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The Influence of Artificial Intelligence on the Transformation and Upgrading of Manufacturing in the Guangdong-Hong Kong-Macao Greater Bay Area

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ABSTRACT

Amid evolving global trade dynamics, China is transitioning from cost-based advantages to embracing technological innovations such as artificial intelligence (AI), crucial for addressing global labor and value chain constraints. The Guangdong-Hong Kong-Macao Greater Bay Area (GBA) emerges as a key player, integrating ports and towns into the Bay Area Economy. With its strategic global economic role, the GBA's manufacturing sector is vital to China's high-quality growth strategy. This study examines AI's impact on the GBA's manufacturing industry, enhancing cost efficiency, resource management, and research and development. It explores AI's development and applications, emphasizing the GBA's shift to a service-oriented economy through collaborative frameworks and industrial clusters. The GBA's AI integration boosts regional and global competitiveness, promoting sustained economic growth through cross-industry collaboration and innovation in intelligent manufacturing.

KEYWORDS

Artificial Intelligence; Manufacturing; Guangdong-Hong Kong-Macao Greater Bay Area (GBA)

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1. Introduction

In the contemporary global landscape, China is undergoing a transformative phase characterized by new international contexts and developmental stages. The traditional foreign trade advantage of "low cost or low price" is facing significant challenges. Overcoming the limitations of being "constrained at the low-end" within the global division of labor system and global value chain (GVC) necessitates navigating a complex terrain of evolving international dynamics and developmental imperatives. Artificial intelligence (AI), acknowledged as a pervasive technology with the potential to drive industrial transformation and exert substantial spillover effects, emerges as a critical focal point in shaping the contours of new competitive advantages. The impact of AI transcends mere cost reduction, enhancing resource and labor efficiency, while simultaneously boosting the efficacy of research and development innovation. The multifaceted contributions of AI to various aspects of industrial dynamics are of paramount importance [1].

The term 'Bay Area' typically denotes a conglomeration of port and town clusters strategically distributed around coastal regions. The economic ramifications stemming from this configuration are often characterized as the Bay Area Economy. From a global perspective, Bay Areas have become crucial focal points for worldwide economic advancement and drivers of international competitiveness, particularly in terms of innovation capabilities, as noted in academic discourse. Within this context, the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) has surfaced as a forward-looking strategy for China to adeptly discern the evolving focal points of international competition. The manufacturing industry, as the cornerstone of China's economy, forms the distinctive backdrop of industries within the GBA, playing a pivotal role in advancing high-quality development in the region [2]. Therefore, exploring how AI can be leveraged to establish novel competitive advantages in the foreign trade of the GBA and drive the digital transformation of the manufacturing industry has emerged as a prevalent and academically significant subject of interest.

Despite extensive research on AI's transformative potential, several gaps remain. Previous studies have predominantly focused on isolated aspects of AI's impact on specific industries or regions, often overlooking the comprehensive and integrative effects AI can have on broader economic and industrial dynamics, particularly within unique economic clusters such as the GBA. Moreover, the rapid evolution of AI technology necessitates continual reevaluation of its applications and implications, as earlier research may not fully capture the latest advancements and trends [3]. Recognizing these research gaps underscores the necessity of the current study, which aims to bridge these deficiencies by providing a holistic analysis of AI's influence on the transformation and upgrading of manufacturing in the GBA.

This paper endeavors to investigate the repercussions of AI technology evolution on the manufacturing industry within the GBA. The objectives of this study encompass elucidating the developmental and applicative trajectories of AI, examining the industrial layout and strategic importance of the GBA), and analyzing the integration of AI within the GBA's manufacturing sector. By addressing these objectives, the study aims to enrich academic discourse by providing insights into the digital transformation driven by AI. This exploration aids the GBA in adapting to the technological changes. The findings are intended to offer recommendations for policymakers and industry stakeholders, enabling them to harness AI's potential to foster

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sustainable and competitive industrial growth in the region.

2. Literature review

In the contemporary landscape of technological innovation, AI has emerged as a transformative force, particularly within the manufacturing sectors of rapidly developing regions such as the GBA. The integration of AI within this sector not only promises enhanced efficiency and productivity but also significantly impacts the industrial layout and economic dynamics of the region.

2.1 Advancements of AI in Industry

The development and application of AI in manufacturing, often referred to as smart manufacturing, encapsulates the use of machine learning, robotics, and big data analytics to streamline production processes and enhance product customization capabilities [4]. In the context of the GBA, a region known for its robust industrial base and technological prowess, AI has facilitated a shift from traditional labor-intensive methods to more knowledge-driven processes. The adoption of AI in the GBA manufacturing sector has increased production efficiency by 25% and reduced operational costs by 30%, thereby significantly impacting the economic output and competitiveness of the area [5].

2.2 Industrial layout and transformation

The industrial layout of the GBA has historically centered around electronics, automotive, and high-tech industries, which are particularly conducive to AI integration. The strategic positioning of these industries has been influenced by the regional governments' policies promoting AI-driven economic growth [6]. These policies have supported the establishment of numerous AI-focused research centers and startups, fostering an innovation ecosystem that is robust and dynamically responsive to the evolving technological landscape. Moreover, the role of AI in the GBA's manufacturing industry extends beyond mere production enhancement. It encompasses a broader spectrum of applications including supply chain optimization, predictive maintenance, and quality control, which are critical to maintaining the region’s reputation for manufacturing excellence [7]. For instance, AI-powered predictive maintenance systems can significantly reduce downtime by predicting equipment failures before they occur, thus ensuring continuous production flows.

However, the transformation brought about by AI is not devoid of challenges. The primary concern is the displacement of low-skilled labor, which necessitates significant workforce retraining and upskilling initiatives [8]. Additionally, the rapid integration of AI technologies requires substantial investments in digital infrastructure and regulatory adjustments to address issues such as data privacy and cybersecurity [9]. The interplay between AI and manufacturing in the GBA also highlights the potential for regional industrial policy to shape technological trajectories. The GBA’s emphasis on AI and high-tech industries has not only facilitated local economic diversification but also contributed to the region’s strategic positioning in global value chains [10].

