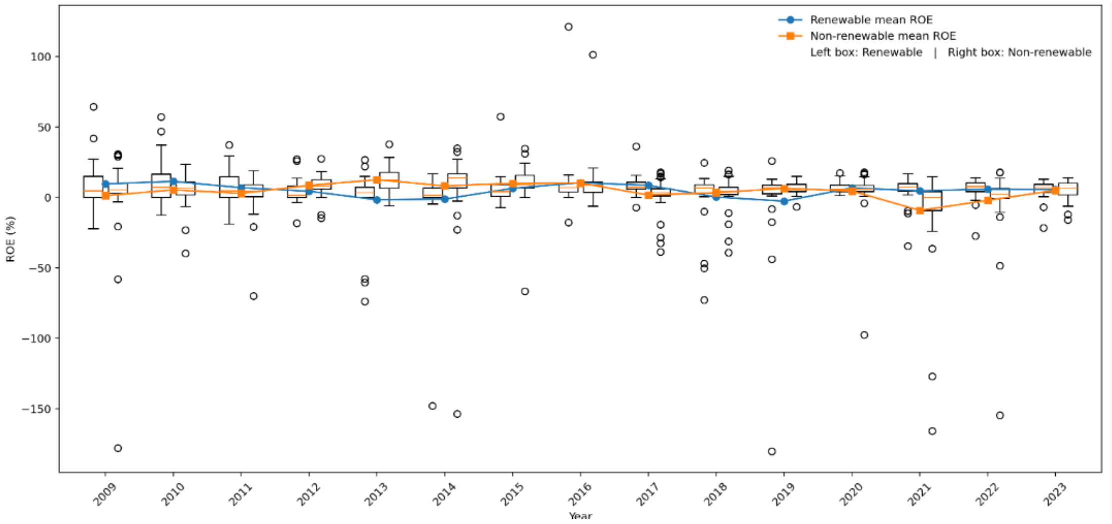


Figure 3.1.1 ROE of renewable energy companies from 2009 to 2023 in China

Source: The author compiled the data based on the Wind database.

Figure 3.1.1 presents the changes in return on equity (ROE) for wind power, photovoltaic, and other types of renewable energy companies from 2009 to 2023. Overall, ROE fluctuates to some extent across different periods and companies. The ROE of most samples is concentrated between -20% and 20%, indicating that the overall profitability of these companies is relatively moderate.

Table 3.1.2 Baseline Regression of phase 1

	(1) ROE
Tax_S	0.108***
	(0.036)
Cash Flow	0.001
	(0.053)
ROA	0.626***
	(0.209)
Tobin's Q (A)	0.248***
	(0.063)
Net Cash Flow from Operating Activities	-0.034
	(0.129)
Company Size	0.006**
	(0.002)
Total Assets	1.628***
	(0.431)
Net Fixed Assets	0.056
	(0.076)

Ending Cash and Cash Equivalents	-0.047**
	(0.021)
Total R&D Investment as a Percentage of Revenue	-0.046
	(0.033)
Total R&D Investment	-0.208*
	(0.119)
R&D Capitalization Ratio - std	0.007
	(0.014)
_cons	0.110
	(0.130)
N	390.000
Controls	YES
Id	YES
Year	YES
R^2	0.523

Standard errors in parentheses * p <0.1, ** p <0.05, *** p <0.01

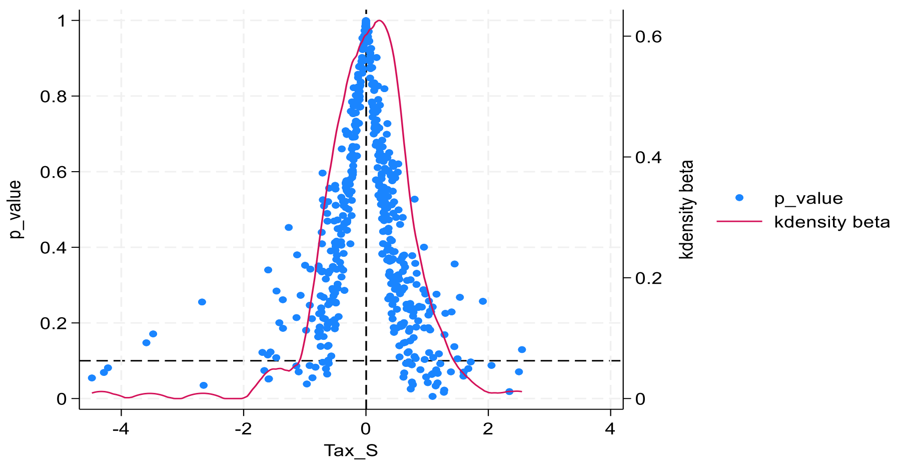
This paper randomly assigns sample companies to a randomly reassigns the tax incentive variable across firms while keeping the sample structure unchanged and repeats the robustness experiment 500 times to verify its robustness. The estimate for each randomization of 500 times is:

$$ROE_{it}=\alpha+\beta_{perm}^{(500)}\cdot TaxSubsidy_{it}^{(500)}+\gamma Xit+\mu_i+\lambda_t+\epsilon \quad (35)$$

$TaxSubsidy_{it}^{(500)}$, based on the construction of randomly assigned processing states, the experimental results are as follows:

Figure 3.1.2 Tax_S robustness experiment 500 time

To test whether the estimated effect of tax incentives is driven by random matching



between the explanatory variable and the outcome variable, this research conducts a permutation-based placebo test. Specifically, while keeping the sample structure, firm-year observations, and control variables unchanged, the tax incentive variable is randomly reassigned across firms (or permuted across firm year observations), and the benchmark regression is estimated 500 times. (Table 3.1.3, Appendix I)

The results show that, under randomized settings, Tax_S variables do not have a systematic explanatory power for ROE. Notably, the estimated coefficient of Tax_S in the actual regression is 0.108, with a corresponding p-value of 0.014, far below the conventional significance level of 0.05, and clearly located at the right tail of the simulation results. Further statistical analysis reveals that in 500 perturbation experiments, the estimated coefficient exceeded the actual regression result only 9 times (i.e., the frequency of coefficients greater than 0.108 under the null hypothesis is 1.8%), indicating that the main conclusion has a high statistical confidence level. This result eliminates accidental significance due to sample partitioning or model specification, further verifying that tax policy has a significant positive impact on ROE.

In the first stage of empirical analysis, this paper uses a regression model to verify a significant positive relations hip between tax incentives and corporate profitability. Specifically, companies enjoying higher tax support have statistically significantly higher return on equity (ROE). This result indicates that tax incentives effectively reduce the burden on enterprises, release more disposable resources, and provide a financial foundation for subsequent investment activities.

3.2 An Empirical Analysis of Tax Incentives for the Renewable Energy Power Generation Industry

After examining the effect of tax incentive intensity on corporate profitability, this study further investigates whether the post-2013 renewable energy of oriented tax support regime also promotes green technological innovation. Tax incentives are not designed merely to improve firms’ short term financial performance. More importantly, they are expected to guide firms toward green and low carbon transformation by encouraging technological innovation. Therefore, the next step is to examine whether renewable energy firms achieved stronger green innovation output after the implementation of the post-2013 tax support regime. Therefore, to identify this causal relationship, this paper uses a difference-in-differences method to construct a quasi-natural experimental design; the basic model settings are detailed in Section 2.2. In the second stage of analysis, this paper further examines the impact path and effects of tax policies on corporate green innovation output. In 2013, China issued a series of new tax incentive policies for the renewable energy industry (Finance and Taxation Document No. 66 of 2013 and Finance and Taxation Document No. 103 of 2013), which included a 50% VAT refund for eligible renewable energy power generation enterprises and preferential income tax for high-tech enterprises. 2013 is treated as the onset of a renewable energy of oriented tax support regime shift, rather than a single isolated policy shock. This provided a quasi-natural experimental scenario for this study. We considered renewable energy firms are treated as the higher exposure group, while traditional power firms serve as the lower exposure comparison group under the post-2013 renewable energy of oriented tax support regime. We used the onset of the post-2013 policy period date to divide the period into two phases: before and after the policy intervention. The identification logic of DID in this paper is not based on an absolute dichotomy of "with policy" and "without policy," but rather on "differences in policy exposure intensity." Since 2013, a set of targeted tax support policies has been implemented for the renewable energy industry. Therefore, the DID coefficient in this paper identifies the marginal net change of the high exposure group relative to the low exposure group under the post-2013 renewable energy oriented tax support regime, the average relative policy effect, rather than simply assuming a completely zero policy shock to the control group. As long as the two groups exhibit parallel trends before the policy, the additional changes observed after the policy can be interpreted as a result of differentiated policy dosage. We constructed an interaction term to capture the differences in changes between the treatment and control groups before and after the policy intervention. The corresponding regression model is set as follows:

$$Y_{it}=\alpha+\beta_1(Treat_i\times Post)+\gamma Xit+\mu_i+\lambda_t+\varepsilon_{it} \quad (36)$$

Where Y_{it} represents the green innovation output level of firm i in year t, and the core explanatory variable $Treat_i \times Post_t$ is the interaction term between the treatment group dummy variable and the onset of the post-2013 policy period time dummy variable. Its coefficient β_1 is the average treatment effect of interest in this study, which captures the net change of the treatment group firms relative to the control group firms and their own time trend after the onset of the post-2013 policy period. The model simultaneously controls for the individual fixed effect μ_i that does not change with time and the time fixed effect λ_t that does not change with individuals to absorb unobservable heterogeneity and common time trends. X_{it} is a set of control variables that change with time and individuals. We can see the Appendix K (Table 3.2.1) from the descriptive statistics in the table above, the mean of the green technology innovation index Y is 0.364, the standard deviation is 0.862, and the maximum value is 5.328. Combined with the median of 0, this indicates a significant divergence in green patent output among the sample companies, showing an overall skewed distribution. Further observation reveals that green patent applications and authorizations are mainly concentrated in renewable energy power generation companies, indicating that these companies are relatively more active in green technology innovation under policy guidance, while the green patent output of most traditional energy companies remains at a low level.

As we shown in Appendix K, the mean of the policy interaction variable did is 0.355 indicating that approximately 35.5% of the observations come from renewable energy companies after the onset of the post-2013 policy period, providing the necessary between group and time dimension structure for the difference-in-differences identification strategy.

Regarding financial characteristics, the mean of cash flow is 5.877, and the standard deviation is 5.366, reflecting significant differences in internal financial conditions among companies. The mean ROA are 1.740, with significant fluctuations. Some companies experienced extreme losses or profits, indicating a broad sample coverage that reflects the diversity of operations within the industry.

Regarding innovation investment, the mean R&D intensity (R&D expenditure as a percentage of revenue) is 1.437%, with a median of 0.495%. The overall distribution is right-skewed, indicating that some companies have a high R&D investment ratio, but most remain at a low level. The mean R&D capitalization ratio is 11.79%, but the maximum reaches 133.6%, significantly higher than the generally reasonable range. If a company has high cash flow and a high R&D capitalization ratio but lacks corresponding green patent output, it may be engaging in "strategic R&D behaviour" aimed at obtaining tax incentives. This phenomenon suggests that some companies may not truly translate R&D investment into technological achievements, but rather enhance their R&D performance through accounting manipulation, potentially indicating faked R&D activities.

Table 3.2.2 Second-stage experimental baseline regression

	(1)
	Y
did	0.402**
	(0.162)
Cash Flow	0.007
	(0.005)
ROA	0.001
	(0.003)
Tobin's Q (A)	0.068
	(0.054)
Net Cash Flow from Operating Activities	0.000
	(0.000)
Company Size	-0.070
	(0.080)
Total Assets	0.000***
	(0.000)
Net Fixed Assets	-0.000***
	(0.000)
Ending Cash and Cash Equivalents	-0.000
	(0.000)
R&D Investment as a Percentage of Revenue	-0.002
	(0.026)
Total R&D Investment	-0.000
	(0.000)

R&D Capitalization Ratio	0.000
	(0.001)
_cons	1.372
	(1.885)
N	524.000
Controls	YES
Id	YES
Year	YES
R^2	0.708

Standard errors in parentheses* p <0.1, ** p <0.05, *** p <0.01

The R^2 of this model is 0.708 (Table 3.2.2), indicating strong explanatory power and a good overall model fit. The coefficient of the core explanatory variable did is 0.402, significant at the 5% significance level (standard error 0.162) After the policy was implemented, the average increase in green innovation activities among enterprises in the treatment group was approximately 49.5%. This indicates that the post-2013 tax support system's promotion of green innovation activities was not a minor marginal improvement, but rather a significant innovation enhancement effect with substantial practical implications. The expected value after the policy's effect is $Y_1=e^{0.402}-1$, $Y_1=1.495-1$ means that for enterprises with a weak foundation in green innovation, tax policies can help them move from a low level of innovation to a more stable range of green invention output; while for enterprises that already have a certain foundation in innovation, this manifests as a significant acceleration in the accumulation of green inventions. This reflects the identifiable and substantial practical driving effect of tax policies on enterprises' green innovation behavior.

Regarding control variables, most did not reach statistical significance, indicating that their direct impact on green innovation output is relatively limited. Among them, total assets showed a significant positive impact on green innovation (coefficient 0.000, $p < 0.01$), while net fixed assets showed a significant negative relationship (coefficient -0.000, $p < 0.01$), which may mean that companies with a strong capital-intensive structure have relatively weaker green innovation output.

To observe the changing trends in corporate green innovation performance before and after the introduction of tax policies, this paper employs an event study methodology.

Using the year of the onset of the post-2013 policy period as a boundary, a relative time window is constructed, extending from 4 periods before the onset of the post-2013 policy period to 10 periods after, i.e., setting PD = -4 to +10. Each period contains exactly 67 observations, accounting for 6.67% of the total sample of 1005 firm-year observations. This table describes the distribution of the event-time variable rather than the final regression estimation sample. Overall, the sample exists continuously before and after the onset of the post-2013 policy period, without significant breaks or large-scale missing data, meeting the sample completeness requirements of event studies. Table 3.2.3 reports the full distribution of the event-time variable PD, not the final estimation sample used in the DID regression.

Table 3.2.3 PD result

PD	Freq.	Percent	Cum.
-4	67	6.67	6.67
-3	67	6.67	13.34
-2	67	6.67	20.01
-1	67	6.67	26.68
0	67	6.67	33.35
1	67	6.67	40.02
2	67	6.67	46.69
3	67	6.67	53.36
4	67	6.67	60.03
5	67	6.67	66.7
6	67	6.67	73.37
7	67	6.67	80.04
8	67	6.67	86.71
9	67	6.67	93.38
10	67	6.67	100.05
Total	1005	100.05	100

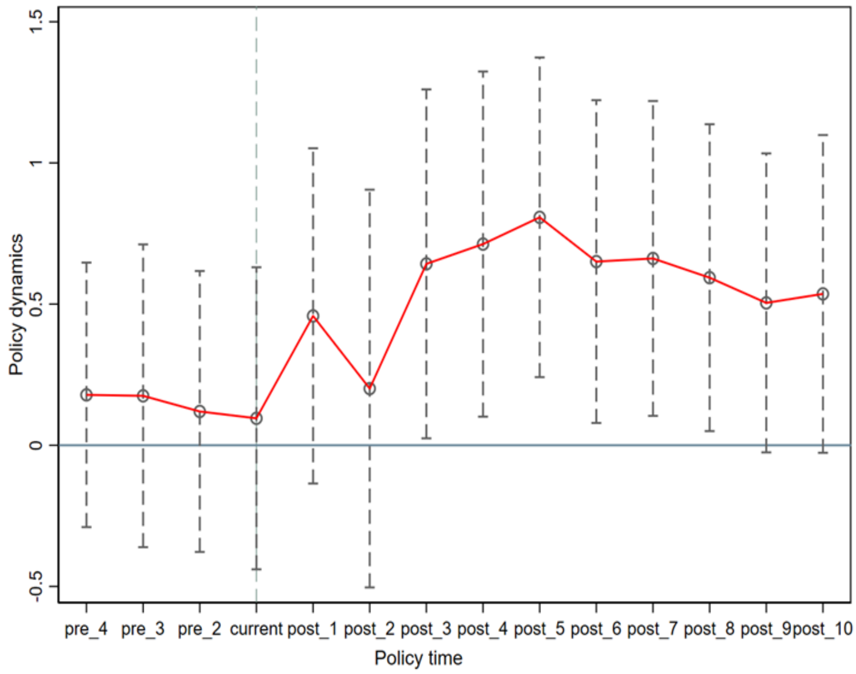


Figure 3.2.1 the onset of the post-2013 policy period Effect Chart

To systematically identify the dynamic impact path of tax incentive policies on enterprises' green technology innovation, this paper constructs an event time window variable and introduces a regression model periodically to track the changing trend of green innovation output before and after the policy. The results show that the regression coefficients for each period before the onset of the post-2013 policy period (pre_4 to current) are not significant (e.g., pre_2 = 0.119, p = 0.692, current = 0.095, p = 0.769), indicating that there was no significant difference in green patent output between the treatment group and the control group before the policy was introduced. This verifies the "parallel trend" hypothesis and provides a premise for the credibility of DID estimation. (Figure 3.2.1)

In the initial stage after the onset of the post-2013 policy period, green innovation output did not immediately increase, exhibiting a certain degree of "lag response." Specifically, the coefficients gradually increased from post1, reaching relative peaks in $post_3$ (coef = 0.644, p = 0.087), $post_4$ (coef = 0.712, p = 0.055), and $post_5$ (coef = 0.807, p = 0.019). This phenomenon indicates that the effects of tax incentive policies are not immediately apparent but require a certain period of time to be reflected in green patent application and authorization data. This lag may stem from the complexity and cyclical nature of green innovation itself; from project initiation and R&D investment to patent application authorization, a considerable amount of time is typically required, especially for technological breakthroughs in the renewable energy field.

However, five years after the policy's implementation, the marginal response of green innovation gradually weakened. Although the coefficients in $post_6$ to $post_{10}$ remained positive (e.g., $post_6$ = 0.662, $post_{10}$ = 0.530), they were statistically insignificant (p-values > 0.1 for all periods), showing a diminishing trend in the incentive effect. One possible reason is that the policy benefits were largely utilized in the early stages, and some companies later used the policies as arbitrage tools, weakening their motivation for innovation. Therefore, the following section will identify this potential "fake R&D."

The significant $\hat{\beta}$ coefficient in the baseline regression may originate from unobservable confounding factors that are simultaneously related to policy allocation and investment decisions. Therefore, this paper performs a systematic set of placebo tests to demonstrate the robustness of the results. First, we conduct a hypothetical policy timing test, artificially setting the onset of the post-2013 policy period year before the actual policy occurred. If the baseline results are reliable, the estimated “treatment effect” at these hypothetical policy points should be statistically insignificant. Second, we perform a treatment state randomization test, constructing an empirical distribution of the estimated coefficients under the null hypothesis (policy ineffectiveness) by repeatedly randomly assigning “treatment group” identities (repeated 500 times) and estimating the model each time.

