Frontiers in Business, Economics and Management
ISSN: 2766-824X | Vol. 19, No. 2, 2025

Decomposition of Driving Factors of Green Innovation in Carbon Emissions Trading Pilot Enterprises

Chao Yang

School of Economics and Management, Tongji University, Shanghai, China

Abstract: This paper investigates the factors driving green innovation in Chinese listed firms from 2012—when China launched its pilot carbon trading policy—through 2022. Building on the logarithmic mean Divisia index (LMDI) decomposition method, we disaggregate changes in green patent applications into four firm-level effects: economic scale, R&D investment intensity, R&D efficiency and green patent share. Our panel dataset combines green and total patent counts from CNRDS with R&D and revenue data from CSMAR, excluding financial and "ST" firms. Time-series decomposition reveals that both pilot and non-pilot firms achieved substantial growth in green patenting, with non-pilot firms slightly outperforming pilots and both groups experiencing a pandemic-related slowdown in 2022. The green share effect proved the most powerful driver, reflecting a widespread strategic reallocation of R&D toward environmental technologies. Pilot firms saw early gains in R&D efficiency under carbon trading, which reversed after 2018 as they shifted toward fewer, higher-value patents. R&D intensity rose most sharply among pilot firms post-2018, indicating that sustained carbon pricing strengthened innovation budgets. Economic scale consistently supported patent growth across all firms. We conclude that market-based carbon regulation can catalyze initial efficiency and investment responses, but lasting green innovation requires a structural shift in corporate R&D priorities. Policy recommendations include expanding carbon market coverage, enhancing targeted R&D incentives, fostering collaborative innovation ecosystems, and integrating environmental regulation with green finance and intellectual property protection.

Keywords: Green innovation; Carbon emissions trading policy; Logarithmic mean Divisia index.

1. Introduction

Climate change has increasingly emerged as one of the most pressing global challenges, compelling nations and international bodies to re-examine their approaches to environmental sustainability and carbon emissions reduction. The rapid rise in global temperatures, largely attributable to escalating greenhouse gas emissions, has spurred widespread concern and prompted initiatives such as the United Nations Framework Convention on Climate Change, the Kyoto Protocol, and the Paris Agreement, all of which underscore the urgent need for mitigating CO_2 emissions [1–3]. Amid this complex global context, China stands out as both a major contributor to global emissions and a proactive leader in pursuing sustainable development. With its unparalleled economic growth in recent decades, China's energy consumption and CO_2 emissions have concurrently surged, making it the world's largest emitter. Faced with the dual challenges of maintaining economic growth while safeguarding its environment, China has undertaken significant policy reforms, including ambitious targets to peak carbon emissions before 2030 and achieve carbon neutrality by 2060. Underpinning these initiatives is the strategic promotion of green innovation—a key driver of technological progress and environmental stewardship. Green innovation, which harnesses technological advancements to reduce environmental impacts and improve energy efficiency, is increasingly recognized as an essential pillar for balancing industrial development with ecological preservation. As the urgency to combat climate change intensifies, fostering green innovation within enterprises has become central not only to achieving sustainable economic growth but also to facilitating global efforts against environmental degradation.

In this study, we focus on decomposing the driving factors behind green innovation in enterprises participating in China's pilot carbon emissions trading policies. The analysis employs the logarithmic mean Divisia index (LMDI) method, a robust quantitative tool that has been extensively used in energy and environmental studies to disentangle the impacts of various determinants on observed outcomes. By evaluating factors such as research and development expenditure, scale effects, policy incentives, and efficiency improvements, our research seeks to illuminate the complex interplay between carbon trading policies and green technological innovation within the Chinese industrial sector. The impetus for this research stems from the widely acknowledged role of green technology innovations in not only reducing emissions but also enhancing industrial competitiveness and promoting sustainable development. Previous studies have provided valuable insights into individual aspects of green innovation, yet a comprehensive decomposition of the contributing factors remains insufficiently explored, particularly in the context of policy-driven market mechanisms. Addressing this gap, our paper contributes to the existing literature by offering an in-depth analysis of how the carbon trading scheme influences technological innovation in China's high-emissions enterprises. The findings of our research are expected to inform policymakers and industry stakeholders by highlighting areas where targeted investments and regulatory adjustments can maximize the dual benefits of environmental protection and economic progress. The remainder of the paper is organized as follows: Section 2 reviews the relevant literature, Section 3 outlines the data sources and describes the LMDI methodological framework, Section 4 presents and discusses the empirical findings, and Section 5 concludes with recommendations for future policy enhancements and research directions.