The deployment of AI technologies in the manufacturing sector of the GBA signifies a pivotal element in the

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region's ongoing industrial transformation and upgrading. It not only brings substantial economic benefits but also requires comprehensive consideration of socio-economic implications and strategic policy interventions. Future research should prioritize longitudinal studies to evaluate the long-term impacts of AI on regional economic structures and the labor market, contributing to a nuanced understanding of this intricate interplay.

3. The Development and Application of AI

3.1 The Development of AI in industry

In the 21st century, the advent of the fourth industrial revolution has ushered in disruptive technologies that are fundamentally challenging traditional manufacturing organizational paradigms. These ground-breaking innovations are intensifying the international division of labor and facilitating the profound restructuring of global value chains. Consequently, this transformation presents a renewed opportunity to reshape the global industrial chain, driving significant advancements and efficiencies. The integration of AI into the manufacturing industry has led to substantial transformations in how businesses operate and compete. AI technologies, such as machine learning, robotics, and predictive analytics, are enabling manufacturers to optimize production processes, reduce downtime, and enhance product quality. Furthermore, AI-driven automation is playing a crucial role in streamlining supply chain management, resulting in increased efficiency and reduced operational costs. These enhancements not only improve productivity but also provide a competitive edge in the global market [11].

Studies examining the impact of AI on the economy typically focus on evaluating the consequences of technological advancements on economic growth and the labor market. The AI industry demonstrates economies of scale and scope, which can be attributed to its substantial data requirements and high expenditures on research and development. As a versatile technology, AI has significant spillover effects that influence various sectors. This influence is particularly noticeable in industries like automotive, electronics, and consumer goods, where AI drives innovation and facilitates the creation of new products and services. The capability of AI to analyze vast amounts of real-time data empowers manufacturers to make informed decisions, anticipate market trends, and respond promptly to changes in demand. Furthermore, the integration of AI into the manufacturing sector has profound implications for the dynamics of the workforce. On one hand, it generates new employment opportunities in AI development, data analysis, and the maintenance of AI systems. On the other hand, it necessitates the reskilling and upskilling of the existing workforce to adapt to the evolving technological landscape. Policymakers and industry leaders increasingly recognize the necessity for comprehensive education and training programs aimed at equipping workers with the skills required in an AI-driven economy [12]. These programs are vital to ensure that the workforce can effectively harness new technologies and widely benefit from the integration of AI.

Consequently, the development of AI in the manufacturing industry is not only transforming production processes and enhancing economic growth but also reshaping the labor market. The integration of AI represents a pivotal shift, necessitating strategic planning and investment in human capital. It underscores the importance of a proactive approach to workforce development, ensuring that employees are equipped with the necessary skills to thrive in an AI-enhanced industrial environment. This comprehensive transformation,

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driven by AI, heralds a new era of efficiency and innovation in the manufacturing sector, particularly within the GBA.

3.2 The Application of AI in industry

If the knowledge externalities within the AI industry stem from a domestic context, implementing strategic trade protection policies can effectively enhance the competitiveness of enterprises [13]. Digital technologies have the potential to reduce international trade costs, leading to projected annual growth rates of 2% in international trade before 2030. [14]. Digital technology has broadly facilitated the expansion of international trade and the growth of GVCs.

Study showed that Asia stands out as the global epicenter for the industrial robot market, boasting the largest installation numbers. In 2022, a total of 404,578 units were installed, representing a 5% increase from the 2021 number of 385,143 units. Impressively, 73% of the newly deployed robots found homes in Asia (compared to 74% in 2021). Over the period from 2017 to 2022, annual robot installations demonstrated robust growth, averaging an 8% increase each year [15]. Notably, three of the top five markets for industrial robots are situated in Asia, with China reigning supreme as the largest and most influential market (Figure 1).

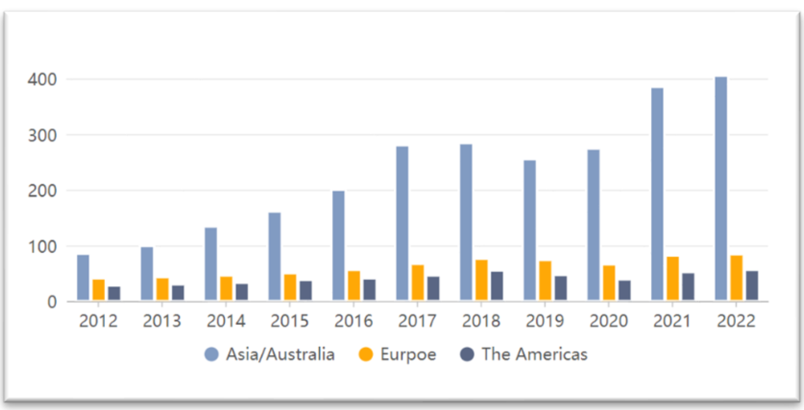

Figure 1 Annual installation of industrial robots (‘000 of units)

Source: World Robotics 2023

One of the central areas of emphasis in the transformation of traditional manufacturing is intelligent manufacturing engineering. Industrial robots serve as a pivotal bridge and essential foundation linking intelligent manufacturing to industrial applications. Leveraging AI technology, they acquire capabilities resembling human perception, collaboration, decision-making, and feedback. Meanwhile, China's diminishing demographic dividend advantage poses a challenge to the traditional industrial manufacturing model. In response, AI products, particularly industrial robots, are transitioning from a mere backup role to an indispensable asset. This shift plays a pivotal role in propelling China's industrial transformation and upgrading, allowing the nation to compete effectively in the high-end segment of the GVC.

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3.3 AI-driven Innovation in Manufacturing Processes

The advent of AI has fundamentally altered the landscape of manufacturing, particularly within the GBA. AI-driven innovation in manufacturing processes is at the heart of this transformation, driving significant advancements in efficiency, productivity, and product quality. This section delves into how AI is revolutionizing manufacturing processes in the GBA, highlighting key innovations and their implications for the industry. One of the most notable impacts of AI in manufacturing is the enhancement of production efficiency. AI technologies, such as machine learning algorithms and predictive analytics, enable manufacturers to optimize their production lines. By analyzing vast amounts of data from various stages of the manufacturing process, AI systems can identify bottlenecks, predict equipment failures, and suggest adjustments to improve workflow. This predictive maintenance reduces downtime and extends the lifespan of machinery, leading to cost savings and more consistent production schedules. Additionally, AI-powered automation has transformed traditional manufacturing practices. Robotics, guided by AI, are increasingly deployed to perform repetitive, high-precision tasks that were once the domain of human workers. These AI-driven robots are not only faster and more accurate but also capable of working continuously without fatigue. This shift boosts productivity and allows human workers to focus on more complex, value-added tasks, thereby increasing overall operational efficiency.