To further verify that the baseline results are not driven by random factors or sample specificity, we perform a treatment state randomization test. This process is repeated 500 times.

$$Y_{it}=\alpha+\beta_{perm}^{(500)}\left(Treat_i^{500}\times Post\right)+\gamma Xit+\mu_i+\lambda_t+\varepsilon_{it} \quad (37)$$

Collect all estimated coefficients generated by randomization, $\left\{\beta_{perm}^{(1)}, \beta_{perm}^{(2)}, \ldots\ldots, \beta_{perm}^{(500)}\right\}$, the empirical distribution of the estimated coefficients under the condition of policy ineffectiveness in 2013 was constructed, and the results are shown in the figure below:

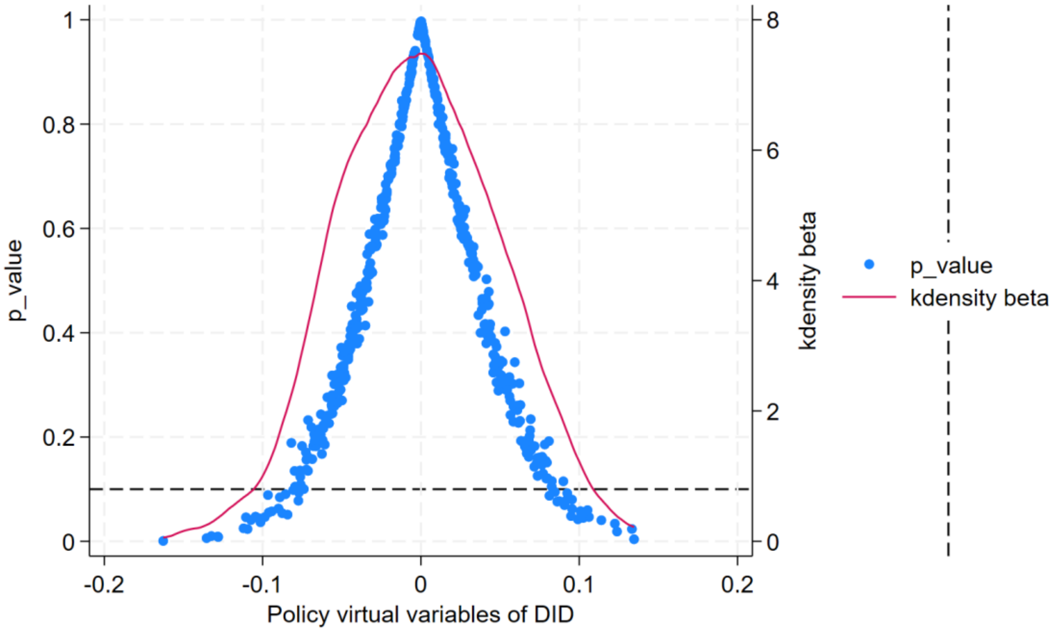


Figure 3.2.2 Phase II placebo test results

As shown in the Figure 3.2.2, the results do not reject the null hypothesis, and the placebo test is successful. The estimated coefficients β of the fictitious policy variables are mostly densely distributed around 0, with their density beta peaking at zero. The p-values are mostly much higher than the conventional significance levels, primarily falling in the high-value range of 0.2 to 0.8. The results show that this identification strategy validates the reliability of the baseline results.

A thorough analysis of the results in Tables 3.2.2, Figures 3.2.1 and 3.2.2 reveals that the DID effect identified in this paper is not due to accidental fluctuations in the sample structure; China's tax incentives for renewable energy have indeed promoted green innovation among enterprises. Secondly, the dynamic effect results show that the impact of tax policies is not fully released immediately upon policy implementation, but rather exhibits a clear characteristic of gradual strengthening. This lag has a reasonable economic explanation. From an accounting perspective, tax incentives first affect enterprises' expectations regarding R&D budgets, project initiation, and funding allocation, and only then gradually transmit to R&D investment, technology accumulation, and patent application authorization results. Therefore, the policy effect usually needs to go through the enterprise's internal decision-making cycle and innovation transformation cycle to fully manifest, which, according to the China Patent Office, is approximately three years. Thirdly, after controlling for potential subsequent policy disturbances, the baseline results remain stable, indicating that this paper mainly identifies the structural impact of the post-2013 renewable energy-oriented tax support system. The DID results in this paper are not only statistically robust but also exhibit a gradual release pattern consistent with enterprise innovation activities in the time series, thus enhancing the credibility of the identification conclusions.

Based on the baseline regression and placebo test, this study will further explore the potential structural differences in policy effects. Following the norms of empirical research, this paper will conduct heterogeneity analysis from three dimensions: regional characteristics, property rights nature, and R&D investment structure, to reveal the distribution patterns and boundaries of policy effects among different market entities, and to determine whether their differences are significant. This aligns with the statement that "H2 tax incentives positively promote green technology innovation output from renewable energy power generation companies."

To further investigate whether there are systematic differences in the impact of tax incentives on corporate green technology innovation, this study conducted a heterogeneity analysis. The baseline regression results revealed the average effect among variables, but may have masked potential heterogeneity issues. Therefore, this paper investigates heterogeneity based on regional heterogeneity, ownership structure, and expensed R&D investment, as detailed below:

Research on regional heterogeneity

$$Y_{it}=\alpha+\beta_1(Treat_i\times Post)+\beta_2(Treat_i\times Post\times Coastal_i)+\gamma Xit+\mu_i+\lambda_t+\varepsilon_{it} \quad (38)$$

$Coastal_i$ is a regional dummy variable, with 1 for eastern regions and 0 for non-eastern regions. The baseline regression results are shown in the figure below:

As we shown in Table 3.2.4 the results show $R^2 = 0.676$, indicating strong explanatory power. Tax incentives have a significant positive impact on green technology innovation output (Y) in non-eastern regions (coefficient 0.499, $p < 0.05$), while in the eastern region sample, the coefficient of the did term is 0.337, failing the statistical significance test. This difference indicates a significant uneven effect of tax policies across different regions.

Currently, most of China's wind and solar power resources are concentrated in the Northwest, North China, and Southwest, and correspondingly, renewable energy power generation companies are mainly located in non-eastern regions, such as Inner Mongolia, Xinjiang, Gansu, and Yunnan. Therefore, these companies naturally become the main beneficiaries of tax policies, and their incentive effect on green innovation is more significant. Conversely, while the eastern region has significant advantages in manufacturing and technological foundations, it has fewer new energy power generation companies due to limited land resources and policy support, and the marginal incentive effect of tax incentives is relatively limited. Therefore, even with the implementation of policies, the actual leverage effect in the east is weak, failing to show statistical significance.

In summary, the marginal effect of tax incentives on promoting my country's green and low-carbon transformation is more pronounced in the central and western regions.To further examine the differences in the impact of tax incentives on green technology innovation among enterprises with different ownership structures, this paper divides the sample into two groups based on ownership type: state-owned enterprises and non-state-owned enterprises, and conducts heterogeneity regression analysis for each group. Therefore, it conforms to hypothesis 3a, and tax incentives have a stronger effect on promoting green innovation output of renewable energy enterprises in the central and western regions.

To further examine the differences in the impact of tax incentives on green technology innovation of enterprises with different ownership structures, this paper divides the sample into two groups according to ownership type: state-owned enterprises and non-state-owned enterprises, and conducts heterogeneous regression analysis for each group.

$$Y_{it}=\alpha+\beta_1(Treat_i\times Post)+\beta_2(Treat_i\times Post\times SOE_i)+\gamma Xit+\mu_i+\lambda_t+\varepsilon_{it} \quad (39)$$

SOE_i is a dummy variable for property rights, with 1 for state-owned property rights and 0 for non-state-owned property rights. The benchmark regression results are shown in the figure below:

As we shown in Table 3.2.4, the model validation results show that the $R^2 = 0.726$ indicates strong explanatory power, with significant results for both state-owned and non-state-owned property rights. To further validate the model's effectiveness, this paper will use the Chow test to examine the structural stability of the regression model across different property rights groups.

$$F=\frac{\left(RSS_P-(RSS_1+RSS_2)\right)/k}{(RSS_1+RSS_2)/(n_1+n_2-2k)} \quad (40)$$

RSS_P：Sum of squared residuals in the combined regression model

SS_1，RSS_2：Sum of squared residuals of regression models for two subsamples (e.g., state-owned enterprises and non-state-owned enterprises)

n_1，n_2：The sample size of the two subsamples.

Chow Test =2.44, P-Value > F(14 ,496) = 0.0025. The test passed, and the experiment is valid.

Regression results shown in Table 3.2.4 that the coefficient of the policy variable DID is positive and statistically significant in both state-owned and non-state-owned enterprises (SOEs), indicating that tax incentives have a positive effect on improving enterprises' green technology innovation output. The p-value is 0.403 ($p < 0.1$) for SOEs and 0.419 ($p < 0.05$) for non-SOEs, with the effects pointing in the same direction, but showing stronger significance and impact in non-SOEs. This is because SOEs typically enjoy stronger resource mobilization capabilities and policy support, and their innovation activities may be somewhat policy-driven, thus their response to marginal tax incentives is relatively limited. Non-SOEs, facing a more market-oriented operating environment, rely more heavily on external policy incentives for green innovation; tax incentives help alleviate their financial pressure, reduce R&D risks, and thus improve innovation output. Furthermore, in non-SOEs, asset structure (such as fixed assets and ending cash) has a significant marginal effect on green innovation, suggesting that their resource allocation is more sensitive and their market-oriented characteristics are stronger. Therefore, it conforms to assumption 3b: tax incentives have an output-generating effect on both state-owned and non-state-owned enterprises.

To further identify the differences in the role of corporate R&D accounting treatment in the tax policy effect, this paper divides the sample into two groups based on the standardized value of "current period expensed R&D investment" and conducts heterogeneity analysis. Enterprises with a higher degree of expense (standardized value of current period expensed R&D investment greater than or equal to -0.221) are assigned to the first group, and enterprises with a lower degree of expense (standardized value less than -0.221) are assigned to the second group. The research model is as follows:

$$Y_{it}=\alpha+\beta_1(Treat_i\times Post_t)+\beta_2(Treat_i\times Post_t\times HighERD_i)+\gamma X_{it}+\mu_i+\lambda_t+\varepsilon_{it} \quad (41)$$

$HighERD_i$ represents the standardized value of the expensed R&D investment in this period. A value greater than or equal to -0.221 corresponds to the experimental group, while a value less than -0.221 corresponds to the control group. The calculation results are as follows:

Table 3.2.4 Heterogeneity test

	different regional heterogeneity baseline regression		different ownership structures		expensed R&D investment in this period	
	I(East)	I(Central and Western)	I(State-owned)	Y(non-state-owned)	Y（low expensed R&D investment in this period.）	Y（high expensed R&D investment in this period.）
did	0.337	0.499**	0.403*	0.419**	0.005	0.460***
	-0.272	-0.198	-0.203	-0.194	-0.311	-0.128
Cash Flow	0.003	0.007	-0.004	0.008	0.013	0.003
	-0.006	-0.015	-0.011	-0.007	-0.009	-0.007
ROA	0.01	0.002	0.005	0.004	-0.005	0.003
	-0.012	-0.006	-0.031	-0.004	-0.012	-0.005
	-0.003	-0.001	-0.016	-0.001	-0.002	-0.003
Tobin's Q (A)	0.108	0.033	-0.073	0.123*	0.175	-0.019
	-0.084	-0.084	-0.091	-0.073	-0.175	-0.043
Net Cash Flow from Operating Activities	0.12	0.345	1.667	0.141	0.175*	-0.032
	-0.097	-0.69	-1.119	-0.097	-0.095	-0.1
Company Size	0.049	-0.183	-0.357*	-0.106	0.234*	-0.258***
	-0.126	-0.162	-0.185	-0.107	-0.14	-0.081
Total Assets	2.138***	2.088*	-4.217	2.091***	0.715	3.031***
	-0.489	-1.24	-5.339	-0.466	-0.637	-0.293
Net Fixed Assets	-1.735***	-1.911*	8.255*	-1.710***	-0.825	-1.876***
	-0.435	-1.011	-4.733	-0.43	-0.564	-0.249

Ending Cash and Cash Equivalents Balance	-0.043	-0.025	1.167*	-0.042	0.075	-0.011
	-0.076	-0.067	-0.673	-0.06	-0.08	-0.046
R&D Investment as a Percentage of Revenue	-0.01	-0.029	-0.016	0.028	-0.052	0.025
	-0.028	-0.05	-0.027	-0.041	-0.049	-0.026
Total R&D Investment	-0.090**	0.25	0.619	-0.086**	-0.038	-0.064
	-0.039	-0.193	-1.011	-0.042	-0.05	-0.044
R&D Capitalization Ratio	-0.003**	0.005**	0.002	-0.001	0.001	0
	-0.001	-0.002	-0.005	-0.001	-0.002	-0.001
_cons	-1.34	4.642	11.880**	2.354	-5.563	6.155***
	-2.994	-4.2	-5.242	-2.619	-3.495	-1.896
N	336	188	121	403	265	250
Controls	YES	YES	YES	YES	YES	YES
Id	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
R^2	0.676	0.803	0.726	0.721	0.741	0.846

Standard errors in parentheses * p <0.1, ** p <0.05, *** p <0.01

As we shown in Table 3.2.4, Empirical results show that the did coefficient in the non-eastern region sample is 0.499 and significant, while the did coefficient in the eastern region is 0.337 and fails the significance test. This indicates that the marginal effect of tax incentive policies is more pronounced in non-eastern regions, especially in resource-rich areas of the central and western regions. This is not only because wind power and photovoltaic resources are mainly concentrated in the Northwest, North China, and Southwest regions, making it easier for tax support to be directly embedded in the investment and technological upgrading process of new energy power generation projects, but also because enterprises in these regions typically face stronger financing constraints and higher innovation costs. Therefore, the improved cash flow, cost mitigation, and increased expected returns brought about by tax incentives have a higher marginal value. At the same time, the development of the new energy industry in the central and western regions is often accompanied by coordinated policies such as local investment promotion, park support, grid connection allocation, and project preference, making it easier for tax incentives to create a synergistic effect with actual investment behavior. In contrast, although the eastern region has a higher concentration of manufacturing capacity, technological foundation, and innovation resources, the distribution of new energy power generation enterprises is relatively limited, and enterprises have more alternative financing channels and stronger land and resource constraints. Therefore, the marginal leverage effect of a single tax incentive is relatively weak. This shows that regional differences not only reflect the differences in the starting point of innovation in different regions, but also the differences in the transmission efficiency of tax policies under different industrial layouts and institutional environments.

Regarding ownership heterogeneity, state-owned enterprises (SOEs) had a did=0.403*, while non-state-owned enterprises (SOEs) had a did=0.419**. Both showed the same direction, indicating that tax incentives can promote green innovation, but the significance was stronger for non-SOEs. If we use approximate percentages, 0.403 corresponds to approximately 49.6%, and 0.419 corresponds to approximately 52.0%. The two are close in magnitude, but the results for non-state-owned enterprises are more stable. This suggests that tax incentives are effective for enterprises of different ownership types, but are more "sensitive" to non-SOEs. SOEs typically possess stronger resource mobilization capabilities and policy support, making incremental tax incentives more of a supplementary tool for them. Non-SOEs, facing a more market-driven competitive environment and greater financial pressure, find tax incentives more likely to alleviate financial pressure, reduce R&D risks, and increase green innovation output.

The high-expense R&D group has a DID of 0.460, which is significantly positive at the 1% level. This indicates that tax incentives are mainly translated into green innovation output in companies with higher current real expensed R&D investment, while they have almost no effective incentive in companies with lower expensing levels. This paper uses whether the standardized value of current expensed R&D investment is higher than -0.221 as the grouping standard. This means that the high expense group is closer to companies that truly include R&D expenditures in current investment, rather than companies that rely more on capitalization. From an economic perspective, 0.005 has almost no substantial impact. This difference shows that tax policy does not automatically drive all companies to increase real innovation, but is more likely to play a role in companies that already have a strong tendency to invest in real R&D. Conversely, for companies with lower expensing levels and a stronger tendency to capitalize, tax incentives may not be able to translate into real green innovation results, but may remain more of a strategic response at the R&D accounting treatment or reporting level. Therefore, although the DID model can identify the promoting effect of tax incentives on overall innovation output, it is still difficult to further distinguish the difference between "real R&D expansion" and "formal R&D reporting". Based on this, the next section will further introduce the indicator of potential fake R&D capabilities of enterprises on the basis of DID analysis, and construct a DDD model to identify the differentiated transmission path of tax incentives in different types of enterprises, thereby revealing how policy incentives are transformed into real green innovation in some enterprises, while being distorted into strategic R&D behavior in others.

Because of the time lag between green technology innovation and output, even if enterprises obtain tax incentives in the current period, it often takes time to convert them into patent outputs. Therefore, to further verify the causal effect of tax incentive policies on enterprise green innovation and to examine whether the policy incentive has a certain degree of persistence and lag response, this paper constructs a regression model with a one-period lag based on the original difference-in-differences model. A regression model with a one-period lag was constructed to lagged the policy variable did_{it-1} in order to capture the delayed response of enterprises under policy stimulus.

$$Y_{it}=\alpha+\beta_1(Treat_i\times Post_t)_{i,t-1}+\gamma X_{it}+\mu_i+\lambda_t+\varepsilon_{it} \quad (42)$$

$Treat_i\times Post_t$ representing a one-period lag are as follows, the calculation results is:

Table 3.2.5 Lag-one model test of baseline test

	(1)
	Y
L.did	0.479***
	(0.149)
Cash Flow	0.005
	(0.005)
ROA	0.002
	(0.003)
Tobin's Q (A)	0.061
	(0.057)
Net Cash Flow from Operating Activities_std	0.122
	(0.089)
Company Size	-0.107
	(0.086)
Total Assets	2.089***

	(0.482)
Net Fixed Assets	-1.701***
	(0.447)
Ending Cash and Cash Equivalents Balance_std	-0.038
	(0.057)
R&D Investment as a Percentage of Revenue	-0.000
	(0.024)
Total R&D Investment	-0.064*
	(0.037)
R&D Capitalization Ratio	-0.000
	(0.001)
_cons	2.533
	(2.057)
N	524.000
Controls	YES
Id	YES
Year	YES
R^2	0.712

Standard errors in parentheses * p <0.1, ** p <0.05, *** p <0.01

As we shown in Table 3.2.5, based on the estimated results lagged by one period, the coefficient of the core explanatory variable L.did is 0.479, which is significantly positive at the 1% significance level. This indicates that, after controlling for other variables, the tax incentives from the previous period still have a significant positive impact on enterprises' green technology patent output in the current period. This lag effect is reasonable, partly because enterprises need time to convert the tax savings they receive from the policy into R&D investment, and partly because the patent R&D, application, and authorization process themselves have inherent time delays. Therefore, this result reflects that the incentive effect of tax incentives on enterprise innovation activities is not limited to the current period, but has a certain degree of continuity and accumulation.

From the perspective of control variables, the standardized value of "Total Assets" is significantly positive in the model, with a coefficient of 2.089, indicating that the larger the enterprise, the greater its green patent output. This may be because large enterprises have more abundant funds and possess more complete R&D systems and technological accumulation. The coefficient of "Net Fixed Assets" is -1.701, significantly negative, indicating that capital-intensive enterprises may have relatively weak output in green innovation, or rely more on equipment upgrades than on independent technological breakthroughs. The standardized coefficient of "Total R&D Investment" is -0.064, significantly negative at the 10% level. This result may indicate that although some enterprises have increased their R&D investment on paper, these investments have not been effectively transformed into green technology outputs, and there is even a tendency to use R&D as a means to obtain tax benefits rather than to truly promote technological progress. In other words, while policies guide innovation, they still need to pay attention to whether enterprises have truly implemented R&D investment and achieved substantial results. There may be a possibility of fake R&D, which will be studied in depth later.

Overall, the one-period lag in empirical results enhances the explanatory power of the policy effects. It also suggests that policy design should focus on the sustainability and genuine effectiveness of incentives, avoiding the dilution of policy intentions by "nominal inputs."

To eliminate the interference of other tax reforms after 2013 on the baseline DID estimation results, this paper setting Mi as comprehensive VAT reform policy and the VAT credit refund policy as representative variables of subsequent tax system shocks. The reasons for choosing these two policies are as follows: First, both are nationwide VAT system reforms with a long duration and wide impact after 2013, and can better represent the systemic changes in the general tax environment during the sample period; second, both can potentially impact corporate R&D investment and green technology innovation behavior by changing corporate tax burden structure, input tax deduction conditions, cash flow status, and financing constraints; third, compared with the special tax incentive policy for the renewable energy industry in 2013, the VAT reform and credit refund are more general tax system changes, so including them in the extended model helps to identify whether the core policy effects of 2013 exist independently of subsequent general tax system reforms. If, after controlling for the above policies, the core interaction term did remains significantly positive, it indicates that the baseline conclusion of this paper is not mainly driven by subsequent tax system reforms. (Appendix G, Appendix F)

$$Y_{it}=\alpha+\beta_1(Treat_i\times Post_t)+\gamma X_{it}+\beta_2(Treat_i\times Post_t)Mi+\mu_i+\lambda_t+\varepsilon_{it} \quad (43)$$

Table 3.2.6 Excluding interference from important policies in other years

	(1)
	Y

did	0.373**
	(0.166)
Tax refund did	-0.253
	(0.166)
did_ to replace the business tax with a value-added tax	-0.247
	(0.216)
Cash Flow	0.007
	(0.005)
ROA	0.000
	(0.003)
Tobin's Q (A)	0.068
	(0.055)
Net Cash Flow from Operating Activities	0.137
	(0.096)
Company Size	-0.066
	(0.080)
Total Assets	2.058***
	(0.467)
R&D Investment as a Percentage of Revenue	-0.003
	(0.026)
Total R&D Investment	-0.066*
	(0.038)
R&D Capitalization Ratio	0.000
	(0.001)
-cons	1.668
	(1.897)
N	524.000
Controls	YES
Id	YES
Year	YES
R^2	0.710

Standard errors in parentheses * p <0.1, ** p <0.05, *** p <0.01

As we shown in table 3.2.6, R^2=0.710 to eliminate the interference of other tax reforms during the same period on the estimation results, the interaction term between the "tax refund for retained earnings" policy and the "VAT reform" policy was further controlled in the model. Regression results show that after adding dummy variables for these two policies, the coefficient of the core explanatory variable remains significantly positive at the 5% level (coefficient = 0.373), while the coefficients of the interaction term between tax refund for retained earnings and VAT reform are not significant. This indicates that the core conclusions of this paper are not driven by these two concurrent policies, and the results are robust. To improve the identification validity of policy evaluation, this paper further introduces a three-level industry fixed effect (Industry-year FE) on top of the baseline regression model.