2. Literature Review

The existing literature on the impact of environmental regulation on green innovation is extensive and diverse. Researchers have long recognized that strict environmental policies can significantly influence the strategic choices and innovation outcomes of firms. Early work by scholars such as Wang [4] laid the foundation for understanding green technology by exploring its definitions, motivations, and determinants. Over time, as the challenges of global climate change and environmental degradation became more pronounced, studies began to focus on how environmental regulations could spur or hinder green innovation at various levels—from national to industrial to firm-specific contexts [5, 7–9]. A substantial body of literature supports the Porter hypothesis, which argues that well-designed environmental regulations can create competitive advantages by stimulating innovation [6, 7]. Some empirical studies, for instance, have demonstrated that environmental regulation encourages firms to undertake exploratory innovation by investing in advanced and cleaner technologies, thereby enhancing overall green innovation performance. However, contrasting perspectives have also emerged, suggesting that overly stringent regulation may impose additional costs, reduce competitiveness, and ultimately have only a limited or even negative impact on green technological progress [11, 12]. In parallel, other research has highlighted additional determinants of green innovation, such as economic development levels, R&D investment, CO_2 emissions, and government subsidies, underscoring the multifaceted nature of innovation drivers [3, 10–13]. Despite this rich research tradition, there is still a noticeable gap concerning the comprehensive decomposition of the innovation-driving factors under the specific influence of environmental regulation. In other words, while many studies have established the direct and indirect relationships between environmental regulation and green innovation, few have systematically dissected how distinct components—such as CO_2 emissions and R&D activities—interact within this framework to shape innovation outcomes.

Parallel to the investigations on policy impacts, the logarithmic mean Divisia index (LMDI) method has been increasingly employed in recent years to decompose the driving factors behind energy consumption, CO_2 emissions, and, more recently, green innovation. The LMDI approach has emerged as a popular and robust tool because it overcomes many shortcomings of other decomposition techniques—it avoids the residual term problem, efficiently handles zero values, and facilitates comparative analyses across different temporal and spatial contexts [15, 16]. Researchers have applied the LMDI method in various contexts to understand the dynamics of CO_2 emissions in energy-intensive industries and the broader economy [17, 19–21]. For instance, studies on industrial energy consumption and carbon intensity have utilized LMDI to attribute changes to scale effects, structural adjustments, and efficiency improvements. In the realm of green innovation, pioneering studies have extended the application of LMDI to decompose green patent counts based on factors such as R&D investment intensity, technological spillovers, and economic scale effects [18, 19, 25]. Notably, Fujii's investigation into China's green technology inventions during different Five-Year Plans [1] and subsequent extensions by researchers like Chen and Lin [24] underscore the method's versatility in revealing the nuanced contributions of various drivers in different policy eras. Despite the widespread use of LMDI in these areas, its application to decompose the determinants of green innovation, particularly those driven by environmental regulation, remains underexplored. Most existing studies have primarily focused on presenting econometric results or employing patent data for standard analyses, without delving into the detailed decomposition of innovation-driving forces under specific regulatory pressures. Moreover, while significant progress has been made in developed countries, there is still a scarcity of research that explicitly addresses how environmental regulation interacts with CO_2 emissions and R&D activities to drive green innovation in developing country contexts, notably in China. This literature gap highlights an urgent need for integrating both environmental regulatory impacts and innovation-related inputs into a unified analytical framework. By doing so, researchers can offer more targeted insights into how policy measures can be fine-tuned to bolster sustainable innovation outcomes. Against this backdrop, our study seeks to fill the existing void by extending the LMDI decomposition framework to account for the distinct roles of CO_2 emissions and R&D activities in shaping green innovation. In this paper, we aim to contribute to the literature by not only isolating the effects of environmental regulation but also by providing a detailed, period-wise decomposition analysis that distinguishes the underlying drivers of green patent applications in China's pilot carbon trading enterprises. This dual analytical approach—combining time-series and period-wise decompositions—promises to yield new empirical evidence that can inform policymakers and industry stakeholders on how to design more effective environmental regulations that simultaneously promote sustainable technological advancement and economic growth.