Quality control is another area where AI is making significant strides. Traditional quality control methods often involve manual inspection, which can be time-consuming and prone to human error. AI-based vision systems, however, can inspect products with unparalleled accuracy and speed. These systems use deep learning algorithms to detect defects and deviations from quality standards in real-time, ensuring that only products meeting the highest quality criteria move forward in the production process. This not only reduces waste but also enhances customer satisfaction by ensuring consistent product quality. Furthermore, the integration of AI in manufacturing processes facilitates mass customization, a growing trend in the industry. AI algorithms can analyze customer preferences and market trends to predict demand for customized products. This capability allows manufacturers to efficiently produce personalized products at scale, meeting the diverse needs of customers without sacrificing efficiency. In the GBA, where consumer markets are highly dynamic and varied, this ability to quickly adapt to changing demands provides a competitive edge.

Moreover, AI-driven supply chain optimization is revolutionizing the logistics aspect of manufacturing. By leveraging AI, manufacturers can enhance their supply chain visibility and responsiveness. AI algorithms can predict supply chain disruptions, optimize inventory levels, and improve demand forecasting. This leads to a more agile and resilient supply chain, capable of adapting to fluctuations in demand and mitigating risks associated with supply chain disruptions. In the context of the GBA, with its complex and interconnected industrial network, such capabilities are invaluable. In addition to these technical advancements, the implementation of AI in manufacturing processes has broader economic and societal implications. The efficiency gains and cost reductions achieved through AI-driven innovations can enhance the competitiveness of the GBA's manufacturing sector on a global scale. This, in turn, attracts investment and drives economic growth in the region. However, it also necessitates a shift in the workforce, requiring workers to acquire new skills to work alongside advanced AI systems. This underscores the importance of strategic workforce development and continuous learning programs to ensure that the labor market can adapt to these technological changes.

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3.4 Impact of AI on Workforce and Employment in the GBA

The advent of AI has profound implications for the workforce and employment landscape in the GBA. As AI technologies become increasingly integrated into the manufacturing sector, significant shifts are observed in both the nature of work and the skills required by the workforce. On one hand, AI-driven automation and smart manufacturing solutions enhance productivity and operational efficiency. On the other hand, they necessitate a transformation in workforce skills, posing both opportunities and challenges for workers in the region. AI's impact on the GBA's workforce can be understood in two main areas, job displacement and job creation. Automation of routine and repetitive tasks, such as assembly line operations and quality control inspections, leads to the displacement of certain low-skilled jobs. This effect is particularly pronounced in labor-intensive industries where AI-driven machines and robots can perform tasks faster, with higher precision, and at lower costs than human workers. Consequently, workers performing these tasks face the risk of unemployment or the need to transition to different roles within or outside the manufacturing sector. The narrative of AI-induced job loss, however, is balanced by the creation of new job opportunities. As AI technologies are adopted, there is a rising demand for high-skilled professionals who can develop, implement, and maintain AI systems, including roles such as data scientists, AI specialists, and robotics engineers. Additionally, AI integration spurs the growth of jobs related to AI system management, cybersecurity, and ethical oversight, ensuring that AI applications are secure, effective, and aligned with societal values. The shift towards a more technologically advanced manufacturing ecosystem necessitates upskilling and reskilling programs to equip the existing workforce with the competencies required for these new roles.

However, the narrative of AI-induced job loss is counterbalanced by the creation of new job opportunities. As AI technologies are adopted, there is a rising demand for high-skilled professionals who can develop, implement, and maintain AI systems. This includes roles such as data scientists, AI specialists, and robotics engineers. Additionally, AI integration spurs the growth of jobs related to AI system management, cybersecurity, and ethical oversight, ensuring that AI applications are secure, effective, and aligned with societal values. The shift towards a more technologically advanced manufacturing ecosystem necessitates upskilling and reskilling programs to equip the existing workforce with the competencies required for these new roles.

Moreover, AI's role in augmenting human capabilities cannot be overlooked. Instead of completely replacing human labor, AI often complements human workers by taking over mundane tasks and allowing employees to focus on more complex, creative, and strategic activities. For instance, AI-powered predictive maintenance systems reduce the burden on maintenance staff by predicting equipment failures and scheduling timely interventions. This not only enhances operational efficiency but also allows workers to engage in higher-value tasks that require human judgment and problem-solving skills. Within the framework of GBA, governments and enterprises are actively responding to these changes through various initiatives aimed at workforce development. Investment in education and training programs is pivotal to preparing the workforce for the AI-driven future. Universities and vocational training centers in the GBA are increasingly offering courses in AI, machine learning, and related fields, ensuring a steady pipeline of skilled professionals. Furthermore, partnerships between industry and academia facilitate the alignment of educational curricula with the evolving needs of the manufacturing sector, fostering a workforce that is adept at leveraging AI technologies.

Therefore, the impact of AI on workforce and employment in the GBA is multifaceted, characterized by both

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challenges and opportunities. While AI-driven automation may displace certain jobs, it simultaneously creates new employment avenues and enhances the overall skill set of the workforce. The successful integration of AI into the manufacturing sector hinges on proactive measures to support workforce transition, emphasizing the importance of education, training, and continuous learning. By embracing these changes, the GBA can not only mitigate the adverse effects of AI on employment but also harness its potential to drive economic growth and innovation in the region.