Traditional energy companies in the control group, especially those in the fossil fuel sub-sector, might have suffered industry-wide negative shocks after 2013, this paper, based on the baseline two-way fixed effects DID model, further incorporates a post-period specific shock control term for the coal and natural gas traditional industries. The "coal and natural gas traditional industry × $Post_t$" interaction term directly illustrates the additional industry downturn shocks that coal and natural gas traditional industry power generation companies in the control group might suffer in the post-2013 window. Coal and natural gas traditional industry have 26 company in China A-share. This incorporates the traditional DID into the coal and natural gas traditional industry specific shock control.

$$Y_{it}=\alpha+\beta_1 did_{it}+\theta ThermalPost_t+\gamma X_{it}+\mu_i+\lambda_t+\varepsilon_{it} \quad (44)$$

$Treat_i$ is the treatment-group dummy variable, which equals 1 if firm i belongs to the high exposure renewable energy group, and 0 otherwise. $Post_t$ is the post-policy-period dummy variable, which equals 1 if t≥2013, and 0 otherwise. $Thermal_i$ is the dummy variable for coal and natural-gas-based traditional energy industries, which equals 1 if the firm belongs to the control group and its industry type is classified as a coal- or natural-gas-based traditional energy industry, and 0 otherwise. X_{it} denotes the vector of control variables. μ_i and λ_t represent firm fixed effects and year fixed effects, respectively.

Table 3.2.7 Second-stage DID regression with Thermal control

Variable	(1) Baseline DID	(2) + Thermal×Post
did	0.401*	0.274*
	(0.152)	(0.145)
Thermal×Post		-0.108
		(0.067)
Cash Flow	0.007	0.007
	(0.005)	(0.004)
ROA	0.001	0.000
	(0.003)	(0.003)
Tobin’s Q (A)	0.067	0.054
	(0.054)	(0.045)
Net Cash Flow from Operating Activities	0.145	0.146***
	(0.000)	(0.048)
Company Size	-0.070	-0.077
	(0.080)	(0.116)
Total Assets	2.067***	1.972**
	(0.793)	(0.807)
Net Fixed Assets	0.000***	-1.678**
	(0.000)	(0.658)
Ending Cash and Cash Equivalents	-0.000	-0.038
	(0.000)	(0.061)
R&D Investment as a Percentage of Revenue	-0.001	0.004
	(0.016)	(0.024)
Total R&D Investment	-0.006	-0.056

	(0.000)	(0.045)
R&D Capitalization Ratio	0.000	0.001
	(0.002)	(0.002)
_cons	1.372	1.215
	(3.119)	(3.023)
N	524	524
Controls	YES	YES
Firm FE	YES	YES
Year FE	YES	YES
R^2	0.539	0.552

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The regression Table 3.2.7 results show that, in the baseline DID model, the estimated coefficient of the core explanatory variable did is 0.4018, with a p-value of 0.0513, indicating a marginally significant positive policy effect. After further introducing the interaction control term "coal and natural gas based on traditional industry × $Post_t$," the coefficient on did declines to 0.2739, with a p-value of 0.0581, but remains positive and marginally significant at the 10% level. Meanwhile, the estimated coefficient on $Thermal_i \times Post_t$ is -0.1075, with a p-value of 0.1087. The relative decline is approximately 31.8%. These results suggest that coal and natural gas based traditional industries in the control group may have experienced a certain degree of additional industry-specific downward pressure in the post-policy period; however, this effect is not statistically significant. In other words, part of the baseline DID effect may indeed have been influenced by such industry specific factors, but this influence does not alter the positive direction of the policy effect.

Overall, after incorporating the post-2013 special control measures targeting traditional fossil energy sub sectors, the core DID coefficient remained directionally unchanged, indicating that the fundamental conclusion of this paper regarding the positive promotion of green innovation by renewable energy enterprises through the post-2013 tax support system still holds true in terms of direction. It should be noted that the DID coefficient has shrunk compared to the baseline model; therefore, the main conclusion of the second-stage DID in this paper has a certain degree of directional robustness, but its effect magnitude still needs careful interpretation. This issue should also be clearly defined as one of the limitations of the identification strategy in this paper.

Since 2015, corporate innovation behavior may be influenced not only by tax factors but also by a series of non-tax factors, such as the significant decrease in the cost of photovoltaic modules and wind power equipment, the promotion of industrial upgrading policies, and local government financial support. If these factors have a significantly stronger impact on renewable energy companies than on traditional energy companies, then the policy effect estimated by the second-stage DID model may not fully represent tax incentives themselves, but rather the combined result of tax support and other non-tax factors. This paper includes the following two categories as the most important competitive non-tax influencing factors in the model control:

First, government subsidies, as a proxy variable for direct fiscal support, are used to control for the impact of industrial policies and fiscal subsidies. According to Accounting Standard No. 16, government subsidies are non-tax incentives. Government subsidies are defined as monetary or non-monetary assets obtained by enterprises from the government free of charge. This indicator is widely used to analyze the impact of fiscal subsidies on corporate R&D, innovation, and efficiency. This indicator is sourced from the Wind database.

$$\text{Non-tax Subsidy}_{it}=\frac{\text{Government subsidies}_{it}}{\text{Operating Revenue}_{it}} \quad (45)$$

In this model, "government subsidies" is calculated using the amount of government subsidies received in the current period from the company's financial statements, and "operating revenue" is used as the standardized denominator for the company's operating scale. This variable reflects the intensity of direct fiscal support received by the company in the current period. To reduce the impact of extreme values, this variable is shortened using the 1% and 99th percentiles to obtain the final variables included in the model:

$$\text{Non-tax Subsidy}_{it}^{W}=\text{Winsorize}(\text{Subsidy}_{it},1\%,99\%) \quad (46)$$

Second, the LCOE of photovoltaic and wind power is used as a proxy for the cost-reduction trend of mainstream renewable power technologies. This indicator is sourced from the National Energy Administration of China. Since publicly available authoritative data does not provide a complete annual LCOE series for Chinese photovoltaic and wind power from 2009 to 2023 using a single unified standard, this paper employs an "authoritative anchor point + annual smoothing construction" method to construct a proxy variable for Chinese renewable energy LCOE. This is based on two factors: firstly, IRENA provides an authoritative trend of long-term decline in global photovoltaic and wind power LCOE; secondly, Bloomberg NEF provides a cost anchor point for the best projects in China in 2023.

Therefore, the specific construction steps are as follows: First, establish annual LCOE proxy series for Chinese photovoltaic and wind power respectively (unit: USD/kWh); second, take the average of the two to obtain the annual composite

$$\text{LCOE:}\text{LCOE}_t=\frac{\text{LCOE}_t^{PV}+\text{LCOE}_t^{Wind}}{2} \quad (47)$$

Thirdly, considering that the model already includes year-fixed effects, the individual LCOE_t will be absorbed by the year-fixed effects. Therefore, this paper uses its interaction with the treatment group term to identify whether "technology cost reduction is more beneficial to renewable energy companies".

$$\text{TreatLCOE}_{it}=\text{Treat}_i\times\text{LCOE}_t \quad (48)$$

The control variables remain consistent with the baseline DID. After incorporating government subsidies and technology cost reduction controls, the formula is as follows:

$$Y_{it}=\alpha+\beta_1(\text{Treat}_i\times\text{Post}_t)+\delta\ \text{Non-tax Subsidy}_{it}^{W}+\phi\text{TreatLCOE}_{it}+\gamma X_{it}+\mu_i+\lambda_t+\varepsilon_{it} \quad (49)$$

Here, μ_i denotes firm fixed effects, λ_t denotes year fixed effects, and ε_{it} is the random error term. All models are estimated using clustered robust standard errors at the firm level.

Table 3.2.8 Second-stage DID regression with Government subsidy + LCOE

Variable	(1) Baseline DID	(2) + Government subsidy	(3) + Government subsidy + LCOE
did	0.423**	0.415**	0.249**
	(0.209)	(0.210)	(0.225)
Government subsidy Intensity		-2.008	-2.039
		(2.736)	(2.845)
Treat×LCOE			-1.776
			(1.659)
Cash Flow	0.007*	0.007*	0.007*
	(0.004)	(0.004)	(0.004)
ROA	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)
Tobin's Q (A)	0.068	0.068	0.067
	(0.046)	(0.046)	(0.046)

Net Cash Flow from Operating Activities	0.145***	0.145***	0.144***
	(0.048)	(0.048)	(0.048)
Company Size	-0.078	-0.078	-0.075
	(0.115)	(0.115)	(0.116)
Total Assets	1.970**	1.962**	1.959**
	(0.803)	(0.805)	(0.805)
Net Fixed Assets	-1.677**	-1.675**	-1.671**
	(0.655)	(0.656)	(0.656)
Ending Cash and Cash Equivalents	-0.038	-0.038	-0.038
	(0.060)	(0.060)	(0.060)
R&D Investment as a Percentage of Revenue	0.004	0.004	0.004
	(0.024)	(0.024)	(0.024)
Total R&D Investment_std	-0.056	-0.056	-0.055
	(0.045)	(0.045)	(0.045)
R&D Capitalization Ratio	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)
_cons	1.210	1.236	1.292
	(3.019)	(3.024)	(3.030)
N	524	524	524
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Controls	YES	YES	YES
Clustered Robust SE	YES	YES	YES
R^2	0.7023	0.7026	0.7037

Standard errors in parentheses* p <0.1, ** p <0.05, *** p <0.01

The table 3.2.8 show the DID regression results after gradually controlling for major non-tax factors. Column (1) is the baseline DID model, with a did coefficient of 0.423, which is significant at the 5% level, indicating that under the policy and institutional shift after 2013, the green innovation output of renewable energy enterprises showed a significantly stronger growth compared to the control group. This result is consistent with the core hypothesis of this paper, namely, that the tax support system has a significant promoting effect on the technological innovation of renewable energy enterprises. Column (2) further introduces the government subsidy intensity variable at the enterprise level to control for direct fiscal support factors. The results show that after adding this variable, the did coefficient only decreased slightly from 0.423 to 0.415, and is still significant at the 5% level; at the same time, the coefficient of the government subsidy intensity variable itself is negative, but does not reach the statistical significance level. This indicates that the positive innovation effect identified by the baseline DID is not mainly driven by direct fiscal subsidies. The authors analyze that although government subsidies constitute an important policy background for enterprise innovation decisions, the positive policy effect in the baseline model of this paper cannot be simply interpreted as a substitute for fiscal subsidies. This result reinforces the explanation of the independent role of tax incentives in this paper. Column (3) further incorporates the $Treat_i \times LCOE_t$ interaction term to control for the impact of renewable energy technological progress and cost reduction. Regression results show that after controlling for government subsidies and technology cost reduction factors, the did coefficient further shrinks from 0.415 to 0.249, but remains positive and significant at the 5% level. This result has important identifying significance. On the one hand, it indicates that there is indeed some additional innovation driven by non-tax factors, especially technology cost reduction factors, in the post-2015 stage; on the other hand, even if these factors are explicitly included in the model control, the core coefficient of the tax support system has not disappeared, indicating that the improvement of the innovation advantage of renewable energy enterprises cannot be fully explained by non-tax factors.

Based on Table 3.2.8, we can conclude that: First, the positive innovation effect identified by the baseline DID model is not a simple mapping of fiscal subsidies; the tax support system still has an independent and significant effect after controlling for direct fiscal support. Second, and most importantly, after controlling for both government subsidies and LCOE, the did coefficient remains significantly positive, indicating that the tax support system's role in promoting green innovation output is independent and robust. Therefore, the core conclusion of this paper remains valid: the tax support system is an important policy tool for promoting technological innovation in renewable energy companies. However, since non-tax factors weaken the coefficient, the interpretation of the policy effect magnitude still needs to be cautious. This paper identifies that tax support has an effect in the post-2013 institutional environment, in conjunction with subsequent technological and market conditions, but the most significant effect still comes from China's tax incentive policies.

This three-level industry classification system has high precision and can effectively distinguish the specific position of new energy enterprises in the actual operation of the industrial chain. This controls for systematic differences among different industries in terms of institutional arrangements, market structure, technological maturity, and policy responsiveness, making the difference-in-differences (DID) term more accurately reflect the marginal effect of the post-2013 policy period on enterprises' green technology innovation.

$$Y_{it}=\alpha+\beta_1(Treat_i \times Post_t)+\gamma X_{it}+\mu_i+\lambda_t+\delta_h+\varepsilon_{it} \quad (50)$$

δ_h represents the third-order industry fixed effects. Controlling for industry heterogeneity, the calculation results of the third-order industry classification model are as follows: Modifying the model settings to add fixed effects.

Table 3.2.9 Modifying model settings to increase the regression results with fixed effects

	(1) Y
did	0.402**
	(0.162)
Cash Flow	0.007
	(0.005)
ROA	0.001
	(0.003)
Tobin's Q (A)	0.068
	(0.054)
Net Cash Flow from Operating Activities	0.146
	(0.095)
Company Size	-0.070
	(0.080)
Total Assets	2.067***
	(0.460)
Net Fixed Assets	-1.718***
	(0.430)
Ending Cash and Cash Equivalents Balance	-0.040
	(0.058)
R&D Investment as a Percentage of Revenue	-0.002
	(0.026)
Total R&D Investment	-0.062
	(0.038)
R&D Capitalization Ratio	0.000
	(0.001)
_cons	1.651
	(1.901)
N	524.000
Controls	YES
Id	YES
Year	YES
R^2	0.708

Standard errors in parentheses * p <0.1, ** p <0.05, *** p <0.01

As we shown in table 3.2.9, the results show that the R^2=0.708 model provides strong empirical support for explaining the impact of tax incentive policies in China's renewable energy sector on corporate green innovation output. The DID coefficient is

0.402, significant at the 5% level, indicating that renewable energy companies enjoying tax incentives since 2013 have, on average, increased their green patent output by 0.402 units compared to traditional energy companies that did not enjoy the incentives. This finding confirms the positive role of fiscal incentives in guiding strategic environmental protection industries to achieve innovative breakthroughs.

Regarding control variables, total assets (std) showed a significant positive correlation with green innovation ($\beta = 2.067$, $p < 0.01$), indicating that companies with stronger capital are better able to absorb policy incentives and transform them into actual innovative achievements. However, net fixed assets showed a significant negative correlation ($\beta = -1.718$, $p < 0.01$), which may reflect the inhibitory effect of asset rigidity and sunk costs on the flexibility of new technology investment for capital-intensive companies.

It is noteworthy that traditional R&D investment indicators, such as R&D intensity, total R&D expenditure, and R&D capitalization ratio, did not show statistical significance in the model. This may indicate that under policy incentives, some companies engage in faked R&D practices, i.e., increasing R&D expenditures on paper to obtain tax benefits without generating substantial technological innovation output. Such behaviour may weaken the true effectiveness of policy tools, suggesting that future supervision and identification of the authenticity of corporate R&D activities should be strengthened. This situation will be studied in more detail later.

To eliminate interference from other policies and further verify whether the impact of the post-2013 tax-support regime on green technology innovation is independent, this paper constructs an alternative policy period variable $Post_{2t}$. 2019 is selected as the experimental year. The value is 1 for years 2019 and later, and 0 otherwise. This interaction term, $Treat_i$, is constructed by multiplying it with the treatment group variable $Did2_{it}=Treat_i \times Post_{2t}$. We introduce $Did2_{it}$ into the original baseline model and include it in the regression along with the initial policy interaction term Did_{it} to examine whether there is a significant difference in the policy impact represented by the two period variables. Control variables are kept consistent, and both firm and year fixed effects are incorporated.

$$Y_{it}=\alpha+\beta_1(Treat_i\times Post_t)+\beta_2(Treat_i\times Post_{2t})+\gamma X_{it}+\mu_i+\lambda_t+\epsilon_{it} \quad (51)$$

Table 3.2.10 Regression results excluding interference from 2019

	(1)
	Y
did	0.394**
	(0.176)
Did2	0.020
	(0.128)
Cash Flow	0.007
	(0.005)
ROA (Return on Assets) Unit	0.002
	(0.003)
Tobin's Q (A)	0.068
	(0.054)
Net Cash Flow from Operating Activities_std	0.144
	(0.095)
Company Size	-0.072
	(0.079)
Total Assets_std	2.073***
	(0.462)
Net Fixed Assets_std	-1.721***
	(0.430)
Ending Cash and Cash Equivalents Balance_std	-0.039
	(0.057)
R&D Investment as a Percentage of Revenue	-0.001
	(0.026)
Total R&D Investment_std	-0.061*
	(0.037)
R&D Capitalization Ratio	0.000

	(0.001)
_cons	1.684
	(1.880)
N	524.000
Controls	YES
Id	YES
Year	YES
R^2	0.708

Standard errors in parentheses * p <0.1, ** p <0.05, *** p <0.01

As we shown in Table 3.2.10, empirical results show that the R^2=0.708 model has strong explanatory power. During the initial policy period, the initial tax incentive policy still has a significant positive impact on green patent output, while the coefficient of the initial tax incentive policy is statistically insignificant, indicating that new policies after 2019 have not systematically affected green technology innovation output. This result strengthens the support for identifying the post-2013 tax-support regime as an exogenous shock of a "quasi-natural experiment," further eliminating the confounding effects of subsequent policy introductions.

Since the traditional energy companies serving as the control group may also be affected by other decarbonization-related policy or tax policy changes between 2013 and 2015, this paper aims to verify the reliability of the DID identification strategy. Even if the baseline DID coefficient is positive and significant, the estimated effect may partially reflect the policy pressures on coal, oil, and gas companies at the time, rather than the renewable energy-oriented tax support mechanisms themselves after 2013.

To further examine whether the main DID conclusion remains directionally stable under bounded deviations from parallel trends, this study additionally applies the Honest DiD [119] framework as a supplementary sensitivity check. Result in Appendix L.

This makes the identification argument more transparent and more defensible. Even if the control group was partially affected by other policy changes, the core direction of the result remains positive within a reasonable range of admissible trend departures.

After analyzing the direct impact of tax incentive policies on green innovation output, this paper constructs a mediation effect model to further reveal its underlying mechanism. The proportion of total R&D expenditure to operating revenue is selected as the mediating variable. Compared to absolute R&D expenditure, this indicator better reflects the true importance that enterprises attach to innovation at different scales and stages. By linking R&D expenditure to main business revenue, this indicator effectively controls the impact of scale differences on investment intensity and can more accurately measure the tendency of enterprises to allocate innovation resources. It helps to identify whether tax policies truly drive companies toward green and low-carbon technologies, rather than using policy incentives for non-productive expenditures or engaging in "fake R&D" behaviour.

$$M_{it}=\alpha+\beta_1 did_{it}+\gamma X_{it}+\mu_i+\lambda_t+\epsilon_{it} \quad (52)$$

M_{it} is the mediating variable representing the ratio of total R&D expenditure to operating revenue.