3. Methodology and Data

3.1. Model Construction

In this study, we develop an extended LMDI (Logarithmic Mean Divisia Index) framework tailored to decompose the drivers of green innovation at the firm level. Distinct from previous approaches that primarily focus on macroeconomic or sector-wide indicators, our model incorporates variables that capture firm-specific dimensions of innovation performance. In particular, the model emphasizes the roles of company size, R&D expenditure, total patent output, and green patent output to explain the variations in green innovation outcomes. The underlying assumption is that a firm's revenue (denoted as Scale) not only reflects its economic magnitude but also its potential capacity to invest in research and development (R&D), which in turn drives innovation activities as measured by patent applications.

In our decomposition framework, the green innovation output is proxied by the number of green patent applications (Green), while overall innovation is captured by the total number of patents (Patent). The framework further accounts for the firm's commitment to research and development through its R&D investment. The core idea is to dissect the green patent output into several contributory factors: the Scale effect, representing the firm's economic size; the R&D intensity effect, which quantifies the proportion of revenue allocated to research and development; the R&D efficiency effect, which measures the output of patents per unit of R&D investment; and finally, the green innovation share effect, which is determined by the proportion of green patents among all patents.

These interactions are encapsulated in our multiplicative LMDI model, expressed as follows:

$$P_{Green_t} = GDP_t \times \frac{R\&D_t}{GDP_t} \times \frac{Patent_t}{R\&D_t} \times \frac{Green_t}{Patent_t} \quad (1)$$

$$P_{Green_t} = G_t \times E_t \times I_t \times S_t \quad (2)$$

$$\Delta Green = Green_t - Green_b = \omega_i ln(\frac{G_t}{G_b}) + \omega_i ln(\frac{E_t}{E_b}) + \omega_i ln(\frac{I_t}{I_b}) + \omega_i ln(\frac{S_t}{S_b}) \quad (3)$$

$$\omega_i = \frac{Green_t - Green_b}{ln(Green_t) - ln(Green_t)} \quad (4)$$

In this formulation, each component has a clear interpretation. The term Scale represents the firm's operating revenue and serves as a proxy for the overall economic scale of the company. The ratio R&D/Scale reflects the intensity of R&D expenditure relative to the economic scale, indicating the firm's commitment to investing in innovation. The subsequent ratio, Patent/R&D, represents the R&D efficiency – that is, how effectively R&D investments are converted into tangible innovation outputs as evidenced by patent filings. Finally, Green/Patent measures the green innovation share, which captures the orientation of the firm's innovation activities toward environmentally sustainable technologies. A higher value of this ratio implies a stronger focus on green technology, which is essential for promoting sustainable development.

By applying the additive version of the LMDI decomposition method, we can calculate the contribution of each factor to changes in green patent applications over time. In this process, the contributions are expressed in absolute terms. A positive decomposition effect indicates that a given factor has a favorable impact on green innovation, whereas a negative value implies a constraining influence. This approach not only allows us to assess the individual impact of each factor but also to understand how these drivers collectively interact to shape the evolution of green patent outputs in the context of environmental regulation policies.

The robust nature of the LMDI method, with its ability to handle zero values and avoid residual terms, makes it particularly well-suited for our analysis. Furthermore, this decomposition model can facilitate a detailed time-series analysis as well as period-wise comparisons, providing valuable insights into the dynamics of green technology innovation at the firm level. Ultimately, our model aims to deliver a nuanced understanding of how economic scale, R&D investment, overall innovation capacity, and the share of green innovation interact, thereby offering meaningful implications for both corporate strategy and policy formulation in the realm of sustainable technology development.

3.2. Data

To implement our extended LMDI decomposition framework, we collected a comprehensive panel dataset covering the period from 2012—when China's carbon trading policy was officially introduced—to 2022. The dataset comprises firm-level information on green patent applications, total patent applications, R&D expenditures, and operating revenue. Green patent data and total patent data are sourced from the Chinese National Research Data Service Platform (CNRDS), which provides a standardized and reliable record of patent activities for Chinese enterprises. In line with international standards, green patent applications are identified according to the World Intellectual Property Organization's (WIPO) classification of green technologies, ensuring that only patents related to environmentally sustainable and energy-efficient innovations are included.