4. Industrial layout in GBA

4.1 Manufacturing-Dominated Industrial Structure

In contrast to established global bay regions that have embraced innovation-driven economies, the GBA is currently transitioning from an industrial to a service-oriented economy. The current composition leans heavily towards manufacturing, necessitating a future shift towards a higher proportion of tertiary industry. Research indicates that the tertiary industry constitutes 62% of the GBA's economic structure. In comparison, the New York Bay Area boasts 89%, the San Francisco Bay Area records 83%, and the Tokyo Bay Area stands at 82% (Figure 2). This significant disparity underscores the challenge faced by the GBA in aligning with these globally renowned bay areas. Despite cities like Shenzhen and Hong Kong embracing characteristics of innovative and service-oriented economies, the majority of cities within the region are still undergoing a transformation from traditional manufacturing to high-end manufacturing and service industries.

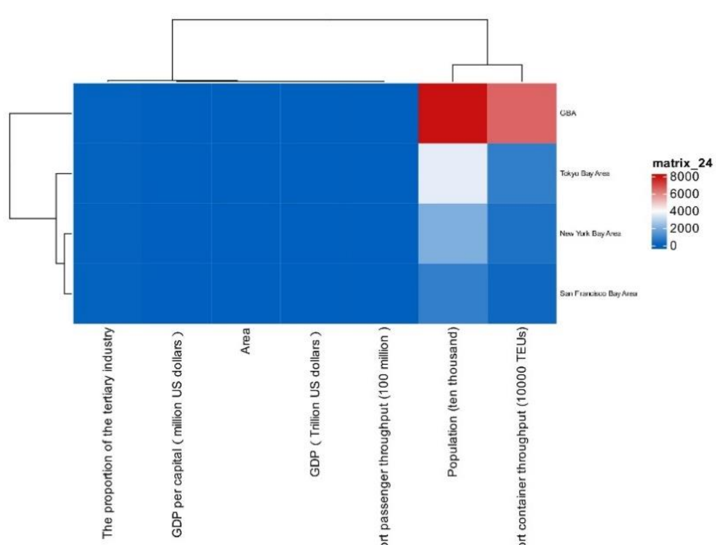

Figure 2 Comparison of data from the four major bay areas

Source: PwC Analysis

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The industrial structure of the GBA remains predominantly manufacturing-oriented, a result of its historical development patterns and policy orientation. Cities such as Dongguan and Foshan have been major centers of traditional manufacturing, hosting numerous factories and production lines that have driven economic growth. However, this concentration of manufacturing industries poses challenges for the region's shift towards a service-oriented economy [16]. High-end manufacturing requires advanced technologies and a skilled workforce, necessitating significant investment in education and training. The GBA must also foster a conducive environment for innovation, enhancing research and development capabilities, encouraging entrepreneurship, and providing support for small and medium-sized enterprises. The integration of AI and other advanced technologies is pivotal in this transition, driving efficiency and innovation in manufacturing processes and creating synergies with the service sector.

Regional governments within the GBA have recognized these needs and are implementing policies to facilitate this transition. Initiatives such as the Outline Development Plan for the GBA emphasize innovation-driven development and the enhancement of the modern service industry. Infrastructure projects like the Hong Kong-Zhuhai-Macao Bridge and the expansion of the high-speed rail network are improving connectivity within the region, which is crucial for economic integration and development. While the GBA is currently characterized by a manufacturing-dominated industrial structure, ongoing efforts aim to create a more balanced economy with a greater emphasis on the tertiary sector. This transition is essential for enhancing the GBA's global competitiveness and achieving sustainable long-term growth. By leveraging its strengths in manufacturing and integrating advanced technologies, the GBA can position itself as a leading innovation-driven economy, comparable to other global bay areas [17].

4.2 Define the functions between cities

The primary industries across various cities in the GBA lack distinctiveness. Therefore, a more granular delineation and elucidation of each city's core strategic roles are necessary. This involves the consolidation of industrial clusters and engaging in the global marketplace with an industry chain perspective. For instance, despite the GBA's competitive port throughput capabilities, there exists redundancy in transport modalities among its ports. The strategic intent behind integrating the GBA's ports lies in the specialization of port functions, allocating specific roles such as container handling, energy and chemical logistics, steel transport, and military supplies, thereby circumventing homogenized competition [18]. This approach aims to enhance operational efficiency and resource sharing, ensuring that each port capitalizes on its unique strengths to contribute effectively to the region's overall economic growth.

Moreover, the differentiation of city functions within the GBA should reflect each city's unique strengths and economic profiles. Cities such as Shenzhen and Hong Kong, for example, have already established themselves as leaders in technology and finance, respectively. In contrast, other cities within the GBA, such as Dongguan and Foshan, should focus on developing specialized manufacturing hubs that leverage their existing industrial bases while integrating advanced technologies to transition towards high-end manufacturing. Figure 3 below illustrates the proportion of primary, secondary, and tertiary industries among cities in the GBA, highlighting the need for a coordinated strategy that minimizes overlap and promotes complementary development. This specialization would allow cities to avoid direct competition with each other and instead collaborate to create

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a cohesive, competitive regional economy.

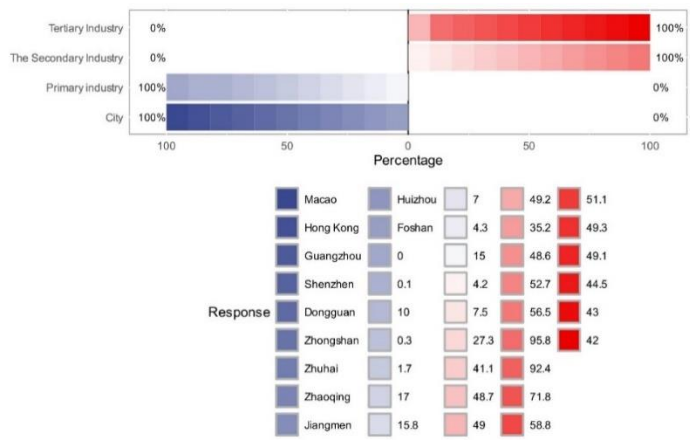

Figure 3 Proportion of industrial structure of each city in GBA 2021

Source: Guangdong Provincial Statistical Yearbook

Importantly, it is unfeasible to directly transpose the developmental paradigms established by other global bay areas to the GBA. There exists an imperative to forge a distinctively "Chinese Model" tailored to the economic cultivation of the Bay Area. This model should emphasize the integration of traditional strengths in manufacturing with emerging sectors such as artificial intelligence, biotechnology, and green energy. By fostering inter-city collaboration and delineating clear strategic roles, the GBA can create a robust and diversified economic structure that not only enhances regional competitiveness but also contributes to the global economy. The development of this unique model requires careful planning, substantial investment in infrastructure and education, and the creation of an innovation-friendly environment that supports both established industries and emerging sectors.