Table 3.2.11 Mediation effect model regression results

	(1) M_{it}
did	1.934***
	(0.347)
Cash Flow	-0.001
	(0.012)
ROA	-0.005
	(0.009)
Tobin's Q (A)	-0.009
	(0.103)
Net Cash Flow from Operating Activities	0.000
	(0.000)
Company Size	0.413***
	(0.120)
Total Assets	-0.000
	(0.000)
Net Fixed Assets	0.000
	(0.000)
Ending Cash and Cash Equivalents Balance_std	-0.000***
	(0.000)
R&D Investment as a Percentage of Revenue	0.983***
	(0.047)
Total R&D Investment	0.000
	(0.000)
R&D capitalization ratio unit	0.004**
	(0.002)
_cons	-10.535***

	(2.885)
N	524.000
Controls	YES
Id	YES
Year	YES
R2	0.930

Standard errors in parentheses * p <0.1, ** p <0.05, *** p <0.01

As we shown in Table 3.2.11, The estimated coefficient of DID for R&D intensity is 1.934, which is significantly positive at the 1% significance level. This means that tax support increases the proportion of corporate R&D expenditure to operating revenue by an average of approximately 1.93 percentage points. The economic implications are even more pronounced when this result is compared with the sample's own distribution characteristics. According to descriptive statistics, the average R&D intensity of the sample is only 1.437%, and the median is only 0.495%, indicating that most companies were originally in a state of low R&D investment. Against this backdrop, the 1.934 percentage point increase not only exceeds the sample average but is also far higher than the median, indicating that tax incentives are not merely a slight adjustment to corporate R&D allocation but significantly alter the degree to which companies allocate operating revenue resources to R&D activities. Further analysis reveals that, from a tax policy perspective, it not only increases companies' willingness to engage in green R&D but also increases the actual weight of companies allocating innovation resources to their main operating revenue. This is a crucial transmission mechanism by which tax incentives can further influence the number of green invention applications and authorizations. Meanwhile, the significantly positive R&D capitalization ratio also suggests that policy incentives may reflect companies' more proactive efforts to commercialize technology, but they may also indicate that some companies have an incentive to use capitalization to enhance their financial statement performance. This result thus supports the view that "R&D intensity is an important mediating mechanism by which tax incentives influence green innovation," and also provides an empirical basis for identifying fake R&D behavior in the following discussion.

3.3 Model of Difference in Difference in Difference (DDD) for identifying the faked

R&D of renewable energy power generation companies

In the first chapter of theoretical research, and the second chapter of current situation analysis, we learned that the current practice of enterprises engaging in fraudulent research and development can lead to the loss of state-owned assets. Therefore, this chapter will construct a DDD model based on the DID model mentioned above to identify fake R&D behavior, and use the Evolutionary Game Theory (EWA) model to evaluate the severity of punishment and find an appropriate level of punishment to encourage companies to conduct fake R&D. In the preceding DID analysis, this research identified that the post-2013 tax incentive regime had a significant relative promoting effect on green technology innovation in renewable energy companies. However, further analysis of samples by year or later reveals a diminishing marginal effect, even becoming statistically insignificant in recent years. This result suggests that the marginal effect of tax incentives may gradually weaken over the long term, potentially even leading to companies engaging in fake R&D practices to defraud the government of taxes.

Based on the theory of information asymmetry, tax incentive policies often face the "incentive compatibility" problem. As rational economic agents, enterprises, in the absence of effective supervision, are motivated to obtain tax credits through accounting manipulation, such as classifying administrative expenses as R&D expenses and increasing the R&D capitalization rate rather than engaging in substantive innovation. This behaviour is known as fake R&D.

Some companies, under the long-term policy environment, gradually develop a "path-dependent" policy arbitrage tendency. This involves structurally adjusting financial statements and optimizing the accounting treatment of R&D expenditures to formally meet the policy incentive conditions, without actually investing funds in substantive green technology innovation. This type of behaviour is categorized in the literature as faked R&D expenditure recognition, and is particularly prone to occur in situations with insufficient external supervision or spatial differences in the onset of the post-2013 policy period.

Corporate innovation investment exhibits significant information asymmetry. Under the influence of long-term tax incentives, if a company fails to achieve technological breakthroughs but continues to maintain high R&D investment, especially with a high proportion of capitalization and low output (such as the number of green invention patent applications), it may indicate that its R&D activities are more for obtaining fiscal benefits than for achieving green transformation goals.

To systematically identify such potential behaviours, this research introduces the indicator "Potential Fake R&D Capability" fake_i. It selects three indicators—Earnings Before Interest and Taxes (EBIT), capitalized R&D investment, and net cash flow from operating activities, as the basis for constructing the new indicator $Fake_i$., and uses principal component analysis as the primary construction method (Table 3.2.1). (The specific construction method is explained in Section 2.2.)

This research selects Earnings Before Interest and Taxes (EBIT), Capitalized R&D Expenditure, and Net Cash Flow from Operating Activities (OCF) to construct a composite identification indicator using Principal Component Analysis (PCA). The core logic is to identify strategic information manipulation by companies under financial and tax incentive pressures, exploiting the boundaries of accounting standards. This indicator selection has a profound institutional background and economic and legal basis: According to Accounting Standard No. 6 Intangible Assets, R&D expenditures are divided into "research stage" and "development stage." The standard stipulates that research stage expenditures must be expensed, while development stage expenditures, in terms of meeting technical feasibility and future economic benefits, largely depend on management's subjective judgment and lack objectively verifiable physical standards.

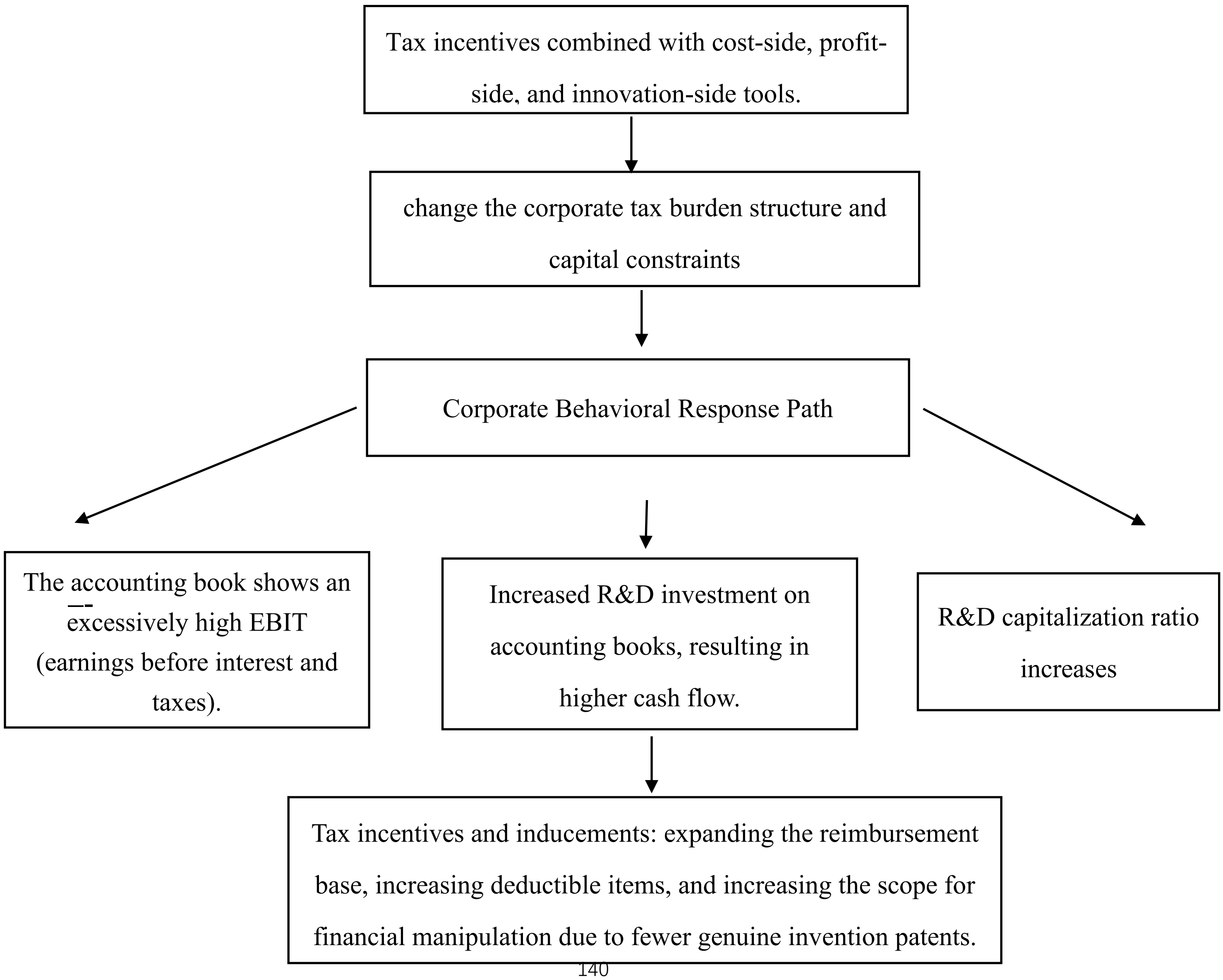
This regulatory ambiguity provides ability for earnings management. Companies more incentivized to take advantage of policy incentives may reclassify substantial R&D expenditures, even routine production-related costs, as R&D expenses. This helps them meet the R&D intensity thresholds required for high technology company certification while avoiding an immediate decline in current earnings due to expense recognition. Since any single accounting metric can be strategically manipulated, this study combines three variables to capture the differences between reported profitability, balance sheet treatment of R&D expenditures, and actual cash support for companies.

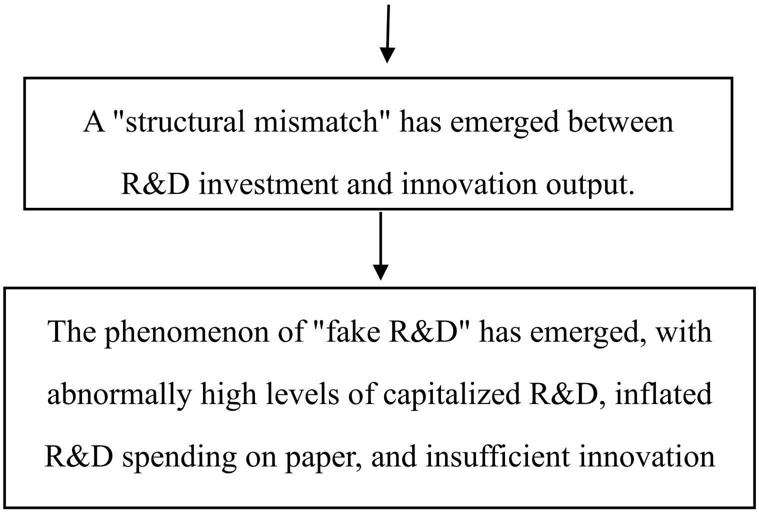
This study uses earnings before interest and taxes (EBIT) to measure a company's actual operating profitability, while avoiding performance metrics directly affected by tax incentives. Net profit is unsuitable for this purpose because it already includes the impact of tax incentives, and using it to explain policy-induced behavior would create a circular endogeneity problem. By eliminating the effects of interest expense and income tax, EBIT more clearly reflects a company's profitability before direct policy incentives are reflected in after-tax earnings. When a company reports substantial R&D spending while maintaining unusually stable or persistently high EBIT, it may indicate that the reported innovation spending serves not only as a reflection of substantial technological progress but also as a financial reporting or signaling function.

The inclusion of capitalized R&D expenditures is intended to reflect management's discretion in accounting treatment. Capitalization itself does not necessarily imply manipulation, but it does suggest a company's ability to defer current costs to future periods. This can improve short-term financial performance and potentially enhance the illusion of a company's technological capabilities. If high levels of R&D capitalization are inconsistent with corresponding patent output or other observable innovations, the economic substance of the reported R&D assets is questionable. Therefore, in this study, capitalized amounts can serve as a measure of the extent to which a company uses accounting estimates for institutional arbitrage.

To construct the potential fake R&D Capability index, this study selects EBIT, capitalized R&D expenditure, and net cash flow from operating activities. The reason is that fake R&D is unlikely to be reflected in a single accounting item; rather, under tax incentive pressures and information asymmetry, it is more likely to appear as a structural mismatch among reported profitability, accounting discretion, and real cash support. EBIT is used instead of net profit because it is less directly affected by tax incentives and therefore better captures the firm’s underlying operating profitability. Capitalized R&D expenditure reflects managerial discretion in the accounting treatment of R&D and helps identify the potential use of capitalization for institutional arbitrage. Net cash flow from operating activities is included to test whether reported R&D is supported by real resource commitment, since cash based measures are generally harder to manipulate than accrual-based earnings. Taken together, these three indicators capture the profitability, accounting, and cash-flow dimensions of firms' latent fake R&D tendency. In conclusion, $fake_i$ is not constructed randomly, but rather based on discretionary power, the difference between accrual and cash basis accounting, and dimensionality reduction of multi-dimensional financial characteristics. This indicator can scientifically identify companies that "package their finances to obtain tax benefits," thus significantly improving the accuracy of the difference in difference in difference (DDD) model in causal identification.

Table 3.3.1 Enterprise potential fake R&D roadmap





Source: Compiled by the author based on the logic of the research.

This approach also offers a methodological innovation by transforming accounting-based variables into a potential construct through PCA, thereby improving robustness and mitigating endogeneity concerns associated with single-variable proxies.

From a policy standpoint, China's escalating R&D tax incentives have significantly lowered the after-tax cost of innovation. However, these incentives may inadvertently encourage firms to reclassify regular expenses as R&D or inflate capitalized R&D figures to claim greater tax benefits. The $Fake_i$ is constructed to capture the behavioral heterogeneity among firms in response to such fiscal policies.

Moreover, in empirical research, the $Fake_i$ offers a way to mitigate endogeneity concerns associated with direct measures of innovation. Rather than relying solely on R&D intensity or patent counts, the $Fake_i$ synthesizes multiple financial signals, profitability (EBIT), accounting discretion (capitalized R&D), and internal cash generation (OCF) into a unified index using Principal Component Analysis (PCA). This approach enhances construct validity and provides a more nuanced view of firms' strategic reporting choices.

The $Fake_i$ is constructed from three standardized financial indicators:

x_1 = extEBIT : Earnings before interest and taxes (a proxy for profit pressure),

x_2 = extCapitalized R&D Expenditures (a proxy for managerial discretion),

x_3 = extOperating Cash Flow (OCF) (a proxy for financing constraint).

These variables are selected based on their established relevance in the literature on discretionary accounting and innovation finance. Each variable is transformed using z-score normalization:

$$\tilde{x}_{ij} = \frac{x_{ij} - \bar{x}_j}{\sigma_j} \quad (53)$$

Before constructing new variables $fake_i$ for EBIT, capitalized R&D expenditures, and net cash flow from operating activities, a KMO test is required. The closer the KMO value is to 1, the more suitable it is for principal component analysis. The Bartlett test of sphericity is used to test whether the distribution of the data satisfies the multivariate normal distribution of the population. If it is significant (i.e., p-value is less than 0.05), it indicates that the data is suitable for principal component analysis.

Table 3.3.2 KMO and Bartlett's tests

KMO		0.630
Bartlett Sphericity test	Approximate Chi-square	822.385
	df	3
	p -value	0.000

As shown in the Table 3.3.2 above, using principal component analysis (PCA) for information condensation, the KMO is 0.630, which is greater than 0.6, meeting the prerequisite requirements for PCA and indicating that the data can be used for PCA research. Furthermore, the data passes Bartlett's test of sphericity ($p<0.05$), demonstrating that the research data is suitable for PCA, thus rejecting the null hypothesis. To verify whether the new indicator fake_i can truly reflect the intrinsic meaning among EBIT (Earnings Before Interest and Taxes), capitalized R&D expenditures, and net cash flow from operating activities, this research uses the variance explained ratio for verification. A larger variance indicates stronger representativeness.

Table 3.3.3 Variance Explained Ratio Table

Number		Principal component extraction

	eigenvalues, variance explained (%), cumulative (%)	eigenvalues, variance explained (%), cumulative (%)	eigenvalues, variance explained (%), cumulative (%)	eigenvalues, variance explained (%), cumulative (%)	eigenvalues, variance explained (%), cumulative (%)	eigenvalues, variance explained (%), cumulative (%)
1	2.391	79.696	79.696	2.391	79.696	79.696
2	0.563	18.762	98.458	-	-	-
3	0.046	1.542	100.000	-	-	-

As shown in the Table 3.3.3 above, the principal component analysis extracted one principal component, with all eigenvalues greater than 1. This single principal component explained 79.696% of the variance, and the cumulative variance explained was also 79.696%. This indicates that the newly constructed index effectively reflects the intrinsic meaning among EBIT (Earnings Before Interest and Taxes), capitalized R&D expenditure, and net cash flow from operating activities, successfully passing the experiment. Next, this research continues to quantify the contribution of each original variable to the principal component and determine the strength of the association. The loading coefficients are shown in the table below:

Table 3.3.4 Load factor table

name	Load factor	Communality (Common Factor Variance)
	Principal component 1	
EBIT	0.954	0.910
Capitalized R&D expenditures	0.756	0.572
Net cash flow from operating activities	0.953	0.909

This Table 3.3.4 shows the information extraction performance of the principal components for the research items, as well as the correspondence between the principal components and the research items. The table shows that the communality values for all research items are higher than 0.4, indicating a strong correlation between the research items and the principal components, and that the principal components can effectively extract information. After ensuring that the principal components can extract most of the information from the research items, the next step is to analyze the correspondence between the principal components and the research items (an absolute value of the loading coefficient greater than 0.4 indicates a correspondence between the item and the principal component).

Table 3.3.5 Linear combination coefficient matrix

name	Element
	Element1
EBIT	0.617
Capitalized R&D investment	0.489
Net cash flow from operating activities	0.617

Linear load composition factor, EBIT is 0.617, Capitalized R&D investment is 0.489, Net cash flow from operating activities is 0.617. The proportions of the three components were relatively balanced, which is consistent with the original hypothesis. (Table 3.3.5)

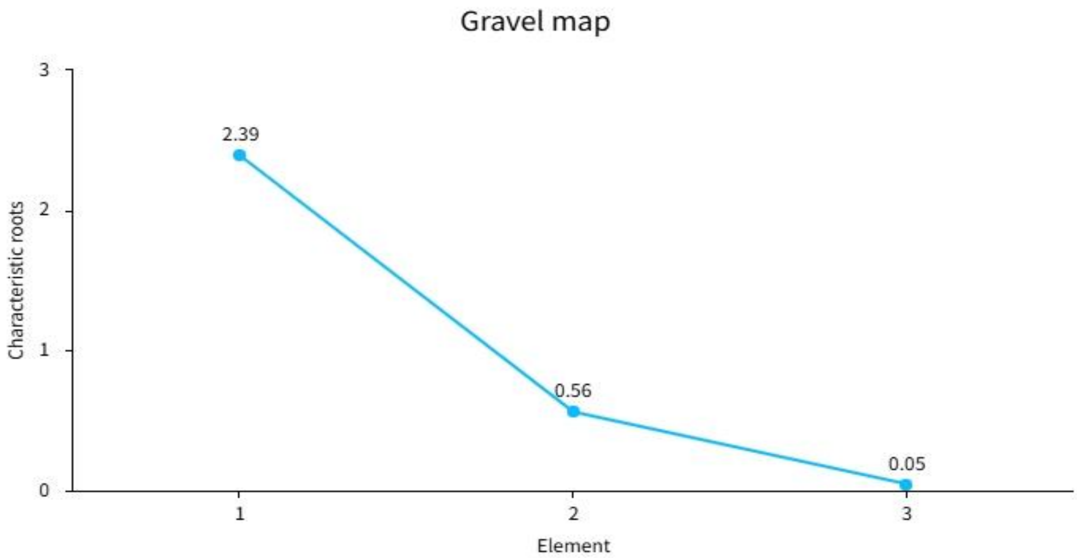


Figure 3.3.1 Gravel map

Table 3.3.6 Linear combination coefficients and weighting results

name	Principal component 1	Overall score coefficient	Weight
Eigenvalues	2.391		
Explanation of variance	79.70%		
EBIT	0.6170	0.6170	35.82%
Capitalized R&D expenditures	0.4890	0.4890	28.39%
Net cash flow from operating activities	0.6166	0.6166	35.79%

The final results of the linear combination coefficients and weights show that the variance explained is 79.70%, the final weight of EBIT is 35.82%, the final weight of capitalized R&D expenditure is 28.39%, and the final weight of net cash flow from operating activities is 35.79%. (Table 3.3.6)

Where x_{ij} denotes the original value for firm i, and $\bar{x}_j$, σ_j represent the sample mean and standard deviation of variable j, respectively.