Firm-level financial and R&D data are obtained from the China Stock Market & Accounting Research (CSMAR) database. These data encompass annual R&D investments and revenue figures, which are essential for capturing the internal drivers of green innovation at the company level. To ensure consistency and comparability over time, all monetary figures have been deflated to a common base year, thereby controlling for inflationary effects and other economic fluctuations.

Our study focuses on Chinese A-share listed companies as well as enterprises engaged in the carbon trading pilot markets. To improve the robustness of our empirical results, firms classified as "Special Treatment" (ST) due to abnormal financial performance are excluded from the sample. Additionally, financial companies are omitted, since their unique capital structures and regulatory frameworks may introduce biases that are not representative of industrial firms operating in the broader market.

This carefully curated dataset allows us to explore the dynamic interplay between economic scale, R&D investment, overall patent output, and green innovation focus within a critical policy context. It provides a robust empirical basis for examining the determinants of green innovation using the extended LMDI decomposition method, thereby offering insights into the effectiveness of China's environmental regulatory measures over the past decade.

4. Results and Analysis

4.1. Overview of the LMDI Method and Decomposition Strategy

To evaluate the driving forces behind green technology innovation, this study applies the logarithmic mean Divisia index (LMDI) method in a time-series manner, selecting 2012 as the base year, the starting point of China's carbon emission trading pilot policy. We analyze and compare the decomposition of green innovation factors for carbon market pilot firms and non-pilot listed companies over the period 2012–2022. Given the varying number of firms in both groups, average annual changes in green patent applications are used as the core metric for decomposition analysis. Four primary driving factors are considered: economic scale effect, R&D input effect, R&D efficiency effect and green technology share effect. This approach allows us to isolate the contribution of each factor to the change in green innovation output across time.

4.2. General Trends in Green Patent Output

From 2012 to 2022, both carbon trading pilot enterprises and non-pilot enterprises experienced substantial increases in the number of green patent applications. Notably, non-pilot firms displayed a slightly higher average growth than pilot firms throughout the period. However, both groups exhibited a mild decline in green patent growth in 2022, which may be attributed to the COVID-19 pandemic's disruptions on R&D activities and firm operations. This overall growth suggests that while carbon trading policy may play a role in influencing innovation, broader systemic factors, such as rising environmental awareness, regulatory tightening, and increased market demand for green technologies, are also critical drivers of patent activity.

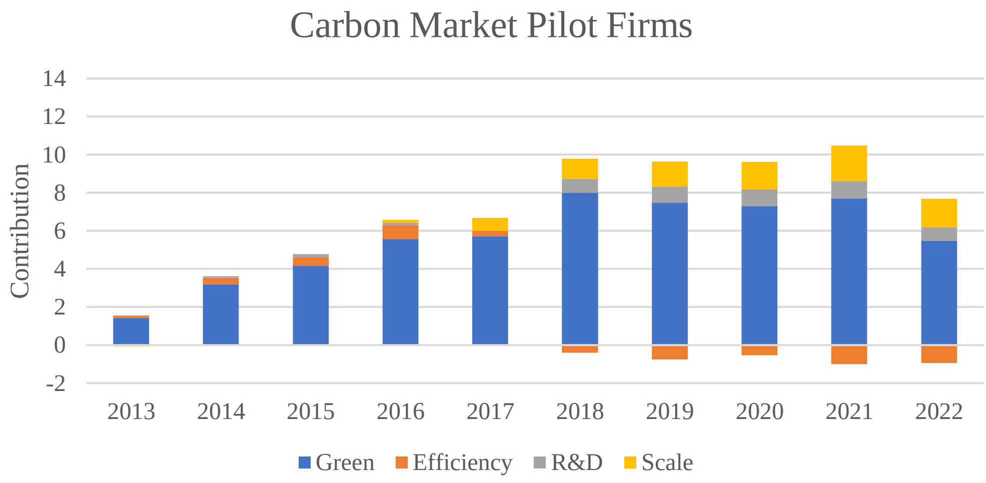

Figure 1. The Contribution rate of each factor in the changes of green patents of pilot firms