5. AI and GBA Manufacturing Industry

5.1 Collaborative Development of Industries

Amidst the evolution of economic theoretical models pertinent to AI and the refinement of databases, scholarly exploration into AI's influence on industrial productivity is experiencing a surge. Enterprise productivity is inextricably linked to international trade dynamics. Technological advancements in AI hold the potential to enhance enterprise productivity, thereby boosting the scope of imports and exports. Such improvements may incentivize broader enterprise engagement and heighten competition within the GVC, stimulating the expansion of international trade. Concurrently, free trade mechanisms contribute to the reallocation of resources away from entities characterized by diminished productivity and lower-tier products

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toward those with robust productivity and high-value offerings [18]. The expanding assortment of traded goods enhances market competitiveness, which could, in reverse, act as an impetus for AI innovation. This symbiotic relationship fosters a progressive enhancement of enterprise productivity, culminating in a beneficial cycle that fuels both technological advancement and economic growth.

The GBA boasts a comprehensive manufacturing ecosystem supported by premier production bases and state-of-the-art hardware facilities, underpinned by years of substantial manufacturing groundwork. In Guangdong Province alone, the manufacturing sector accounts for over 90% of the added value in large-scale industries. Central to "Made in China 2025" is the ambition to establish a dominant manufacturing superpower. Figure 4 shows the industry distribution of the top 100 innovative enterprises in Guangdong. The data shows that as of 2023, the manufacturing industry accounts for 52% of all industries, which is the highest proportion among all industries. The initiative sets forth objectives to escalate the annual output of domestically-branded industrial robots from 17,000 units in 2014 to 100,000 by 2020, with an overarching goal to secure China's position as a world leader in artificial intelligence by 2030 [19].

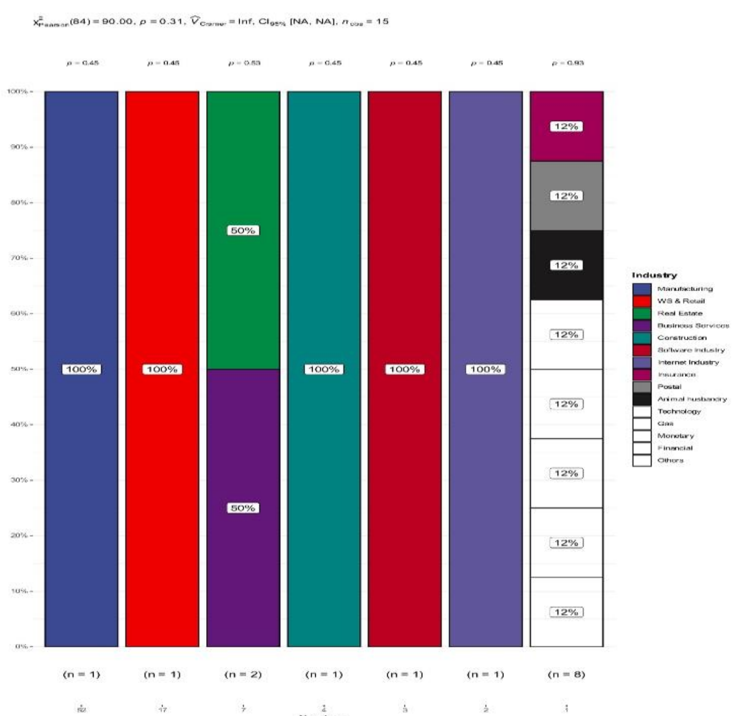

Figure 4 Distribution of Guangdong's Top 100 Innovative Industries in 2023

Source: Guangzhou Daily Data &Digit Institute

As cutting-edge sectors such as AI, big data, and cloud computing increasingly intersect with traditional manufacturing, they are catalyzing a shift toward intelligent manufacturing paradigms. In parallel, concerted

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efforts in cooperation and technological innovation across Guangdong, Hong Kong, and Macao have been gaining momentum [20]. The evolution of the GBA has thus transitioned from a resource-dependent ‘front shop, back factory’ model to a tripartite propulsion system that integrates scientific research and innovative industries, advanced manufacturing, and the modern services sector. This transformation herald’s substantial momentum and harbors significant potential for the rejuvenation and elevation of the manufacturing industry [21].

5.2 Collaboration between manufacturing enterprises

In the context of the widespread adoption of advanced digital technologies, product functionalities are evolving to become increasingly intricate, characterized by the integration of numerous components and services. This complexity has rendered the reliance on internal resources alone for product manufacturing both inefficient and costly for manufacturing enterprises. Consequently, there is a growing imperative for these enterprises to leverage external resources more extensively. To mitigate costs and foster the development of innovative products and services, enterprises must seek to integrate into and capitalize on the synergies within broader ecosystems, encompassing manufacturing and technology clusters as well as strategic partnerships. Moreover, the emergence of cross-border ecosystems amplifies the potential for overlap with other ecosystems, thereby offering enterprises enhanced opportunities for innovation and market penetration [22].

The imperative to elevate the GBA manufacturing sector to align with the global innovation network necessitates a significant enhancement in its foundational research capabilities. Although the GBA has seen the commencement of collaborative innovation, there is a need to further reinforce its basic research proficiency for fostering leadership in innovation within the industry. Currently, there exists a dichotomy in the GBA’s innovation chain, with strengths in application research, experimental development, and industrialization, juxtaposed against relatively weak foundations in basic research. The nature of basic research is characterized by time-intensive processes and gradual results generation, often making it challenging to directly convert into profitable products [23]. However, basic research is integral to technological advancement and economic growth as it underpins the establishment of new technologies and processes, thereby facilitating the development of novel processes and products.

Investment in basic research should be seen as a foundational element of innovation and long-term economic sustainability. The GBA could prioritize the enhancement of its basic research capabilities to create a robust innovation ecosystem. This involves not only increased funding for research initiatives but also the establishment of collaborative frameworks that connect academic institutions, research centers, and industry players. By fostering a culture of collaboration and continuous learning, the GBA can strengthen its position within the global innovation network. Moreover, such investments will ensure that the region remains competitive and capable of driving future technological advancements and economic growth.