To extract the common latent factor from the standardized variables, Principal Component Analysis (PCA) is employed. Let $\tilde{x}_i=[\tilde{x}_{i1},\tilde{x}_{i2},\tilde{x}_{i3}]$. The first principal component is calculated as:

$$Fake_i=w_1\cdot\tilde{x}_{i1}+w_2\cdot\tilde{x}_{i2}+w_3\cdot\tilde{x}_{i3} \quad (54)$$

Thus, the final $Fake_i$ use score coefficients in formula becomes:

$$Fake_i=0.617\cdot\widetilde{EBIT}_i+0.489\cdot Cap\widetilde{R\&D}_i+0.616\cdot\widetilde{OCF}_i \quad (55)$$

For interpretability, the normalized contribution shares are 35.82%, 28.39%, and 35.79%, respectively. This index captures the joint manifestation of operating profitability, accounting discretion, and operating cash-flow capacity, which together reflect the potential risk of opportunistic R&D capitalization.—key signals of potentially opportunistic R&D capitalization.

Given the high intercorrelation and conceptual similarity among the input variables, and the fact that the first principal component explains nearly 80% of the total variance, the scoring coefficients obtained for $Fake_i$ closely resemble the component loadings. This convergence is mathematically consistent and indicates strong unidimensionality of the latent construct

The$Fake_i$ distribution is left-skewed, suggesting that while most firms display low to moderate levels of disguised innovation behavior, a subset of firms presents extreme avoidance or conservatism.

To verify that these three indicators are not arbitrarily combined, a robustness test was performed on them. Specifically, EBIT, capitalized R&D expenditure, and operating cash flow were successively removed, and the index was reconstructed each time using only the remaining two standardized variables. This step aimed to examine whether the benchmark $Fake_i$ index was mechanically determined by a single dominant variable or reflected a stable underlying structure captured by these three financial signals. The benchmark $Fake_i$ index was constructed from standardized EBIT, standardized capitalized R&D expenditure, and standardized operating cash flow using principal component analysis (PCA). The eigenvalue of the first principal component was 2.3909, explaining 79.70% of the total variance. Based on this, three alternative indices were reconstructed using a leave-one-out test: EBIT, capitalized R&D expenditure, and operating cash flow were removed, respectively. For each alternative index, this study reports its first eigenvalue, the variance explained by the first principal component, and the Pearson correlation coefficient with the benchmark $\mathrm{fake_i}$ index. The results are shown in Table 3.3.7.

Table 3.3.7 Leave-one-out sensitivity test of the $\mathrm{fake_i}$ index

Index construction	First eigenvalue	Variance explained by PC1	Correlation with baseline $\mathrm{fake_i}$
Baseline $\mathrm{fake_i}$	2.3909	0.797	1
EBIT	1.5504	0.7752	0.9708
Capitalized R&D expenditures	1.9537	0.9769	0.9649
Net cash flow from operating activities	1.5523	0.7762	0.9706

As shown in Table 3.3.7, after sequentially removing each variable, the newly reconstructed indices remain highly correlated with the baseline $Fake_i$ index, with correlation coefficients ranging from 0.9649 to 0.9708. At the same time, the variance explained by the first principal component remains high, ranging from 77.52% to 97.69%. These results indicate that the $Fake_i$ measure is not mechanically generated by any one of the three input variables.

More importantly, the leave-one-out results show that EBIT, capitalized R&D expenditures, and operating cash flow each contribute useful but non-exclusive information to the identification of potential disguised or opportunistic R&D behaviour. In other words, the three indicators are not arbitrarily selected. Instead, they jointly capture operating profitability, accounting discretion, and internal cash-flow capacity, which together form the economic basis of the $Fake_i$ construct.

Therefore, the leave-one-out sensitivity test provides additional evidence that the

$Fake_i$ index is a structurally stable composite identification measure rather than an artifact of a single variable choice. On this basis, the baseline PCA-based $fake_i$ index is retained for the subsequent DDD regression analysis.

To improve the interpretability of the PCA-based $fake_i$ index, this study further normalizes the original PCA $fake_i$ score into a 0–1 interval. The original PCA $fake_i$ score is calculated from three standardized indicators: EBIT, capitalized R&D expenditure, and net cash flow from operating activities. Since the PCA score is a principal component score, its value is not naturally restricted to the range between 0 and 1. It can take negative values or values greater than 1. Using $Fake_i^{norm} = \frac{fake_i - fake_{min}}{fake_{max} - fake_{min}}$,

where $fake_{it}$ is the original PCA $fake_i$ score of firm i in year t, $fake_{min}$ is the minimum value of the original Fakei score in the sample, and $fake_{max}$ is the maximum value of the original $fake_i$ score in the sample.

In this study, the observed minimum and maximum values of the original PCA $fake_i$ score are: $Fake_{min} = -1.656968$, $Fake_{max} = 10.959003$. Therefore, the normalized index is calculated as: $fake_i^{norm} = \frac{fake_i - (-1.656968)}{10.959003 - (-1.656968)}$, or equivalently $Fake_i^{norm} = \frac{fake_i + 1.656968)}{12.615971}$. For descriptive analysis and heat-map visualization, the normalized index is further divided into three equal-width risk zones $0 \le Fake_i^{norm} < \frac{1}{3}$, indicates a low-risk zone $\frac{1}{3} \le Fake_i^{norm} < \frac{2}{3}$, indicates a medium-risk zone $\frac{2}{3} \le Fake_i^{norm} < 1$.

As we shown in figure 3.3.2 and figure 3.3.3. The thresholds of $\frac{1}{3}$ and $\frac{2}{3}$ are obtained by dividing the normalized 0-1, $Fake_i^{norm}$,

index into three equal-width intervals. This rule is used to create an intuitive low, medium, and high risk classification for descriptive analysis and visualization. The classification does not come from the PCA estimation and does not replace the continuous $fake_i$ index in the baseline DDD regression. Therefore, it improves the interpretability of the $fake_i$ index without changing the main econometric specification.

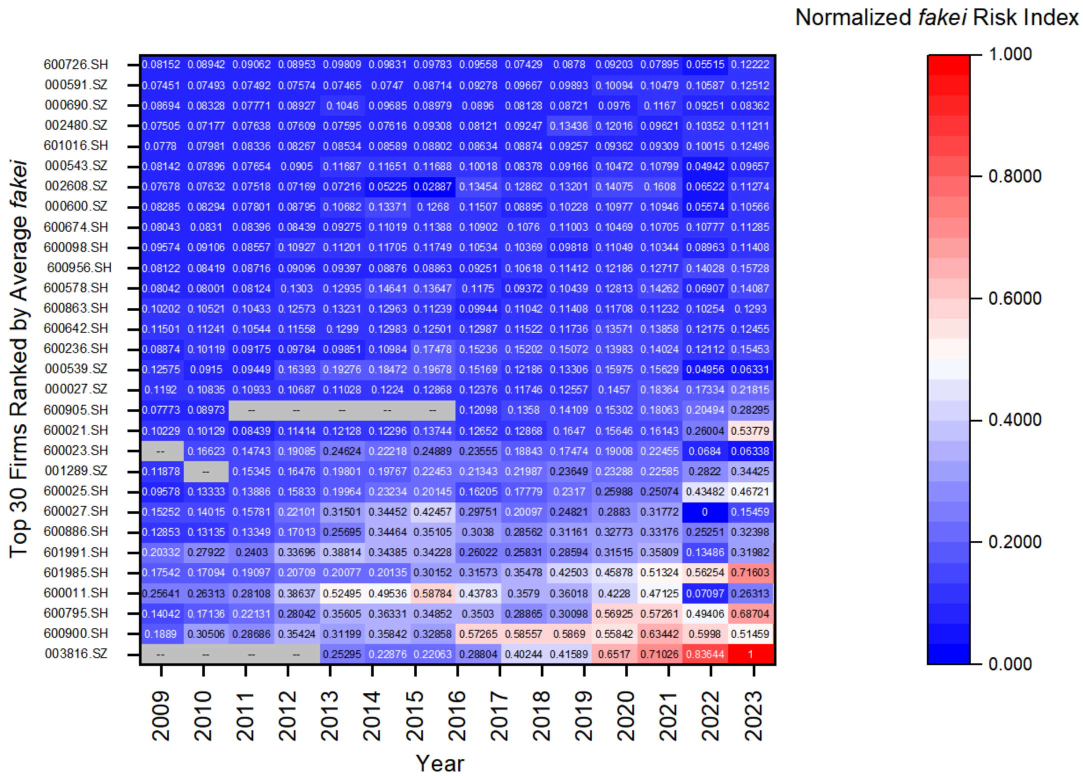


Figure 3.3.2 Annual Heat Map of Normalized fakei Risk Index for Firms Ranked 1–30

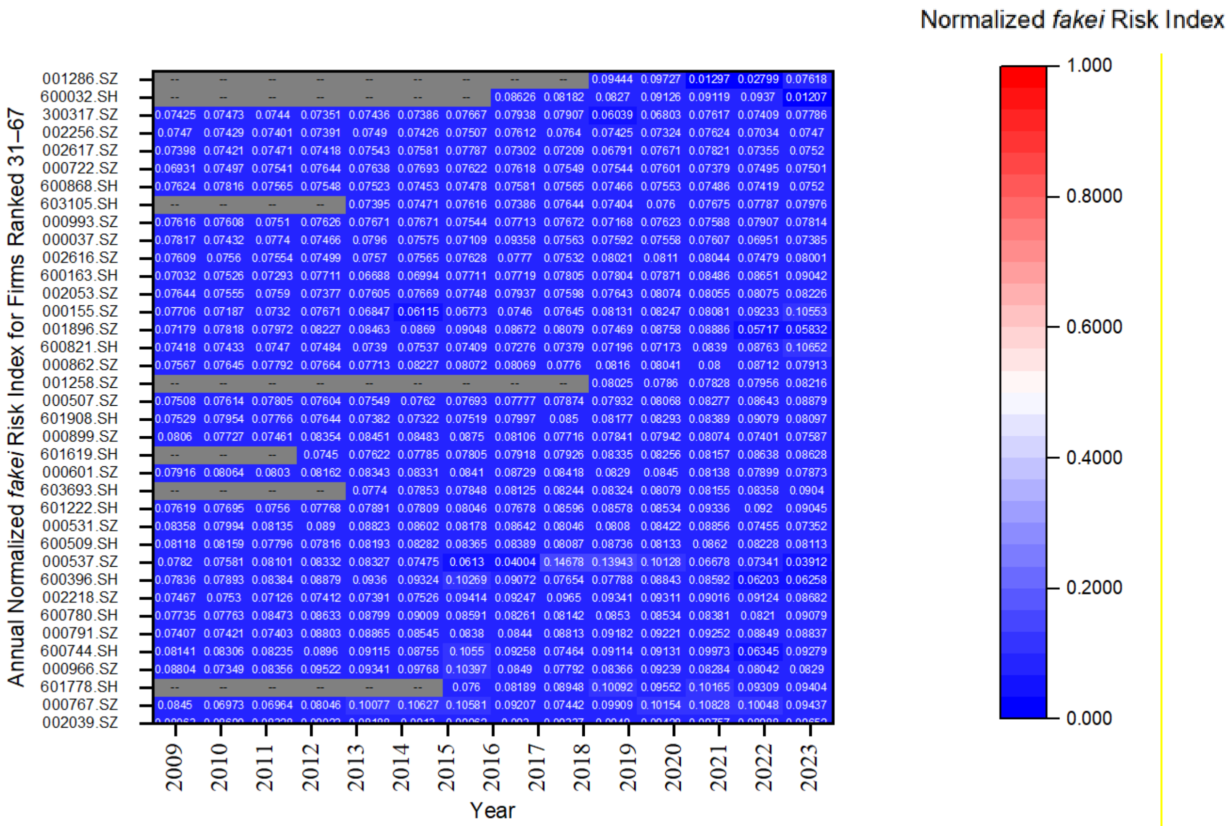


Figure 3.3.3 Annual Heat Map of Normalized fakei Risk Index for Firms Ranked 31-67

The $Fake_i$ index is utilized in subsequent regression models to assess its moderating effect on the relationship between tax incentives and innovation outcomes. The sample as exhibit a slightly negatively skewed distribution, with a group of firms possessing significantly high $Fake_i$. These firms tend to show higher capitalized R&D expenditure, relatively high or stable EBIT, and stronger operating cash flow. This pattern indicates that they may have both the accounting discretion and internal financial capacity to strategically report R&D activities under tax incentives. However, a high $Fake_i$ value does not directly prove fake R&D; it indicates a higher potential risk of opportunistic R&D capitalization, especially when reported R&D expansion is not matched by corresponding green innovation output.

$$Y_{it} = \alpha + \beta_1(Treat_i \times Post_t) + \beta_2(Treat_i \times Post_t \times fake_i) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (56)$$

$Treat_i \times Post_t \times Fake_i$ ： After 2013, will the impact of tax incentive policies on green innovation of new energy companies change depending on their propensity for fake R&D.

$Treat_i \times Post_t$： DID effect of benchmark standards (average impact of policy on normal firms)

X_{it}： A series of control variable vectors

μ_i： Firm Fixed Effects， Controlling enterprise characteristics that do not change over time.

λ_t： Year Fixed Effects， Controlling macroeconomic shocks that change over time.

ε_{it}： random error term

Table 3.3.8 $fake_i$ baseline regression result

	(1) I
c.Treat#c.Post#c. $fake_i$	0.406**
	(0.197)
c.Treat#c.Post	0.063
	(0.153)
Cash Flow	0.007
	(0.005)
ROA	0.002
	(0.003)
Tobin's Q (A)	0.062
	(0.053)

Net Cash Flow from Operating Activities	0.000
	(0.000)
Company Size	-0.075
	(0.085)
Total Assets	0.000***
	(0.000)
Net Fixed Assets	-0.000***
	(0.000)
Ending Cash and Cash Equivalents	-0.000
	(0.000)
R&D Investment as a Percentage of Revenue	-0.001
	(0.025)
Total R&D Investment	-0.000*
	(0.000)
R&D Capitalization Ratio	-0.000
	(0.001)
_cons	1.655
	(2.047)
N	524.000
Controls	YES
Id	YES
Year	YES
R2	0.709

Standard errors in parentheses * p <0.1, ** p <0.05, *** p <0.01

The results shown in Table 3.3.8, that $Fake_i$ significantly moderates the impact of tax incentives. The triple-interaction term $Treat_i \times Post_t \times Fake_i$ is positive and significant (β = 0.406, p < 0.05), indicating that firms with stronger fake R&D tendencies display a greater apparent policy response after the tax incentive reform, likely driven by accounting adjustments rather than substantive green innovation.

The interaction $Treat_i \times Fake_i$ is significantly negative (–0.288, p < 0.05), suggesting that firms engaging in fake R&D already performed worse in green outcomes prior to the policy. Meanwhile, the standard DID term Treat × Post is insignificant, implying that the tax incentive has no uniform effect across all firms and mainly affects those with incentives to manipulate R&D reporting.

Most control variables are insignificant, reinforcing the conclusion that the differential policy effect is linked to the authenticity of innovation activities rather than firm fundamentals. Overall, the findings suggest that latent fake-R&D propensity can distort the measured innovation effect of tax incentives, generating superficial increases in reported innovation-related responses rather than corresponding improvements in substantive green innovation output.

Table 3.3.9 PD result

PD	Freq	Percent	Cum
-4	67	6.67	6.67
-3	67	6.67	13.34
-2	67	6.67	20.01
-1	67	6.67	26.68
0	67	6.67	33.35
1	67	6.67	40.02
2	67	6.67	46.69
3	67	6.67	53.36
4	67	6.67	60.03
5	67	6.67	66.7
6	67	6.67	73.37
7	67	6.67	80.04
8	67	6.67	86.71
9	67	6.67	93.38
10	67	6.67	100.05
Total	1005	100	

The table reports the distribution of the policy-time window (Policy Window, PD) used in the event-study design. The PD variable ranges from –4 to +10, representing four periods prior to onset of the post-2013 policy period and ten periods afterward. Each period contains exactly 67 observations, accounting for 6.67% of the total sample of 1005 firm year observations The cumulative percentage (Cum.) increases uniformly from 6.67% to 100%. This tabulation indicates that the event time window is symmetrically defined at the design stage, but it does not imply that the final regression sample is perfectly balanced after variable screening. Such balance is crucial, as it ensures that dynamic policy effects are not driven by uneven sample composition across periods and that the estimated time-path of the policy impact is statistically reliable. (Table 3.3.9)

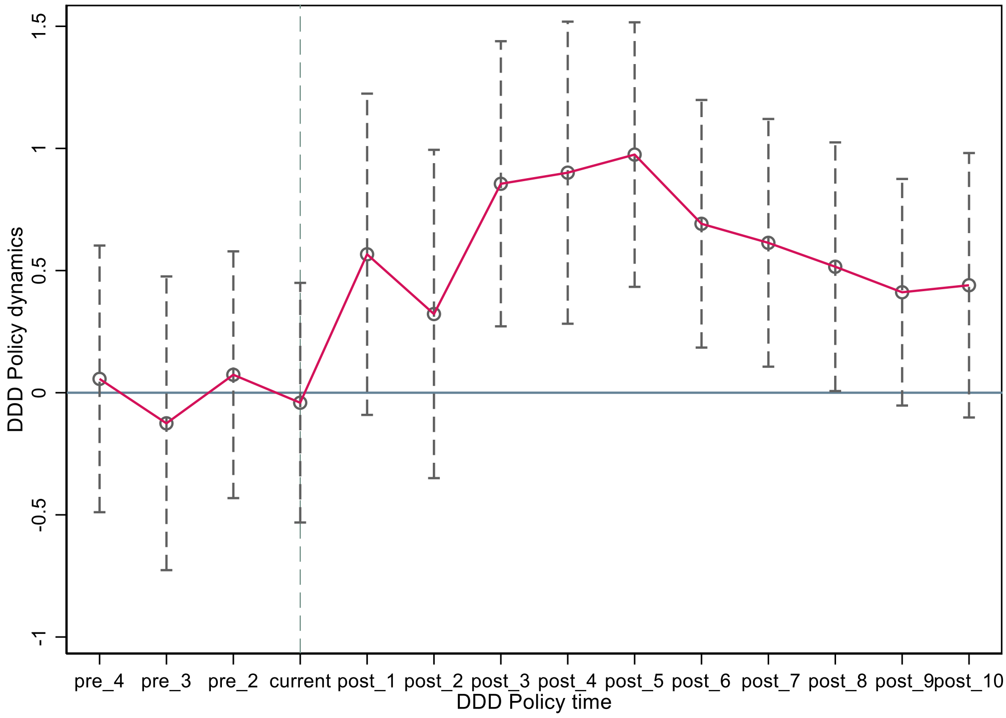


Figure 3.3.4 Policy implementation effect diagram

Figure 3.3.4 reports the dynamic treatment effects from the DDD event-study specification, which allows us to trace how the impact of the tax incentive unfolds over time. In the pre-treatment window (pre_4 to pre_1), the estimated coefficients fluctuate narrowly around zero and their confidence intervals systematically include zero. This absence of statistically significant pre-trends suggests that treated and control firms follow comparable trajectories before the reform, thereby lending empirical support to the parallel trend assumption underpinning our identification strategy.

After the introduction of the tax incentive ($post_1$ onward), the coefficients turn positive and become statistically distinguishable from zero, with the magnitude of the effects increasing gradually and peaking around $post_3$–$post_5$. This lagged and cumulative pattern is consistent with the institutional and real adjustment frictions faced by firms: tax incentives first relax financial constraints and alter the expected returns to green projects, but it takes time for firms to adjust their R&D portfolios, initiate green projects, complete internal approval and budgeting procedures, and translate these changes into observable green sustainable development performance. The concentration of the strongest effects in the medium term suggests that the reform does not merely induce a one-off shock, but instead operates through a buildup of green innovation activities and environmental management practices.

In the later periods ($post_6$ to $post_{10}$), the estimated dynamic effects remain positive, although their magnitude stabilizes or slightly attenuates. This plateau is informative for two reasons. First, it indicates that the policy impact is persistent rather than transitory, pointing to some degree of institutionalization of green-oriented behaviour within firms once new routines and capabilities have been established. Second, the absence of an ever-increasing trajectory suggests that the policy does not indefinitely escalate green innovation output, which is consistent with capacity constraints, diminishing marginal returns to fiscal support, or partial saturation in firms' ability to absorb additional incentives.