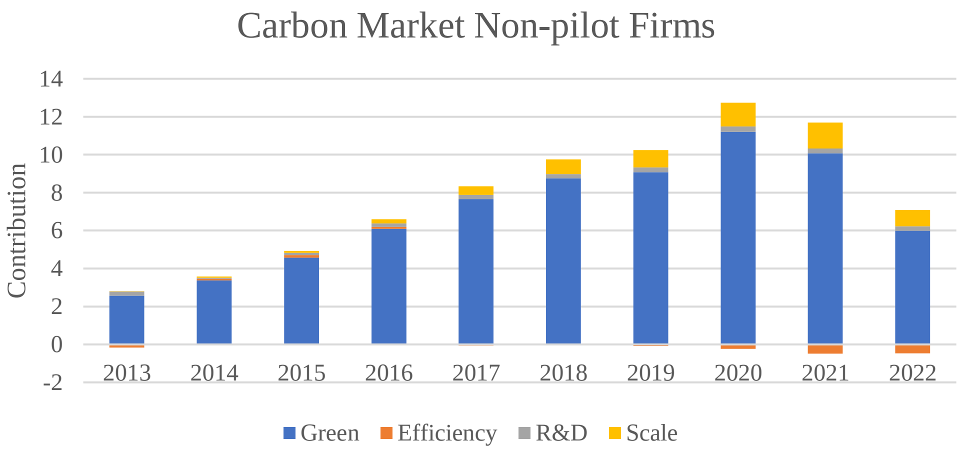

Figure 2. The Contribution rate of each factor in the changes of green patents of non-pilot firms

4.3. Contribution of Green Share Effect

Among all the decomposed factors, the green technology share effect emerged as the most dominant contributor to the increase in green patent applications for both pilot and non-pilot firms. This effect captures the proportional shift in innovation efforts toward green technologies. Over the ten-year period, the growing focus on sustainability, environmental regulation, and the commercialization of green markets led firms to direct more of their inventive activity toward environmentally friendly solutions. For both firm types, this effect accounted for the largest share of total change, underscoring a broader transformation in the innovation orientation of Chinese listed companies toward green objectives.

4.4. R&D Efficiency Effect

A striking contrast emerged between pilot and non-pilot firms in the role of R&D efficiency. For carbon market pilot firms, improvements in R&D efficiency significantly contributed to the growth of green patent applications in the early and mid-stages of the policy period (2012–2017). This suggests that the presence of market-based environmental instruments, such as carbon trading, may initially have catalyzed more effective conversion of R&D inputs into innovation outputs. However, after 2018, this factor turned negative for pilot firms, indicating a declining marginal return on innovation investment or a strategic reorientation toward fewer but higher-quality patents. The post-2018 trend might also reflect a shift in innovation quality rather than quantity, as firms concentrated efforts on breakthroughs or core technologies rather than volume-based patenting.

In contrast, non-pilot firms demonstrated a more stable and moderate R&D efficiency trajectory, with lower contribution rates and fewer fluctuations. This indicates that while pilot firms initially reaped more innovation efficiency gains under the carbon trading regime, these advantages may have plateaued or even reversed in the longer term due to evolving innovation strategies or regulatory fatigue.

4.5. R&D Input Effect

The R&D input effect, reflecting the role of increased investment in research and development, was more prominent for pilot firms than non-pilot ones, especially in the period after 2018. The implementation and expansion of carbon trading policies likely signaled stronger regulatory commitment, thereby incentivizing pilot firms to allocate more resources toward technological innovation aimed at emission reduction and environmental compliance. The accelerated contribution of this factor post-2018 aligns with national efforts to strengthen innovation-driven development under the 13th and 14th Five-Year Plans. In non-pilot firms, although R&D investment also increased, the intensity and responsiveness to environmental regulation were relatively weaker, suggesting the crucial role of policy-induced motivation in driving green-oriented R&D.

4.6. Economic Scale Effect

For both pilot and non-pilot enterprises, economic scale was the second most important factor contributing to the growth of green patent applications. The expansion of firm revenue and output provides a broader base for innovation funding and implementation, particularly in capital-intensive green technologies. This effect remained largely positive throughout the study period, indicating that economic growth and innovation in green technologies are mutually reinforcing. However, a slight weakening of this factor's contribution after 2020 could be linked to pandemic-related slowdowns and macroeconomic uncertainty, which may have dampened firms' capacity or willingness to pursue aggressive innovation agendas.

Interestingly, although both firm types benefited from scale-related growth in innovation, pilot firms appeared to leverage economic growth more effectively in the early years, suggesting that carbon market participation may have helped align firm development strategies with innovation-based compliance and competitiveness.