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6. Conclusion and discussion

6.1 The Development of AI in industry

AI has fundamentally transformed the manufacturing industry in the GBA, driving both technological advancements and economic efficiency. The adoption of AI technologies has revolutionized traditional manufacturing processes, leading to significant improvements in production efficiency and cost reduction. This transformation is marked by a shift towards high-end manufacturing, where AI enables predictive maintenance, smart manufacturing, and real-time data analysis, thereby optimizing operations and minimizing downtime. These advancements have enhanced the competitive edge of GBA's manufacturing sector, allowing enterprises to innovate and adapt swiftly to changing market demands.

Furthermore, AI has fostered a collaborative ecosystem within the GBA's manufacturing sector, where enterprises can leverage external resources and strategic partnerships. This collaboration has amplified innovation potential and market penetration, aligning the GBA more closely with global innovation networks. The integration of AI has enabled manufacturers to develop more complex and customized products, meeting the increasingly sophisticated needs of consumers. By creating a more interconnected and intelligent manufacturing environment, AI supports both immediate technological and economic benefits and positions the GBA for sustained long-term growth and leadership in the global manufacturing arena. This ongoing transformation underscores the critical role of AI in reshaping the manufacturing landscape and driving the GBA's economic evolution.

6.2 Integration and Application of AI Technologies

AI technologies have become instrumental in optimizing manufacturing processes, bringing unprecedented efficiencies and innovations to the industry. These technologies enable real-time data collection and analysis, predictive maintenance, and smart automation, leading to enhanced productivity and reduced operational costs. By leveraging Integration and Application of advanced AI technological Technologies frameworks, AI manufacturers can technologies gain have deep become instrumental in optimizing manufacturing insights into their operations, processes, bringing allowing unprecedented efficiencies for and more innovations to informed decision the industry.-making These and strategic technologies planning enable real.-time data The collection seamless integration of these and AI technologies analysis, has predictive allowed maintenance manufacturers, to and streamline smart their automation, operations which lead, anticipate and to enhanced mitigate potential productivity issues and reduced operational costs.

In the context of the GBA, the application of AI has not only improved operational efficiency but also driven the development of high-end, customized products that meet the evolving demands of consumers. The collaborative ecosystem fostered by AI integration has facilitated partnerships between manufacturing enterprises and technology firms, enhancing the region's innovation potential. This synergy has enabled the GBA to align more closely with global innovation networks, thereby increasing its competitiveness in the global market. The ongoing advancements in AI applications underscore the transformative impact of these

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technologies on the GBA's manufacturing landscape, highlighting their critical role in driving economic growth and sustainability. As AI technologies continue to evolve, their integration will remain pivotal in shaping the future of manufacturing in the GBA, ensuring the region's leadership in the global industrial arena.

6.3 Socio-Economic Implications of AI in GBA

The integration of AI technologies in the GBA has profound socio-economic implications, fostering economic growth and transforming various sectors. AI's role in boosting productivity is evident in the GBA's manufacturing and service sectors, enhancing efficiency and competitiveness. Additionally, the rise of AI generates demand for a highly skilled workforce, leading to improved job quality and opportunities. Educational institutions and training programs are adapting to this shift, offering specialized courses to equip the workforce with relevant skills, thereby driving innovation and entrepreneurial activities.

Moreover, AI technologies in the GBA improve public services, addressing urban challenges in areas such as public safety, healthcare, and transportation. However, the widespread implementation of AI raises concerns regarding data privacy, ethical use, and the digital divide. Policymakers must ensure stringent data protection and ethical standards, while initiatives to bridge the digital divide are essential for equitable access to AI benefits. The successful integration of AI in the GBA highlights its transformative potential, emphasizing the need for robust policies and inclusive strategies to maximize AI benefits for all members of society.

6.4 Strategic Recommendations for Policymakers and Industry

To maximize the benefits of AI integration in the Greater Bay Area (GBA), it is crucial for policymakers and industry leaders to adopt strategic measures that address both opportunities and challenges. Firstly, establishing a robust regulatory framework is essential to ensure the ethical and responsible use of AI technologies. This includes developing clear guidelines for data privacy, security, and ethical considerations. Moreover, implementing stringent data protection laws, promoting transparency in AI systems, and continuously monitoring AI applications to adapt regulations to emerging challenges and technological advancements will build public trust and prevent the misuse of AI.

Secondly, fostering a collaborative ecosystem that encourages innovation and knowledge sharing is vital for sustainable growth. Policymakers and industry leaders should promote partnerships between academia, industry, and government to facilitate research and development in AI. In addition, creating platforms for collaboration, establishing innovation hubs, and providing incentives for startups and small enterprises can accelerate the commercialization of AI technologies and stimulate entrepreneurial activities. These efforts, in turn, will drive the region's technological advancement and maintain its competitive edge.

Lastly, investing in education and training programs is critical to preparing the workforce for the evolving demands of the AI-driven economy. Policymakers and industry leaders should support initiatives that offer specialized AI and data science courses in educational institutions. Furthermore, continuous professional development programs for current employees are necessary to keep pace with new technologies. By doing so, the workforce will be equipped with relevant skills, ensuring a steady supply of talent to support the GBA’s AI-driven growth. In conclusion, strategic recommendations for the GBA should focus on establishing a robust regulatory framework, fostering a collaborative ecosystem, and investing in education and training.

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These measures, collectively, will unlock the full potential of AI, driving sustainable economic growth and maintaining the region's competitive advantage.