Taken together, the dynamic profile depicted in Figure 3.3.4 reveals a coherent narrative: a statistically flat pre-policy baseline, a delayed but progressively strengthening post-policy response, and a subsequent stabilization of the treatment effect. This temporal structure not only reinforces the credibility of the causal interpretation of our DDD estimates, but also aligns closely with the theoretical mechanism whereby tax incentives work through easing financing constraints, raising the expected payoff to green innovation, and gradually reshaping firms' investment and environmental strategies within the Chinese institutional context. Therefore, it conforms to hypothesis 5, and tax incentives may induce potential "Fake R&D" behaviour by companies.

3.4 Predictions of the Outcome of Government Punishment Measures for Faked Research and Development

While the empirical analysis in the previous section used historical data to revealed distortion heterogeneity associated with latent fake-R&D propensity, regression analysis can only assess the average effect of policies that have already occurred and cannot answer counterfactual questions such as "what would happen if penalties were increased" or "what would happen if quotas were introduced." Therefore, this chapter, based on the behavioral characteristics of firms revealed by the empirical analysis , such as cost sensitivity and strategic responses, constructs an evolutionary game model to conduct forward-looking simulations of the diffusion paths of green R&D under different policy combinations. We have already learned that tax incentives may induce companies to engage in “fake R&D” and thus defraud the government of taxes, making punitive measures by the government necessary. This chapter continues to examine the most reasonable range of punitive methods and measures. An empirical analysis is conducted using the model described in Section 2 of Chapter 2.

Under the premise of bounded rationality, based on the experience-weighted attraction (EWA) mechanism and the principle of replicator dynamics, the strategic evolution of renewable energy companies among "real green R&D" (strategy 1), "fake-R&D" (strategy 2), and "maintaining existing traditional production" (strategy 3) can be rigorously characterized by replicator dynamic equations. Assume that at time t, renewable energy companies choose among three strategies: real green R&D (x), fake R&D (y), and conventional production (z). respectively (satisfying x + y + z = 1). Based on the unified payoff framework established in Section 2.3, the expected return functions (Π_1, Π_2, Π_3) for these strategies are defined as follows:

$$F(x)=\frac{dx}{dt}=x(1-x)(\Pi_1-\Pi_3)-xy(\Pi_2-\Pi_3) \quad (57)$$

$$F(y)=\frac{dy}{dt}=y(1-y)(\Pi_2-\Pi_3)-xy(\Pi_1-\Pi_3) \quad (58)$$

F(x)=0, F(y)=0,E1(0,0), E2(1,0), and E3(0,1), The imprisonment stability of the system at each equilibrium point can be determined by the eigenvalues of the Jacobian matrix J.

$$J=\begin{bmatrix} \frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} \\ \frac{\partial F(y)}{\partial x} & \frac{\partial F(y)}{\partial y} \end{bmatrix}=\begin{bmatrix} J_{11} & J_{12} \\ J_{21} & J_{22} \end{bmatrix} \quad (59)$$

This research focuses on renewable energy power generation as the subject for examining green R&D diffusion. Based on recent updates from the Energy Bureau, the national feed-in tariff for offshore renewable energy power was switched to a guide price starting in 2019, and all newly approved offshore wind projects now determine tariffs through competitive bidding, with state subsidies no longer provided. The guide price for offshore renewable energy power in 2021 was set at 0.75 yuan per kWh.

Similarly, China has revised its benchmark feed-in tariffs for onshore renewable energy power several times. Since 2021, newly approved onshore projects have achieved full grid parity, removing the need for state subsidies. As of 2022, all new grid-connected projects operate at grid parity. The onshore wind electricity prices are set at 0.29 RMB/kWh in Resource Area I (eastern), 0.85 RMB/kWh in Resource Area II (central), 0.70 RMB/kWh in Resource Area III (western), and 0.47 RMB/kWh in Resource Area IV.

According to data from the National Bureau of Statistics (NBS), China's total electricity consumption in 2023 reached 9224.1 billion kWh, marking a 6.7% increase from the previous year. renewable energy power contributed 809 billion kWh to this total.

In order to supervise and manage the renewable energy power generation, China has formulated relevant laws and policies. World justice project in 2023 published the'2023 Rule of Law Index Report. China's supervisory and enforcement index is 0.49, and for the validity of the experiment the supervisory capacity of regions I, II, and III will be set to ε 0.29 for region I in the East, II 0.1 for region I.(Figure 3.4.1)

Expenses incurred by enterprises in developing innovative technologies, products, and processes, which are excluded from the current profit and loss calculations, are eligible for an additional 75% deduction of the R&D costs, beyond the standard allowable deduction., i.e. ι = 75%. Intangible assets, once recognized, are amortized at 175% of their cost. Furthermore, local governments often provide financial subsidies to support the central government's industrial strategies. For example, in Shanghai, companies can claim a 10% subsidy for R&D expenses, with a cap of 1 million yuan per enterprise, while in Shenzhen, firms with R&D spending exceeding 10 million yuan are eligible for a 1-million-yuan subsidy. Additionally, the Ministry of Industry and Information Technology has established a requirement for renewable energy power enterprises to allocate at least 3% of total sales, or no less than 10 million yuan, toward R&D, as per the Specification Conditions for the renewable energy power Manufacturing Industry. In line with this, the

R&D subsidy (S) for renewable energy power enterprises is set at 1 million yuan.

In the construction of the evolutionary game model, two key parameters require careful specification: the penalty coefficient applied to strategic misreporting, and the scale of network externalities across regions.

According to China's Regulations on Penalties for Fiscal Violations, enterprises that fraudulently obtain public funds through misrepresentation or falsified declarations are subject to fines ranging from 10% to 50% of the misappropriated amount. This legal standard is codified into the model as a penalty multiplier $\gamma \in [1.10,1.50]$, where $\gamma=1+r$, and ris the statutory penalty rate. The selected range reflects the enforceable limits of administrative penalties and is consistent with documented cases in the renewable energy sector. This modeling assumption ensures that the deterrent effect of regulatory risk is explicitly embedded within the payoff matrix. Network Size. The response of firms to tax policy is assumed to be influenced by the size of the policy network to which they belong. Network size, in this study, refers to the number of member firms within the China Renewable Energy Power Industry Association, proxied by data from the Wind Energy Professional Committee of the Chinese Renewable Energy Society (CWEA). As of 2023, CWEA reports approximately 270 active member firms with the following estimated regional distributions: 5% in Region I, 25% in Region II, and 70% in Region III. Based on this proportional structure and extrapolating to broader sectoral participation, we assume representative network sizes of 14, 68, and 188 firms for Regions I, II, and III, respectively.

This research sets R&D quotas at $\eta=0$、$\eta=0.05$、$\eta=0.10$ represents the baseline scenario where there is no mandatory R&D threshold; $\alpha=0.05$ represents a lower level of R&D quota constraint; and $\eta=0.05$ represents a higher level of R&D quota constraint. The reason for this choice is that the Ministry of Industry and Information Technology's regulations for the wind power manufacturing industry clearly stipulate that enterprises' R&D investment should not be less than 3% of sales revenue. Therefore, this research extrapolates from this actual policy baseline to 5% and 10% to characterize different levels of institutional requirements. Furthermore, 5% and 10% are two representative constraint levels constructed upwards from the actual minimum R&D requirements. Thus, this setting takes into account the realistic basis, the need for scenario comparison, and the model's identifiability.

The rationale for embedding network size into the model stems from the literature on information diffusion and policy compliance in industrial ecosystems. Larger networks facilitate more robust peer effects, information spillovers, and reputational constraints, all of which amplify behavioral conformity to policy signals. Accordingly, firms embedded in larger regional networks are more responsive to fiscal incentives and more sensitive to reputational penalties. To ensure robustness, supplementary simulations are conducted with ±30% perturbations in assumed network sizes to verify the structural stability of the equilibrium outcomes.

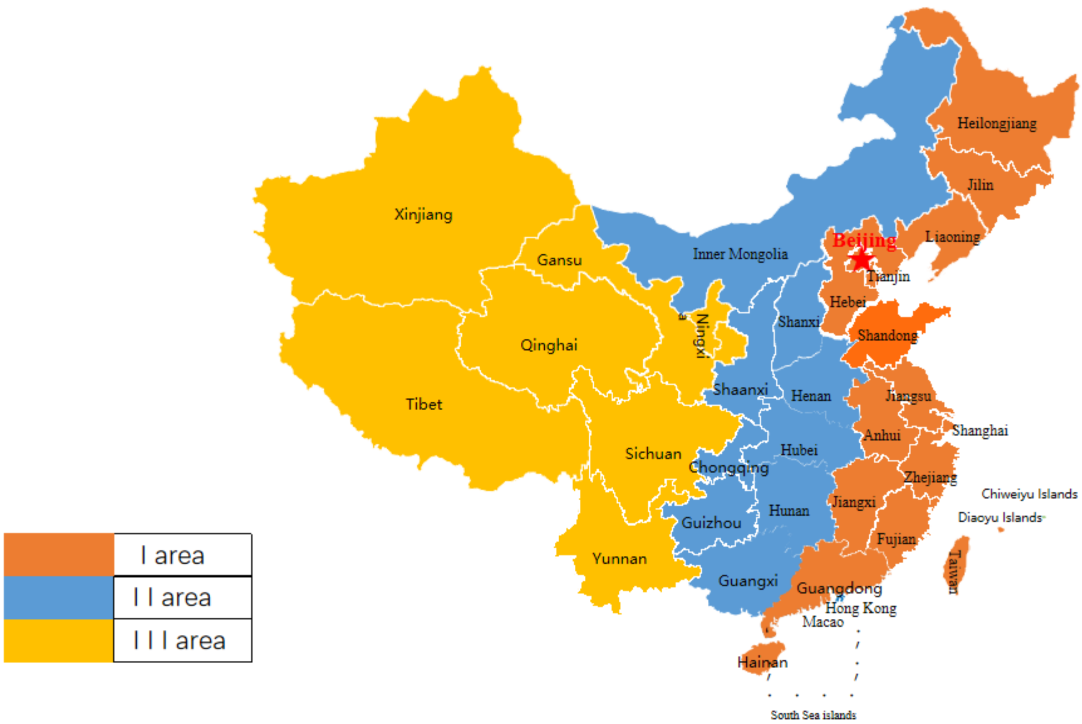


Figure 3.4.1 China map

Source: China government website

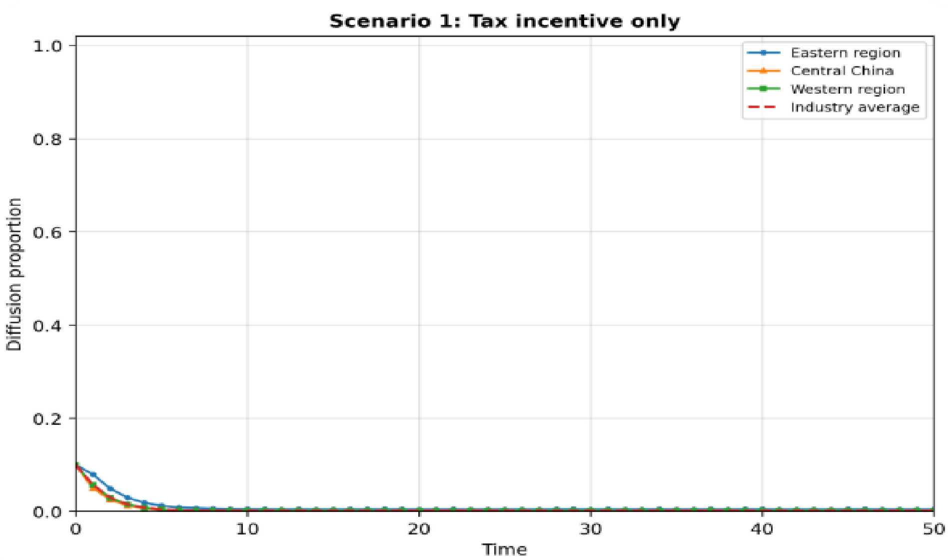
Scenario 1: No quota mandate in the electricity market (η=0) and government imposes R&D tax incentives (ι=75%)

As shown in Scenario 1, genuine green R&D diffusion was almost nonexistent. The initial diffusion rates in the East, Central, and West regions were close to 0.10, but quickly contracted, reaching almost zero by the tenth period. At the end of the fiftieth period of the randomized trial, the results were 0.004 for the East, 0.001 for the Central region, and 0.001 for the West, with an industry average of 0.001. This result indicates that without quota constraints and strong penalties, tax incentives alone are insufficient to support companies' continued adoption of genuine green R&D strategies, easily leading to "fake R&D." This is mainly because while tax incentives can reduce some R&D costs, they are essentially just "cost compensation" and do not generate sufficiently strong market returns. When comparing "genuine R&D" and "fake R&D," companies find that genuine green R&D involves R&D costs, failure risks, and learning costs, while without quota constraints, green products do not gain a clear additional market share, thus lacking diffusion momentum. The rapid decline of the curve in the figure precisely illustrates that tax incentives, without the support of market constraint mechanisms, are insufficient to support green R&D diffusion on their own. (Figure 3.4.2).

Figure 3.4.2 Green R&D Diffusion Results of renewable energy power Energy in Scenario 1

Scenario 2: No quota mandate in the electricity market ($\eta = 0$), government tax incentives for R&D ($\iota = 75\%$) and severe penalties ($\gamma = 1.5$)

Compared to Scenario 1, Scenario 2 shows a slightly higher rate of genuine R&D



diffusion, but the difference is limited, almost zero in the tenth period of the randomized experiment. At the end of the fiftieth period of the randomized experiment, the results were 0.0044 in the East, 0.0010 in the Central region, 0.0010 in the West, and 0.0012 for the industry average. This result is due to the strong penalty $\gamma = 1.5$. Strong penalties do increase the risk cost of fake green R&D or strategic fraud, thus having a certain inhibitory effect on the mechanism. However, this deterrent effect is mainly a "negative constraint"; it can only reduce the attractiveness of non-compliant strategies but cannot automatically create high returns from genuine green R&D. Without a quota system to provide additional market space, even if companies dare not easily fake it, they may not necessarily turn to genuine green R&D, and are more likely to choose to shrink their R&D activities or remain at a low-input equilibrium. Therefore, this figure illustrates that penalties can increase compliance pressure, but without supporting market incentives, they can only play a marginal corrective role and cannot independently create a diffusion breakthrough.

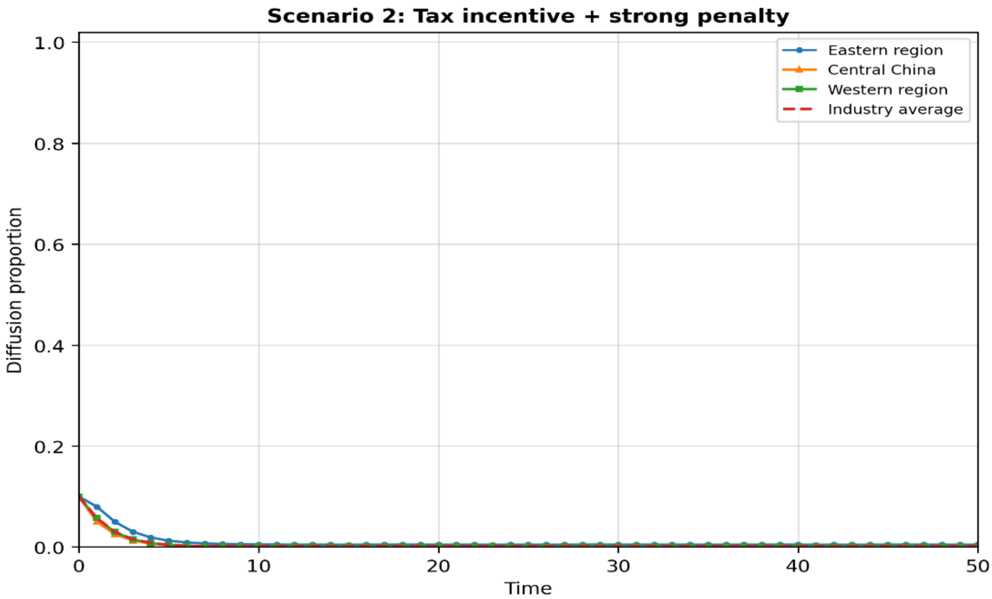


Figure 3.4.3 Green R&D Diffusion Results of renewable energy power Energy Industry in Scenario 2

Scenario 3: The electricity market introduces a green R&D quota $\eta = 0.05$ and the government imposes R&D tax incentives ($\iota = 75\%$) and severe penalties ($\gamma = 1.5$)

In Scenario 3, with quota $\eta = 0.05$, R&D tax incentives ($\iota = 75\%$), and severe penalties ($\gamma = 1.5$), companies begin truly diffuse. Even with a relatively small quota ($\eta = 0.05$), genuine green R&D innovation can still be promoted. The quota system diverts a portion of market demand from the general market, specifically reserving it for companies that successfully engage in green R&D. This transforms genuine green R&D from a "high-cost, high-risk" activity into a strategy that can generate additional market benefits. Combined with tax incentives and strong penalties, the relative attractiveness of genuine green R&D significantly increases, raising the diffusion rate from near zero to around 0.15–0.20. Furthermore, due to higher electricity prices and a larger network scale in western China, when comparing the eastern, central, and western regions, western companies, under the impact of policy, experience stronger expected benefits and network externalities from green R&D, resulting in a higher diffusion curve.

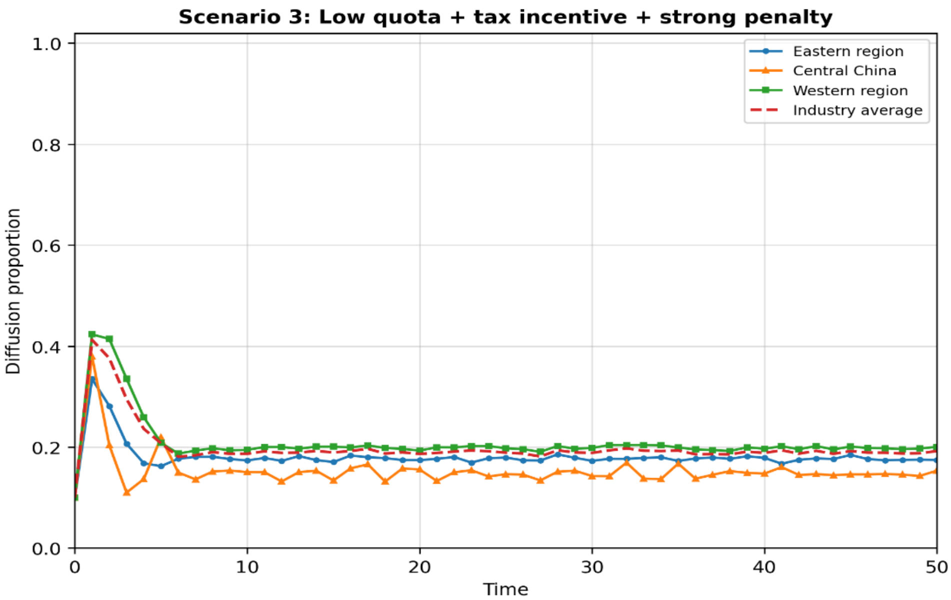


Figure 3.4.4 Green R&D Diffusion Results of renewable energy power Energy Industry in Scenario 3

Scenario 4: Increasing the green R&D quota in the electricity market to η = 0.1, with government-imposed R&D tax incentives (ι = 75%) and severe penalties (γ = 1.5)

In the scenario setting of a green R&D quota in the electricity market to η = 0.1, with government-imposed R&D tax incentives (ι = 75%) and severe penalties (γ = 1.5), the inference evolution in scenario four is the most effective among the five experimental groups. Compared to scenario 3, the western region almost jumps to a level close to complete diffusion. This indicates that under the model mechanism, when the green R&D quota increases from 0.05 to 0.10, the market demand redistribution towards green R&D enterprises is significantly strengthened, thus enabling genuine green R&D to obtain sufficiently strong expected returns. Tax incentives continue to reduce R&D costs, strong penalties continue to compress the space for disguised strategies, and high quotas truly make "doing green R&D" a more proactive and dominant choice. Scenario 4 effectively demonstrates the synergistic effect of the policy combination between tax incentives and penalties. Furthermore, with the quota system of $\eta = 0.1$, tax incentives, penalties for disguised R&D, and the quota system combined, enterprises face a comprehensive incentive structure, thus enabling genuine green R&D diffusion to rapidly reach a high level.