5. Conclusions and Implication

5.1. Conclusions

This study has examined the key factors driving green patent applications among Chinese listed firms from 2012—the inaugural year of China's pilot carbon trading policy—through 2022, employing an additive LMDI time-series decomposition.

Both pilot and non-pilot enterprises exhibited substantial increases in green patenting, with non-pilot firms slightly leading in average annual growth. The Green Share Effect emerged as the most powerful driver, reflecting a widespread reallocation of R&D efforts toward environmentally sustainable technologies. Early in the policy period, pilot firms achieved notable gains in R&D efficiency, converting investment into green patents more effectively than non-pilot firms; however, this efficiency advantage reversed after 2018, suggesting a strategic shift toward higher-value patents.

Concurrently, R&D investment intensity grew most sharply among pilot firms, especially post-2018, indicating that sustained exposure to carbon pricing mobilized greater corporate R&D budgets. Economic scale consistently supported green innovation for both groups, underscoring the importance of robust financial health in enabling R&D activities. A minor residual effect captured additional exogenous influences, such as policy announcements and subsidies. Collectively, these findings demonstrate that while carbon trading pilots catalyze initial efficiency and investment responses, enduring progress in green innovation arises from a structural transformation of corporate R&D priorities underpinned by economic strength.

5.2. Policy Implications

Based on these conclusions, China should continue to strengthen and expand its carbon market to sustain innovation incentives, ensuring allowance caps and price signals remain robust enough to encourage ongoing R&D investment.

Complementary R&D support—such as targeted grants and tax credits for breakthrough green technologies—can mitigate the observed post-2018 decline in efficiency gains by directing firms toward high-impact inventions. Building collaborative innovation ecosystems through public-private partnerships and technology incubators will help diffuse best practices from pilot firms to the broader corporate sector, enhancing overall green share across industries.

Finally, integrating environmental regulation with green finance instruments and reinforcing intellectual property protection for green inventions will lower the cost of capital for sustainable projects and safeguard returns on R&D, thereby maintaining firms' long-term commitment to green technological advancement.

References

[1] FUJII H, KONDO Y. Decomposition analysis of food waste management with explicit consideration. of priority of alternative management options and its application to the Japanese food industry from 2008 to 2015 [J]. JOURNAL OF CLEANER PRODUCTION, 2018, 188: 568-574.

[2] CHEN Y, LIN B. Decomposition analysis of patenting in renewable energy technologies: From an extended LMDI approach perspective based on three Five-Year Plan periods in China [J]. JOURNAL OF CLEANER PRODUCTION, 2020, 269.

[3] LEI H, XIA X, LI C, et al. Decomposition Analysis of Wastewater Pollutant Discharges in Industrial Sectors of China (2001-2009) Using the LMDI I Method [J]. International Journal Of Environmental Research And Public Health, 2012, 9(6): 2226-2240.

[4] WANG Q, WANG S. Decoupling economic growth from carbon emissions growth in the United States: The role of research and development [J]. Journal Of Cleaner Production, 2019, 234: 702-713.

[5] Brunnermeier S, Cohen M. Determinants Of Environmental Innovation In Us Manufacturing Industries [J]. Journal Of Environmental Economics And Management, 2003, 45(2): 278-293.

[6] Wang K, Li L, Xue W, et al. Electrodeposition Synthesis of PANI/MnO2/Graphene Composite Materials and its Electrochemical Performance [J]. International Journal Of Electrochemical Science, 2017, 12(9): 8306-8314.

[7] Fang W, Tang L, Cheng P, et al. Evolution Decision, Drivers and Green Innovation Performance for Collaborative Innovation Center of Ecological Building Materials and Environmental Protection Equipment in Jiangsu Province of China [J]. International Journal Of Environmental Research And Public Health, 2018, 15(11).

[8] Zhang D, Rong Z, Ji Q. Green Innovation and Firm Performance: Evidence From Listed Companies In China [J]. Resources Conservation And Recycling, 2019, 144: 48-55.

[9] Ahn S, Yoon H. "Green chasm" in clean-tech for air pollution: Patent evidence of a long innovation cycle and a technological level gap [J]. Journal Of Cleaner Production, 2020, 272.

[10] Braun E, Wield D. Regulation As A Means For The Social-Control Of Technology [J]. Technology Analysis & Strategic Management, 1994, 6(3): 259-272.