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Exploring the evolution of City Diplomacy：through the case of Nagasaki

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ABSTRACT

City diplomacy is actively engaged in transnationally coordinated efforts to address critical global challenges such as climate change, pandemics, and terrorism. This phenomenon has garnered substantial scholarly attention within the fields of international relations, urban studies, and security studies. However, the pioneering initiatives of the mayors of Nagasaki in their Mayors for Peace campaign and related efforts to advocate for a nuclear-free world since the 1970s have been insufficiently examined in the context of city diplomacy research. This article, drawing extensively on archival research from Nagasaki, addresses a pivotal issue in the field: the profit of city diplomacy. The mayors of Nagasaki have consistently, sometimes jointly and sometimes individually, endeavored to establish their legitimacy at local, national, and international levels. Each register manifested through cooperation with the national government, confrontation with the national government, and collaboration with cities, nongovernmental organizations, and individuals outside Japan is relational and has involved distinct spatiotemporal reconfigurations. City diplomacy researchers have convincingly argued that the rise of city diplomacy symbolizes a structural transformation of the global order, where actors and issues transcend local, national, or global boundaries. How do cities participate in diplomacy? This article explores contemporary theories of city diplomacy and various aspects of International Relations theory by examining the case of Nagasaki's city diplomacy. We recommend further investigation into Nagasaki's diplomatic activities, including its involvement in the Mayors for Peace organization, its domestic public diplomacy initiatives, and its sister city relationships.

KEYWORDS

City diplomacy; Japan politic; Nagasaki city

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1.Introduction

At the beginning of the 21st century, foreign affairs are still mainly managed by national governments and their foreign ministries. However, the state is no longer the only player in diplomacy. While a lot of attention has been given to new actors like NGOs and multinational corporations, less focus has been on the growing role of cities in diplomacy. Today, global cities are becoming major players in international politics. They form networks, create partnerships, share information, sign cooperation agreements, help draft national and international policies, provide development aid, assist refugees, and promote themselves through city-to-city cooperation [1]. Cities have been the main actors, and they might once again become the primary units of international communication[2].

Mayors worldwide are increasingly participating in global policy discussions on climate change, international security, public health, and other pressing issues. This involvement in city diplomacy raises critical questions of legitimacy at local, national, and international levels. Why do mayors, whose primary responsibilities are centered on local governance, seek to extend their influence globally? How do they justify using their city hall's limited resources—such as tax revenue and staff time—for international travel and engagement in global policy debates on issues that seem to fall outside their jurisdiction?

The current global prominence of the mayors of Nagasaki is unsurprising, given the profound historical significance of these two cities. As the only cities to have suffered nuclear attacks, their legacies and memories are deeply embedded in the global historical consciousness through a myriad of moral, philosophical, religious, literary, and other representations of the bombings. Perhaps more importantly, many citizens of and Nagasaki have long been actively involved in various forms of local, national, and international peace activism. Within this context, the mayors of Nagasaki have endeavored to serve as “moral witnesses” to the horrors of nuclear warfare on the global stage.

The involvement of the mayors of Nagasaki in UN diplomacy was not a direct consequence of the atomic bombings of August 1945, nor was it merely the result of vigorous civic activism stemming from their personal experiences with the bombings (several past mayors were atomic bomb survivors). Rather, their entry into UN diplomacy was a carefully and strategically orchestrated endeavor. Furthermore, these mayors have consistently worked to cultivate, maintain, and demonstrate the legitimacy of their diplomatic efforts at local, national, and international levels.

In this article, it will explore an agenda for exploring the city diplomacy of Nagasaki, with a particular focus on the Mayors for Peace organization, its domestic public diplomacy efforts, and its sister city relationships. Such an investigation holds the potential to yield new insights into international relations theory broadly and city diplomacy theories specifically.

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2. City Diplomacy's development

2.1 The origin of the modern diplomacy

It is often asserted that modern diplomacy, characterized by the establishment of permanent missions' resident in the capital of a foreign country, finds its origin in the Peace of Westphalia. However, the basics of diplomacy were already in place long before 1648. Back then, the idea of a nation-state didn't exist, and city-states were the main players in international relations [3]. So, diplomacy is older than the modern state system. For instance, in ancient Greece, city-states like Athens and Macedon often sent and received embassies for specific purposes, appointing ambassadors to negotiate and represent their interests. Later, during the Renaissance, powerful Italian city-states like Venice and Milan were the first to set up permanent diplomatic missions abroad and develop an organized system of diplomacy. Following the Treaties of Westphalia, cities such as Venice could no longer maintain their monopoly over foreign policy. Diplomacy became the prerogative of the newly established European nation-states. The standardization of diplomatic practices after the Congress of Vienna in 1815, along with the concurrent evolution of state sovereignty and diplomacy, further entrenched the state-centric nature of both international relations theory and diplomatic practice [4].

Diplomacy is how countries and other groups represent themselves and their interests to each other. When cities do this, it's called city diplomacy. Cities use city diplomacy to engage in international relations, representing themselves and their interests on the global stage [5].

City diplomacy involves cities taking on roles in international relations and foreign policy that used to belong only to countries. Cities use their economic, cultural, and political power to build international networks, strengthen economic ties, solve global problems, and promote cooperation and understanding. Key parts of city diplomacy include economic cooperation, cultural exchanges, sustainable development, public health projects, and educational collaborations. Through these activities, cities help shape global affairs and support the efforts of countries.

2.2 The determinants in city diplomacy

Traditional definitions of modern diplomacy are usually based on three principles: conducting peaceful relations, between mutually recognized sovereign states, and expecting long-term relationships. These state-centered ideas are theoretically valid because the state plays a significant role in diplomacy [6].

Since the end of World War II, new actors have appeared on the diplomatic stage beyond traditional nation-states. These include non-state actors like NGOs, multinational corporations, and cities. The rise of these territorial non-state entities in diplomacy is due to globalization. Globalization, defined as the spread and movement of products, people, images, and ideas across borders, has made this possible.

Global issues like global warming become national concerns when droughts threaten crops, and national issues like the nuclear weapons threaten multiple countries. The responsibilities between states and territorial non-state actors have shifted. As globalization reduces some state functions, new opportunities arise for non-

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state actors to engage in economic, cultural, and political activities. Advances in information and communication technologies have also increased the ability of these peripheral actors to stay informed and influence decision-making at the center. This evolving diplomatic mode presents an interesting paradox [7].