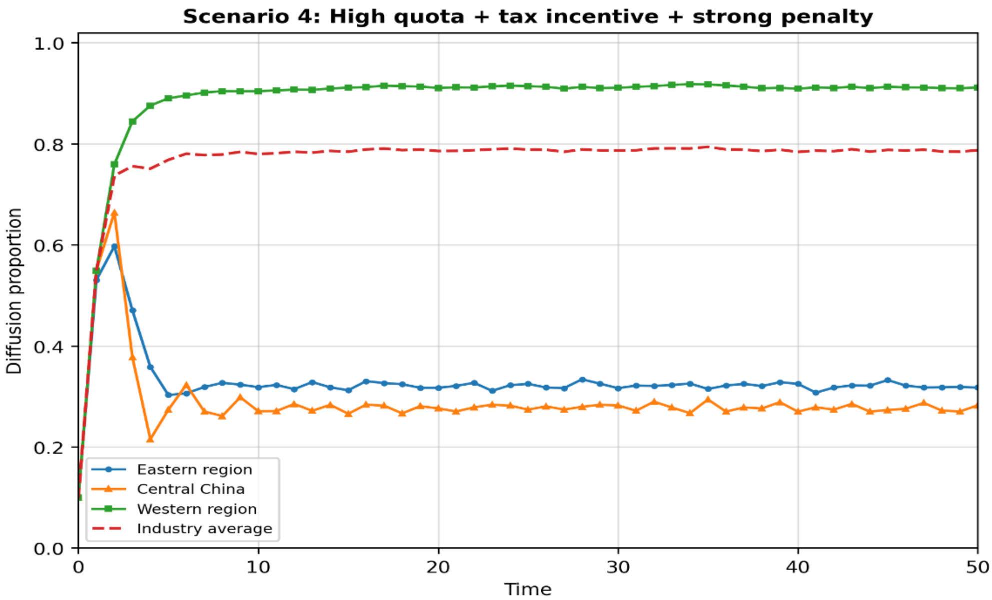


Figure 3.4.5 Green R&D Diffusion Results of renewable energy power Energy Industry in Scenario 4

Scenario 5: The green R&D quota in the electricity market is set at 0.1, and firms need to achieve at least 10 per cent of green R&D or face strong penalties ($\gamma = 1.5$)

As the graph shows, the curve for Scenario 5, where the green R&D quota in the electricity market is set at 0.1 and firms need to achieve at least 10 percent of green R&D or face strong penalties ($\gamma = 1.5$), is almost identical to that of Scenario 4, rising rapidly in the early stages and stabilizing at a high level in the later stages; however, each curve is slightly lower than that of Scenario 4. This indicates that under high quota constraints, market returns themselves have become the main driver of real green R&D. Even if tax incentives are removed, and only high quotas and strong penalties are retained, companies will still massively shift towards green R&D. Therefore, the reason Scenario 5 can still maintain high diffusion is not because of tax incentives, but because high quotas have already strongly reshaped the market incentive structure, although high quotas are only a relatively idealized situation. At the same time, the value of Scenario 5 is slightly lower than that of Scenario 4, which also indicates that tax incentives are positive and can achieve a strengthening of marginal effects.

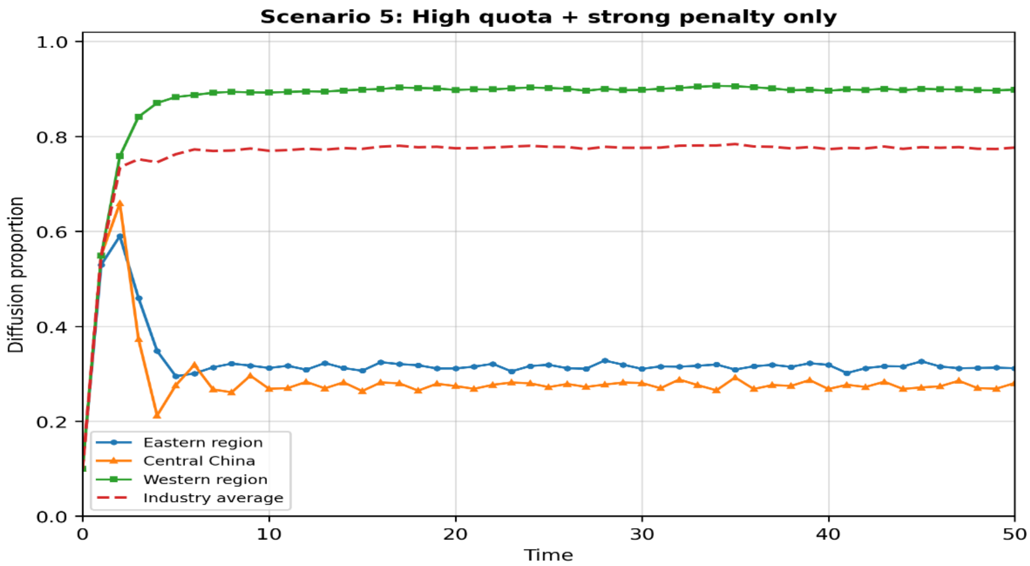


Figure 3.4.6 Green R&D Diffusion Results of renewable energy power Energy Industry in Scenario 5

On the basis of retaining the foregoing five benchmark policy scenarios unchanged, we further conducts a sensitivity analysis of the penalty coefficient in order to examine how variations in punitive intensity affect the diffusion path of genuine green R&D. Specifically, using the benchmark policy environment corresponding to Scenario 4 as the reference case, and holding $\eta=0.10$ and $\iota=75\%$ constant, three penalty levels are introduced, namely $\gamma=1.10$, $\gamma=1.25$, and $\gamma=1.50$, to test the sensitivity of the diffusion outcomes to changes in the penalty coefficient. The sensitivity analysis follows the same dynamic simulation logic adopted in the main scenario analysis. Parameters explicitly reported in the dissertation are retained, including the anticipated adjustment multiplier $\xi=0.5$, the network-effect index $\beta=1.5$, the past experience discount factor $\rho=0.25$, the attractiveness discount factor $\nu=0.5$, and the noise level $1/\alpha=0.1$. The benchmark setting also preserves the regional network sizes identified in the dissertation, namely 14 firms in the eastern region, 68 in the central region, and 189 in the western region.

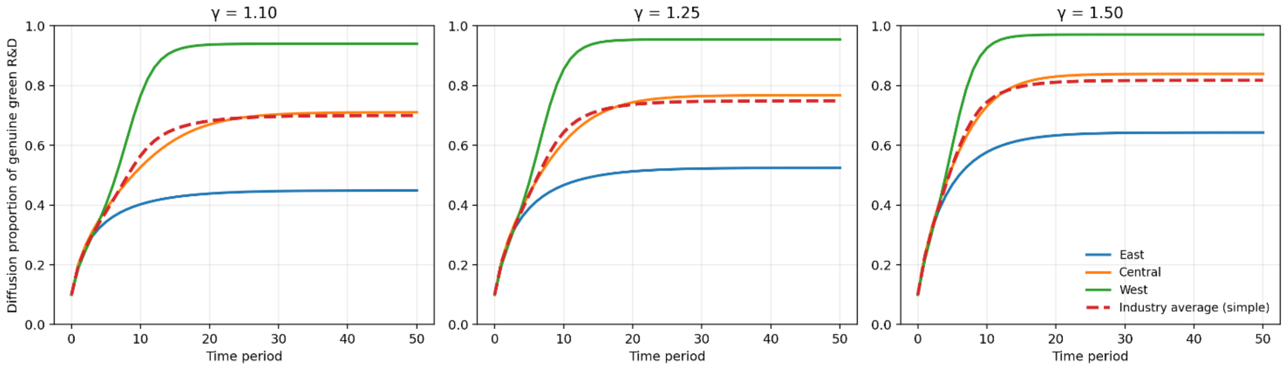


Figure 3.4.7 Sensitivity analysis of the penalty coefficient under the benchmark policy environment (η=0.10,ι = 75%)

The results show that figure 3.4.7, keeping other conditions constant, increasing the penalty coefficient γ from 1.10 to 1.25 and then to 1.50 significantly increased the proportion of genuine green R&D diffusion in the eastern, central, and western regions, as well as the industry average, with a correspondingly faster convergence speed. This indicates that a stronger penalty mechanism can effectively suppress $fake_i$ behavior and improve the diffusion efficiency of $fake_i$. Regional differences are evident, under all three penalty levels, the pattern remains highest in the west, followed by the central region, and lowest in the east. When γ= 1.50, the steady-state level in the west is close to 0.97, in the central region it is approximately 0.83, in the east it is approximately 0.64, and the industry average is approximately 0.82. This indicates that while strengthening the penalty did not change the regional ranking, it significantly improved the steady-state diffusion level of genuine green R&D in each region.

3.5 Advice for China and Implications for other major countries

Based on the empirical analysis of this study, it is clear that China's current tax incentives for the new energy industry have demonstrated a robust and significant positive impact on improving corporate financial conditions, increasing R&D investment intensity, and promoting green innovation output. However, the effects of these policies show significant differences across regional distribution, enterprise type, and the time frame of the onset of the post-2013 policy period. To ensure that tax policies continue to drive green technology progress in the future, avoid diminishing returns after long-term use, and reduce the space for enterprises to obtain tax benefits through financial manipulation, China's green tax system reform still needs further deepening in four aspects: precise design, differentiated support, verifiable results, and policy system synergy.

China needs to gradually shift its tax incentive system from the traditional "input-oriented" to a dual-track structure that emphasizes both input and results. The mechanism analysis in this study shows that tax incentives are effective because they effectively increase enterprises' R&D investment intensity, which is a key mediating factor driving green patent output. Therefore, while maintaining the stability of the current R&D expense deduction policy, it is even more necessary to strengthen the policy's results oriented nature. It is advisable to link some tax credits to enterprises' substantial innovative achievements. For example, differentiated credits could be implemented based on the number of high-quality invention patents obtained, the degree of breakthrough in key core technologies, and the level of technology industrialization. For enterprises with an abnormally high R&D capitalization ratio but low green innovation output, their tax credits could be appropriately reduced, ensuring that tax resources flow primarily to enterprises genuinely engaged in R&D activities, thus reducing the risk of the policy being transformed into a financial manipulation.

China should further strengthen the synergistic effect of tax policy with fiscal, financial, and carbon markets. The time effect analysis of this study shows that tax incentives typically produce significant innovation effects three to five years after the onset of the post-2013 policy period, while their driving force weakens after six years. To avoid this phenomenon of "insufficient incentive momentum," a three-pronged green technology innovation system linking "taxation, public finance, and finance" can be constructed: tax policies should reduce cost pressures in the early stages of R&D; public subsidies should focus on tackling core technologies requiring long-term investment; green loans and green bonds should reduce enterprises' medium- and long-term capital costs; and the carbon market mechanism should further incentivize enterprises to increase investment in green technology R&D through emissions revenue. Furthermore, a "phased, tiered tax incentive structure" can be explored emphasizing cost reduction in the early stages of the policy, rewarding innovative achievements in the middle stages, and implementing a moderate exit strategy in the later stages, making tax incentives more rhythmic and sustainable.

China's green tax system urgently needs to achieve long-term sustainability and transparency at the legislative level. On the one hand, a nationally unified green tax expenditure performance evaluation system should be established, and information on the scale, structure, and effects of tax expenditures should be made public to enhance public oversight and policy credibility. On the other hand, green tax policies with long-term significance should be incorporated into the legal framework, giving enterprises stable policy expectations when formulating R&D plans and investment layouts. Furthermore, tax incentives should be closely integrated with the national strategy of carbon peaking and carbon neutrality, electricity market reform, energy regulatory mechanisms, and carbon trading systems to build a cross departmental collaborative governance network for green development policies.

Overall, based on the empirical findings of this study regarding the effectiveness of China's new energy tax incentive policies, Russia, in building its own green development and new energy technology innovation system, also faces the challenge of how to leverage fiscal and tax tools to enhance corporate innovation capabilities, optimize industrial structure, and address the challenges of energy transition. Given Russia's high dependence on fossil fuels, weak renewable energy industry chain, significant regional imbalances, and nascent green finance system, its policy formulation must fully consider these practical constraints. In this context, China's experience can offer several directions for Russia to learn from, but it must be localized within Russia's institutional conditions and economic structure.

Based on the international comparisons in Section 1 of Chapter 2 and the empirical analysis in Chapter 3, it is evident that there is no single, easily replicable "standard answer" for new energy tax systems. The differences in policy tool configurations, incentive priorities, and institutional logic among Russia, China, the United States, Germany, Denmark, and Japan stem primarily from variations in their resource endowments, energy structures, and industrial bases. Furthermore, they are closely related to their respective stages of energy transition and policy objectives. Therefore, this comparative analysis does not aim to prove the universal optimality of any particular type of tax tool, but rather to demonstrate that tax incentives can only truly transform into an effective force for promoting green technology progress when embedded within a country's existing energy system, industrial structure, and institutional environment.

From an institutional function perspective, major countries worldwide should not view tax incentives merely as fiscal concessions to expand project investment during their new energy transition. Instead, they should position them as medium to long-term institutional arrangements serving technological progress, industrial upgrading, and innovation diffusion. This comparative analysis reveals that the United States has established a relatively complete multi-layered support system across cost, benefit, and innovation ends. Germany and Denmark have also enhanced the guiding role of tax tools in the evolution of green industries through differentiated environmental tax systems, consumer incentives, and the integration of innovation policies. In contrast, China's intervention on the cost side is the most comprehensive, exhibiting a clear front end compensation characteristic. However, on the innovation side, it still relies heavily on general classifications such as high technology enterprises, and there is ability for further refinement in the identification and outcome constraint mechanisms for green industries. Therefore, the future direction for major countries to improve their new energy tax systems should not focus on increasing the number of tools, but rather on the intrinsic connection between tax incentives and innovation performance, especially the correlation between tax incentives and green patents, breakthroughs in high-end equipment, and the efficiency of technology industrialization.

Furthermore, the comparative results of this research show that the policy effects of new energy tax incentives exhibit distinct heterogeneity, both within a single country and between countries. Even within the same country, different regions, enterprises with different ownership types, and market entities with different innovation foundations respond differently to tax incentives. At the international level, different countries, due to differences in energy lock-in, industrial chain positions, and institutional arrangements, are even less likely to achieve identical policy outcomes. The institutional characteristics of the United States are closer to a high policy stock model under full life-cycle support; Germany and Denmark demonstrate high structural transformation efficiency; while China exhibits a characteristic of rapid policy expansion and continuous institutional adjustment in parallel. Russia's energy tax system has long revolved around the fossil fuel sector, resulting in relatively limited dedicated tax tools for renewable energy. During the sample period, the proportion of renewable energy consumption remained relatively low and fluctuated, illustrating that the effectiveness of tax systems is profoundly influenced by existing energy structures and development paths. Therefore, major countries worldwide should emphasize differentiated adaptation in their institutional design, rather than mechanically transplanting a single policy template.

At a deeper level, this international comparison also demonstrates that tax incentives alone are insufficient to independently accomplish the institutional tasks of new energy transformation and the diffusion of green innovation. What truly determines policy sustainability is not the intensity of tax incentives themselves, but whether tax incentives can form a stable synergy with regulatory constraints, market mechanisms, and industrial policies. This finding has universal significance for major countries worldwide: the focus of new energy tax reform should not simply remain on the quantitative dimension of how much preferential treatment, but should further shift to the governance dimension of "how to improve the authenticity of incentives, enhance behavioral constraints, and maintain the verifiability of the system." Only when a relatively stable institutional equilibrium is formed between tax tools, regulatory mechanisms, and the market environment can tax policy truly become a long-term supporting force for promoting technological progress and industrial upgrading in new energy.

CONCLUSION

This research studies listed companies in the energy sector of China's Shanghai and Shenzhen A-share markets, constructing a causal identification framework of tax incentives corporate green technology innovation to systematically evaluate the true impact of new energy tax preferential policies before and after 2013 on corporate green innovation output and its possible distortion mechanisms. Based on unbalanced panel data from 67 energy companies , including 26 renewable energy companies and 41 non-renewable energy companies from 2009 to 2023, this research uses 2013 as the post-2013 policy regime point, setting renewable energy companies as the treatment group and traditional energy companies as the control group. The DID model identification is implemented under a two-way fixed effects framework for both companies and years, and an event study is further used to characterize the dynamic path of the policy effect. The impact of tax incentives on green innovation shows a significant lag-accumulation characteristic, the effect is not significant in the early stages of the post-2013 policy regime, but gradually strengthens in the medium term and reaches its peak after about 3-5 years, then stabilizes. This suggests that tax incentives are more likely to be transmitted to observable patent output through internal project initiation, budgeting, and R&D cycles, rather than forming an immediate impact. Based on this, a DDD model is constructed to identify the overestimation of policy effects caused by disguised R&D. The results show that companies with a high tendency for disguised R&D show a stronger "apparent response" after the policy, suggesting that relying solely on tax incentives may induce companies to amplify the appearance of R&D investment through accounting treatment, which may not correspond to substantive green innovation. Finally, evolutionary game theory simulation is used to predict future policy outcomes, overcoming the limitations of previous static evaluations. The study shows that a single incentive measure leads to structural inefficiency, while a strategic combination of weak quotas, strong incentives and add strict penalties" can produce a Pareto optimal outcome. In summary, tax incentives can promote green technology innovation in renewable energy companies, but their mechanism is not linear or immediate, exhibiting significant lagged and cumulative characteristics. Under insufficient supervision or information asymmetry, tax incentives may also induce companies to inflate "reported R&D" through financial and accounting manipulations to meet policy thresholds, leading to statistical overestimation of policy effectiveness and distorted resource allocation. Therefore, green innovation policies should not be limited to the single dimension of increasing incentive intensity, but should instead form a combined governance framework of tax incentives, quota constraints and penalty constraints: tax incentives are used to reduce innovation costs, quota targets provide a minimum input boundary, and penalty mechanisms increase the cost of fraudulent R&D and strengthen authenticity constraints. Scenario simulations further show that introducing penalty mechanisms can significantly suppress fraudulent R&D and accelerate the diffusion of green R&D. Adding appropriate quota constraints on top of penalties and tax incentives helps to further improve industry diffusion efficiency, but it also amplifies regional differences in innovation capabilities. This suggests that when strengthening constraints, policies should simultaneously consider the resource endowments and R&D capabilities of different regions to avoid excessively high compliance costs and long unsustainability in strong constraint and weak capability regions.

Future research directions will be further deepened in three aspects based on the existing foundation. First, the sample scope and research level will be further expanded. Subsequent research can extend the sample to non-listed new energy companies, companies in specific industry segments, and over a longer time span to improve external validity and identify differences in policy responses at different development stages. Second, the precision of identifying real innovation versus disguised innovation will be further enhanced. This research has constructed potential fake R&D indicators using EBIT, capitalized R&D investment, and operating cash flow. However, future research will use data combining patent quality, patent maintenance years, green patent citation frequency, R&D expense details, audit opinions, and tax audit data to provide a more granular characterization of companies' strategic reporting behavior, thereby enhancing the ability to identify the authenticity of policies and the effectiveness of incentives. Third, the analysis of policy combinations and institutional linkages will be further expanded. The evolutionary game simulation in this research has shown that the combination of weak quotas, strong incentives and severe penalties is more likely to form Pareto improvements. Future research can build on this by incorporating tax incentives, carbon trading, fiscal subsidies, green credit and regional regulatory capacity into a unified analytical framework, and constructing dynamic comparative models across policy tools, regions and countries to more systematically evaluate the long-term synergistic effects and institutional optimization paths of the green innovation policy system.