[11] Kondo M. R&D dynamics of creating patents in the Japanese industry [J]. Research Policy, 1999, 28(6): 587-600.

[12] Ma Y, Zhang Q, Yin Q. Influence of Environmental Management on Green Process Innovation: Comparison of Multiple Mediating Effects Based on Routine Replication [J]. International Journal of Environmental Research and Public Health, 2019, 16(22).

[13] Dong J, Wang Q, Deng C, et al. How to Move China toward a Green-Energy Economy: From a Sector Perspective [J]. Sustainability, 2016, 8(4).

[14] Li Z, Yang W, Wang C, et al. Guided High-Quality Development, Resources, and Environmental Forcing in China's Green Development [J]. Sustainability, 2019, 11(7).

[15] Stucki T. Which firms benefit from investments in green energy technologies? - The effect of energy costs [J]. Research Policy, 2019, 48(3): 546-555.

[16] Lindman Å, Söderholm P. Wind energy and green economy in Europe: Measuring policy-induced innovation using patent data [J]. Applied Energy, 2016, 179: 1351-1359.

[17] Zhao X Li, Yang J, IEEE. A Decomposition Analysis on Influencing Factors of Industrial Energy Consumption - A Case Study On "the Tenth Five-Year Plan" for Beijing[C]//2008 4th International Conference on Wireless Communications, Networking And Mobile Computing, Vols 1-31. 2008: 8150-8153.

[18] Liu J, Yang Q, Zhang Y, et al. Analysis of CO2 Emissions in China's Manufacturing Industry Based on Extended Logarithmic Mean Division Index Decomposition [J]. Sustainability, 2019, 11(1).

[19] Xiong C, Chen S, Gao Q, et al. Analysis of the influencing factors of energy-related carbon emissions in Kazakhstan at different stages [J]. Environmental Science And Pollution Research, 2020, 27(29): 36630-36638.

[20] Zhao J. Analysis on the Influence Factors of Carbon Dioxide Emission from Energy Consumption in Beijing [C]//LEE G. 2014 2nd International Conference On Psychology, Management And Social Science (PMSS 2014), PT 2. 2014: 182-185.

[21] Xin M, Guo H, Li S, et al. Can China achieve ecological sustainability? An LMDI analysis of ecological footprint and economic development decoupling et al. [J]. Ecological Indicators, 2023, 151.

[22] Liu Chong, Bai Mingguo. Change in Industrial Water Use in Anhui Province Based on LNDI [J]. Resources Science, 2012, 34(12): 2299-2305.

[23] Huang C, Gan X, Wan Y, et al. China contributed to low-carbon development: carbon emission increased but carbon intensity decreased [J]. Frontiers In Ecology And Evolution, 2024, 12.

[24] Chen Y, Lin B. Decomposition analysis of patenting in renewable energy technologies: From an extended LMDI approach perspective based on three Five-Year Plan periods in China [J]. Journal Of Cleaner Production, 2020, 269.

[25] Peng X, Tao X. Decomposition of carbon intensity in electricity production: Technological innovation and structural adjustment in China's power sector [J]. Journal Of Cleaner Production, 2018, 172: 805-818.

[26] Zhao Ao, Wu Chunyou. Decomposition of Driving Factors Affecting China's Carbon Dioxide Emissions Based on Comparative Analysis between Modified Kaya Identity and IPAT Equation [C]//Zhu K, Zhang H. Contemporary Innovation And Development In Statistical Science. 2012: 521-526.

[27] Yang J, Cai W, Ma M, et al. Driving forces of China's CO2 emissions from energy consumption based on Kaya-LMDI methods [J]. Science Of The Total Environment, 2020, 711.

[28] Zhou X, Yu Y, Yang F, et al. Spatial-temporal heterogeneity of green innovation in China [J]. Journal Of Cleaner Production, 2021, 282.

[29] Guan H, Sun Z, Zhao A. Spatio-temporal evolution and influencing factors of net carbon sink in marine aquaculture in China [J]. Frontiers In Environmental Science, 2022, 10.

[30] Zhang Chenjun, Zhang Hengquan, Gong Yayun. Structural Upgrading,Technological Progress and Water Resource Consumption Based on a Refined LMDI Method [J]. Resources Science, 2014, 36(10): 1993-2002.