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List of abbreviations

E.U. - European Union

OECD - Organisation for Economic Co-operation and Development

R&D - research and development

VAT - Value-added tax

DID-difference-in-differences

ITS-Information transmission

SRTS-software and information technology

WSR -wholesale and retail trade

RE -real estate

WPFM-warehousing and postal services

WSR-water conservancy

LBS-leasing and business services

SRTS-scientific research and technical

HSW- health and social work as HSW

AC-accommodation and catering

AFAHF-agriculture forestry animal husbandry and fishery

PTC-Production Tax Credit

EBIT-Earnings Before Interest and Taxes

ITC- Investment Tax Credit

Appendix A

Table 1.3.1 Preferential Policies for Turnover Tax

Serial number	Year	Relevant Policy
1	1997	The State Council promulgated the Notice on Adjusting Tax Policies for Imported Equipment (State Council Document [1997] No.37), which exempts tariffs and value-added tax (VAT) on imported equipment used in the construction, operation, and management of wind power and other new energy power station projects during the importation process.
2	2007	The Notice on Implementing Import Tax Policies Related to the State Council's Guidelines on Accelerating the Revitalization of the Equipment Manufacturing Industry (Revenue Tariff[2007] No.11) classified high-power wind turbine generators as a critical key technological equipment domain in China. For such equipment, import tariffs and value-added tax (VAT) levied during the import process are to be collected first and refunded later. The refunded taxes shall be used for corporate R&D, production, and independent innovation activities
3	2008	The Ministry of Finance (MOF) and the State Taxation Administration (STA) jointly issued the Notice on Value-Added Tax Policies for Resource Utilization and Other Products (Finance and Taxation [2008] No.156), which implements a 50% immediate VAT refund policy on electricity generated from wind power projects. This marked the first preferential treatment applied to the end-product of new energy power generation in China's tax policy framework.
4	2010	The Ministry of Finance and the State Taxation Administration jointly issued the Notice on Value-Added Tax, Business Tax, and Corporate Income Tax Policies for Promoting the Development of Energy Conservation Service Industries (Finance and Taxation [2010] No. 110). The notice states that for energy management projects undertaken by energy conservation service companies, the transfer of taxable goods to energy-using enterprises will be subject to a temporary suspension of value-added tax. This measure ensures preferential policies for energy enterprises at the institutional level.
5	2012	The Ministry of Finance issued the Notice on Adjusting the Catalogue for Import Tax Policies Concerning Major Technical Equipment (MOF Circular [2012] No.14), exempting import tariffs and value-added tax (VAT) on solar power generation equipment, marking the first dedicated tax incentive policy for the solar energy sector.
6	2015	The Ministry of Finance and the Tariff Commission jointly issued the Circular on Adjustments to the Import Tax Policy for Major Technological Equipment (Revenue Tariff [2015] No.51), which stipulates that import tariffs and value-added taxes on complete wind turbine generators and their components are exempted.
7	2015	The Ministry of Finance (MOF) and the State Taxation Administration (STA) jointly issued the Notice on Value-Added Tax Policies for Wind Power Generation

		(Finance and Taxation [2015] No.74), stipulating that taxpayers utilizing self-produced wind power for internal consumption shall be entitled to a 50% immediate VAT refund, thereby incentivizing the adoption of new energy electricity.
8	2020	The State Council Tariff Commission issued the"Notice on the Adjustment Plan for Provisional Import Tax Rates and Other Measures in 2020" (Tariff Commission [2020] No.50), which lowers the import tariff rate for wind power equipment to 5%, implementing preferential tax policies at the import stage.

Source: compiled by the authors based on data from China Statistics Bureau.

Appendix B

Table 1.3.2 Income Tax Preferential Policies

Serial number	Year	Relevant Policy
1	2010	The Ministry of Finance and the State Taxation Administration jointly issued the "Notice on Value-Added Tax, Business Tax, and Enterprise Income Tax Policies for Promoting the Development of the Energy Service Industry" (Finance and Taxation [2010] No.110), which implements a policy of three exemptions and three 50% reductions for eligible projects undertaken by energy service companies.
2	2018	Pursuant to the Enterprise Income Tax Law of the People's Republic of China promulgated by the State Council, qualified wind power technology enterprises and wind farm construction projects are subject to a preferential enterprise income tax rate of 15%.
3	2019	The State Council has adopted the “Implementation Regulations of the Enterprise Income Tax Law of the People's Republic of China (2019 Revision)”to implement a three-year exemption and three-year 50% reduction policy on the income derived from investment and operation of state-supported electric power infrastructure projects.

Source: compiled by the authors based on data from China Statistics Bureau.

Appendix C

Table 2.1.1 Tax incentive documents issued in 2013

Category	Tax type	specific policies	fiscal impact/explanation
Cost side	Value-added tax incentives	Finance and Taxation Document No. 66 of 2013: A 50% tax refund policy will be implemented on the sale of photovoltaic products, effective from October 1, 2013.	Reduce the actual tax burden on enterprises to 6.5%; a single photovoltaic project can save 300,000 to 1 million yuan in taxes annually.
	Consumption tax	Maintain tax exemption for new energy products	Maintain price advantage over end products such as photovoltaic cells and fuel cells
	Customs duties and import value-added tax	The policy framework of 2012 will be maintained, and key imported components will be exempt from tariffs and value-added tax (continuing the 2009/2012 catalog).	Reduce import costs for complete machine manufacturers and stabilize the equipment supply chain.
Profit side	Resource tax and surcharges	The renewable energy surcharge standard has been adjusted to 0.015 yuan/kWh (Ministry of Finance Announcement).	Increased revenue from the renewable energy fund will be used to subsidize expansion.
Innovation-side	Corporate income tax	Article 28 of the Enterprise Income Tax Law stipulates that high-tech enterprises are subject to a 15% tax rate, covering approximately 20,000 new energy-related enterprises in 2013.	The estimated annual tax reduction exceeds 100 billion yuan, of which approximately 15-20% is in the new energy sector.

Source: Compiled by the author from the State Taxation Administration

Appendix D

Table 2.1.5 Summary of China's Business Tax to VAT Reform (2013–2016) and Input VAT Credit Refund Policy (2018–2023)

Year	Policy Phase	Key Content	Sectors Covered
2012	Pilot Launch (Shanghai)	Shanghai first pilot: Transportation and modern service industries included in VAT.	Transportation, modern service industries
2012	Second Pilot Phase	Expanded to 8 provinces (e.g., Beijing, Tianjin), covering more service sectors.	Transportation, modern services
2013	Third Pilot Phase	Expanded to 10 provinces (e.g., Jiangsu, Zhejiang), broader industry coverage.	Transportation, modern services
2014	Fourth Pilot Phase	Railway, postal, and telecom sectors included in pilot.	Transportation (railway, postal, telecom)
2015	Fifth Pilot Phase	Construction, real estate, finance, and living services included.	Construction, real estate, finance, living services
2016	Full Implementation	Business Tax abolished; VAT fully replaced Business Tax nationwide.	All sectors (including services and construction)

Appendix E

Table 2.1.6 Overview of Electricity Generation from Various Energy Sources in China from 2009 to 2023

(Unit: Billion Kilowatt-hours)

Year	Thermal Power	Hydropower	Wind Power	Solar Energy	Total Power Generati	Total power generation from renewable energy sources
2009	30116	5717	276	0	37145	6692
2010	33319	7222	446	1	41727	8408
2011	38337	6990	703	6	46900	8563
2012	38928	8721	959	36	49876	10690
2013	42470	9203	1412	84	54316	11815
2014	44001	10729	1600	235	57945	13889
2015	42842	11303	1858	395	58146	15263
2016	44371	11841	2371	665	61332	17009
2017	47546	11979	2972	1178	66045	18610
2018	50963	12318	3660	1769	71661	20690
2019	52202	13044	4057	2240	75034	22825
2020	53303	13552	4665	2611	77791	24491
2021	57703	11840	5667	1837	81122	23419
2022	58888	13522	7627	4273	88488	29600
2023	62658	12859	8859	5842	94565	31907

Source: compiled by the authors based on data from China Statistics Bureau

Appendix F

Table 2.3.1 Renewable Energy Preferential Policies for Other Relevant Tax Categories

Tax category	Document	Specific policies
Value-added Tax	Finance and Taxation [2015] No.74	Starting from July 1, 2015, a 50% VAT refund-upon-collection policy has been implemented for wind power products.
	Finance and Taxation [2016] No.36	Energy Service Companies (ESCOs) implementing eligible Energy Performance Contracting (EPC) projects are exempt from Value-Added Tax (VAT) for both:
	Finance and Taxation [2013] No.66, [2016] No.81	From October 1, 2013, to December 31, 2018, a 50% value-added tax (VAT) refund policy upon collection was implemented for solar power products.
	Finance and Taxation [2019] No.60 [2021] No.40	From March 1, 2022, sales of renewable resource products such as electricity, heat, and biodiesel that comply with regulations for comprehensive utilization are eligible for the value-added tax (VAT) immediate levy-and-refund policy.
Import value-added Tax and Customs duties	Revenue Tariff [2014] No.2	Import Value-Added Tax (VAT) and tariffs are fully exempted for imported components and raw materials required in the manufacturing of state-supported major new energy technology equipment.
Consumption Tax	Finance and Taxation [2015] No.16	Exempt solar cells, fuel cells, and other new energy products from consumption tax.

Source: compiled by the authors based on data from China Statistics Bureau

Appendix G

Table 2.3.5 Input VAT Credit Refund Policy (2018–2023)

Year	Policy Phase	Key Content	Sectors Covered
2018	Pilot Launch	First pilot: Refunds for advanced manufacturing (equipment, R&D, software).	Advanced manufacturing (equipment, R&D, software)
2019	Expansion Phase	Extended to pharmaceuticals, chemicals, energy, and telecommunications.	Pharmaceuticals, chemicals, energy, telecom
2022	Large-Scale Implementation	Full refunds for SMEs and manufacturing sectors to mitigate pandemic impacts.	SMEs, manufacturing, R&D, transportation, energy
2022	Temporary Extension	Extended refunds for manufacturing and tech firms until December 2022.	Manufacturing, tech firms, SMEs
2023	Continuation Policy	Policy extended to 2023, prioritizing SMEs and manufacturing.	SMEs, manufacturing, tech firms

Appendix H

Table 3.1.1 Variable Name Description

Variable Type	Variable Name	Variable Description
Explained Variable	ROE	Return on Equity, used to measure the profitability of an enterprise.
Explanatory Variable	Tax Support Intensity	The ratio of tax rebates received by an enterprise to various taxes paid.
Explained Variable	Y (Green Innovation Output)	The logarithm of the sum of the number of green patent applications and the number of grants, measuring green innovation output.
Explanatory Variable (DID Double Interaction)	Treat	Whether it is a renewable energy enterprise (1=yes, 0=no).
	Post	Whether it is after the onset of the post-2013 policy period.
Explained Variable	Y (Green Innovation Output)	The logarithm of the sum of the number of green patent applications and the number of grants, measuring green innovation output.
Explanatory Variable (DDD Triple Interaction)	did	Treat × Post, identifying the average relative effect of the post-2013 renewable-energy-oriented tax-support regime
	$fake_i$	A dummy variable constructed using PCA based on EBIT, capitalized R&D investment, and net cash flow from operating activities, reflecting potential faked R&D capability.
Control Variable	Cash Flow	Net cash flow from operating activities / total assets, reflecting internal financial conditions.

	Return on Total Assets (ROA)	Net profit / average total assets, measuring overall profit-making efficiency.
	Tobin's Q	Market value / book value of assets, reflecting expectations of enterprise growth.
	Net Cash Flow from Operating Activities	The net cash inflow generated by the main business, reflecting operational quality.
	Enterprise Size	The natural logarithm of the company's total assets, indicating enterprise scale.
	Net Fixed Asset Value	The proportion of net fixed asset value to total assets, measuring the degree of capital intensity.
	Shareholding Proportion of the Largest Shareholder	The shareholding proportion of the largest shareholder, reflecting equity concentration.
	End-of-Period Cash Balance	The balance of cash and cash equivalents at the end of the year, reflecting short-term debt-paying ability.
	R&D Intensity	R&D expenditure / operating revenue, reflecting the willingness for R&D investment.
	Total R&D Expenditure	The total annual R&D expenditure (logarithm), measuring the scale of R&D investment.
	Ratio of Capitalized R&D Expenditure	The proportion of capitalized R&D expenditure to total R&D expenditure, reflecting the tendency of result recognition.

Source: The author compiled based on the content of the article.

Appendix I

Table 3.1.3 Phase 1 Descriptive Statistics

Variable	N	Mean	p50	SD	Min	Max
ROE	390	0.613	0.616	0.062	0	1
Tax_S	390	0.034	0.013	0.085	0	1
Cash Flow	390	0.637	0.65	0.1	0	0.922
ROA	390	0.662	0.667	0.058	0.078	1
Tobin's Q (A)	390	1.56	1.32	0.807	0.77	9.33
Net Cash Flow from Operating Activities	390	0.128	0.117	0.042	0	0.519
Company Size	390	0.235	0.403	0.759	-2.587	0.92
Total Assets	390	5.22	1.3	8.82	0	5.51
Net Fixed Assets	390	0.031	0.009	0.067	0	0.574
Ending Cash and Cash Equivalents	390	0.045	0.015	0.09	0	0.706
R&D Investment as a Percentage of Revenue	390	0.075	0.011	0.124	0	1
Total R&D Investment	390	0.008	0.001	0.018	0	0.174
R&D Capitalization Ratio	390	0.202	0.168	0.118	0	1

Appendix J

Table 3.1.4 List of companies analyzed empirically

Stock Code	Stock Abbreviation	Industry	Administrative Region	Founding Date
000027.SZ	Shenzhen Energy	Thermal Power	Guangdong Province	1993-08-21
000037.SZ	Shennan Electric A	Thermal Power	Guangdong Province	1990-04-06
000155.SZ	Sichuan Energy Power	Wind Power	Sichuan Province	1997-10-20
000507.SZ	Zhuhai Port	Wind Power	Guangdong Province	1986-06-20
000531.SZ	Suiheng Energy A	Thermal Power	Guangdong Province	1992-11-30
000537.SZ	China Green Energy	Wind Power	Tianjin Municipality	1986-03-05
000539.SZ	Guangdong Electric Power A	Thermal Power	Guangdong Province	1996-02-05
000543.SZ	Anhui Energy Power	Thermal Power	Anhui Province	1993-12-13
000591.SZ	Solar Energy	Photovoltaic Power	Chongqing Municipality	1993-04-12
000600.SZ	Jiantou Energy Huaneng International	Thermal Power	Hebei Province	1994-01-18
000601.SZ	Shanghai Electric Power	Hydropower	Guangdong Province	1993-06-14
000690.SZ	Zhejiang Energy Power	Thermal Power	Guangdong Province	1997-01-20
000722.SZ	Huaneng Hydropower	Hydropower	Hunan Province	1993-08-12
000767.SZ	Huadian International	Thermal Power	Shanxi Province	1993-02-08
000791.SZ	Zhejiang New Energy	Hydropower	Gansu Province	1997-09-23
000862.SZ	Guangzhou Development	Wind Power	Ningxia Hui Autonomous Region	1998-06-28
000899.SZ	Zhongmin Energy	Thermal Power	Jiangxi Province	1997-11-04
000966.SZ	Guoguan Power	Thermal Power	Hubei Province	1995-04-07
000993.SZ	Huadian Liaoning Energy	Hydropower	Fujian Province	1998-12-30
001258.SZ	Tianfu Energy	Wind Power	Xinjiang Uygur Autonomous Region	2013-08-28

001286.SZ	Beijing Energy Power	Thermal Power	Shaanxi Province	2003-09-03
001289.SZ	Shenergy	Wind Power	Beijing	1993-01-27
001896.SZ	Sichuan Investment Energy	Thermal Power	Henan Province	1997-11-25
002039.SZ	Huadian Energy	Hydropower	Guizhou Province	1993-10-12
002053.SZ	Huayin Power	Wind Power	Yunnan Province	2002-07-25
002218.SZ	Tongbao Energy	Photovoltaic Power	Guangdong Province	2002-08-15
002256.SZ	Guodian Power	Photovoltaic Power	Guangdong Province	1995-12-20
002480.SZ	Jinkai New Energy	Photovoltaic Power	Sichuan Province	2001-03-28
002608.SZ	Inner Mongolia Huadian	Thermal Power	Jiangsu Province	2003-06-16
002616.SZ	Meiyan Jixiang	Other energy generation	Guangdong Province	1993-08-06
002617.SZ	Guotou Power	Photovoltaic Power	Zhejiang Province	1989-05-24
003816.SZ	Yangtze Power	nuclear power generation	Guangdong Province	2014-03-25
300125.SZ	Three Gorges Energy	Photovoltaic Power	Liaoning Province	2005-12-12
300317.SZ	Xintian Green Energy	Photovoltaic Power	Guangdong Province	1993-07-17
600011.SH	Energy Saving Wind Power	Thermal Power	Beijing	1994-06-30
600021.SH	Linyang Energy	Thermal Power	Shanghai Municipality	1998-06-04
600023.SH	Jiaze New Energy	Thermal Power	Zhejiang Province	1992-03-14
600025.SH	Jinko Technology	Hydropower	Yunnan Province	2001-02-08
600027.SH	Jingyuntong	Thermal Power	Shandong Province	1994-06-28
600032.SH	China Nuclear Power	Photovoltaic Power	Zhejiang Province	2002-08-01
600098.SH	Datang Power	Thermal Power	Guangdong Province	1992-11-13
600163.SH	Xineng Technology	Wind Power	Fujian Province	1998-05-26
600236.SH	Jiangsu New Energy	Hydropower	Guangxi Zhuang Autonomous Region	1992-09-04
600396.SH	Huadian Liaoning Energy	Thermal Power	Liaoning Province	1998-06-04
600509.SH	Tianfu Energy	Thermal Power	Xinjiang Uygur Autonomous Region	1999-03-28
600578.SH	Beijing Energy Power	Thermal Power	Beijing	2000-03-10

600642.SH	Shenergy	Thermal Power	Shanghai	1993-02-22
600674.SH	Sichuan Investment Energy	Hydropower	Sichuan Province	1988-04-18
600726.SH	Huadian Energy	Thermal Power	Heilongjiang Province	1996-10-28
600744.SH	Huayin Power	Thermal Power	Hunan Province	1993-03-22
600780.SH	Tongbao Energy	Thermal Power	Shanxi Province	1992-08-28
600795.SH	Guodian Power	Thermal Power	Liaoning Province	1992-12-31
600821.SH	Jinkai New Energy	Photovoltaic Power	Tianjin Municipality	1997-03-27
600863.SH	Inner Mongolia Huadian	Thermal Power	Inner Mongolia Autonomous Region	1994-05-12
600868.SH	Meiyan Jixiang	Hydropower	Guangdong Province	1993-01-01
600886.SH	State Power Investment Corporation	Hydropower	Beijing	1996-06-18
600900.SH	Yangtze Power	Hydropower	Beijing	2002-11-04
600905.SH	Three Gorges Energy	Wind Power	Beijing	1985-09-05
600956.SH	Xintian Green Energy	Wind Power	Hebei Province	2010-02-09
601016.SH	Energy Saving Wind Power	Wind Power	Beijing	2006-01-06
601222.SH	Linyang Energy	Photovoltaic Power	Jiangsu Province	1995-11-06
601619.SH	Jiaze New Energy	Wind Power	Ningxia Hui Autonomous Region	2010-04-16
601778.SH	Jinko Technology	Photovoltaic Power	Jiangxi Province	2011-07-28
601908.SH	Jingyuntong	Photovoltaic Power	Beijing	2002-08-08
601985.SH	China Nuclear Power	nuclear power generation	Beijing	2008-01-21
601991.SH	Datang Power	Thermal Power	Beijing	1994-12-13
603105.SH	Xineng Technology	Photovoltaic Power	Zhejiang Province	2008-07-09
603693.SH	Jiangsu New Energy	Wind Power	Jiangsu Province	2002-10-17

Source: Wind data

Appendix K

Table 3.2.1 Second-stage descriptive statistics

Variable	N	Mean	p50	SD	Min	Max
Y	524	0.364	0	0.862	0	5.328
did	524	0.355	0	0.479	0	1
Cash Flow	524	5.877	6.156	5.366	-21.86	27.84
ROA	524	1.740	2.365	6.505	-76.89	18.20
Tobin's Q Ratio	524	1.301	1.098	0.631	0.765	9.334
Net Cash Flow from Operating Activities	524	0.159	-0.367	1.232	-1.505	7.386
Net Fixed Asset	524	23.85	23.79	1.594	20.20	27.07
Company Scale	524	0.183	-0.359	1.210	-0.587	5.652
Total Assets	524	0.164	-0.351	1.199	-0.564	5.344
Ending Cash and Cash Equivalents	524	0.153	-0.338	1.108	-0.663	6.423
R&D investment as a Percentage of Revenue	524	1.437	0.495	2.178	0	20.06
Total R&D Expenditure	524	0.0120	-0.302	1.033	-0.355	9.393

R&D Capitalization Ratio	524	11.79	0	24.64	0	133.6

Appendix L

Table 3.2.12 Identified set for the average post3–post5 effect

$\bar{M}$	Maximum bias	Lower bound	Upper bound
0	0	0.719	0.719
0.25	0.148	0.571	0.868
0.5	0.297	0.423	1.016
0.75	0.445	0.274	1.165
1	0.594	0.126	1.313
1.25	0.742	−0.023	1.462