Globalization and decentralization are powerful forces that empower cities as international actors. Globalization changes the role and functions of states by altering the relationship between a state's components (territory, population, government) and the international environment. Neil Brenner explains that globalization has reconfigured state territorial organization, making cities more global while states become more local[8]. The McKinsey Global Institute estimates that by 2025, 136 new cities from developing countries will join the 600 cities with the highest GDP, with 100 of these cities in China. Tokyo, with a GDP-PPP of $1.6 trillion, is nearly as large as all of South Korea's economy and would rank as the 15th largest economy in the world if it were a country. New York City's $1.5 trillion GDP places it among the world's twenty largest economies, just below Spain and Canada [9].

Globalization increases the influence and importance of cities in international economic relations. Unlike states, cities can form cooperative networks more easily because they lack sovereignty and are not constrained by national interests. Mayors are often more pragmatic and willing to compromise than state leaders, focusing on effective management and practical problem-solving. This pragmatic approach helps mayors gain significant social trust, allowing them to operate more efficiently and with greater public confidence than state authorities.

Common traits of cities worldwide include citizen trust, participation, a disregard for national borders and sovereignty, a drive to create networks, creativity, innovation, and cooperation.

On one hand, global politics are becoming more international and unified, as national governments struggle to address transnational challenges like climate change and cross-border crime on their own. On the other hand, there's a growing focus on local engagement, with sub-national actors taking on more roles as these global issues become relevant to local communities [10].

Territorial non-state actors, such as regions, states, and cities, are both participants in and influenced by globalization. Increased global migration, driven by technology and conflicts, has made these areas more international. They are affected by policies from the World Bank, the IMF, and development plans from global institutions. They also see an influx of foreign goods, multinational corporations, and international organizations. Global cities like New York, London, and Tokyo, which attract diverse populations and global capital, exemplify this trend [11].

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2.3 The forms of city diplomacy

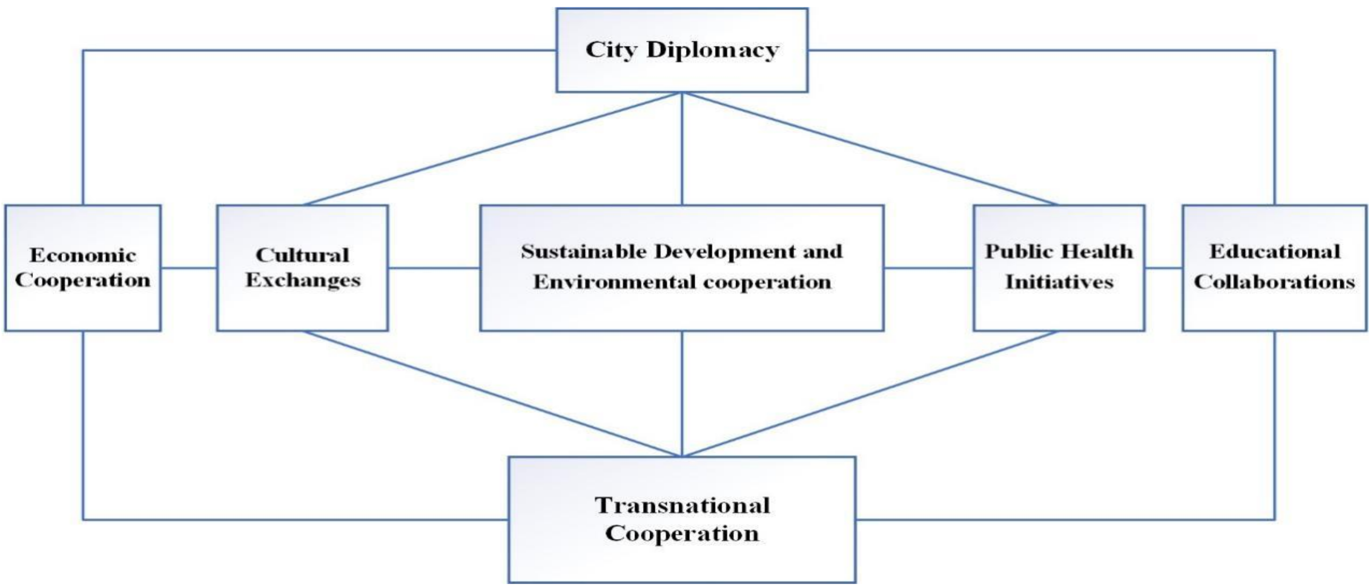

Figure1 The cooperation in city diplomacy

Economic Cooperation. Cities engage in international economic cooperation to attract foreign investment, stimulate local economies, and create employment opportunities. For example, a city might host international trade fairs, business forums, and investment summits to showcase its economic potential. Cities like New York, London, and Shanghai have dedicated agencies that promote the city as a prime location for business. These agencies work on building relationships with foreign investors, facilitating business ventures, and providing incentives for companies to set up operations in the city. Such economic cooperation often involves signing Memoranda of Understanding with other cities to foster mutual economic growth.

Cultural Exchanges. Cultural aspects plays a crucial role in city diplomacy, where cities promote their cultural heritage and diversity on an international stage. This includes organizing cultural festivals, arts exhibitions, and performance tours. For instance, the city of Paris might organize a French film festival in Tokyo, showcasing French cinema to Japanese audiences, thereby promoting cultural exchange and mutual appreciation. Cities also enter into sister city agreements, which often include cultural exchange programs. These programs can involve student exchanges, artist residencies, and joint cultural projects, aimed at fostering long-term relationships and understanding between different cultures.

Sustainable Development and Environmental cooperation(SDEC). Cities are at the forefront of tackling global environmental challenges. Through city diplomacy, urban centers collaborate on sustainability initiatives and climate action plans. For example, cities participating in the C40 Cities Climate Leadership Group commit to reducing greenhouse gas emissions and sharing best practices for urban sustainability. A city like Copenhagen might collaborate with San Francisco on renewable energy projects, exchange knowledge on efficient waste management systems, or co-develop green building standards. These

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collaborations often result in pilot projects, joint funding applications, and the development of innovative technologies that are shared across the participating cities.

Public Health Initiatives. In the realm of public health, cities work together to combat global health crises and improve health outcomes for their residents. This can involve sharing data on disease outbreaks, coordinating responses to pandemics, and collaborating on public health research. For example, during the COVID-19 pandemic, cities like Seoul and Milan exchanged information on containment strategies, testing protocols, and vaccination rollouts. Public health partnerships can also include joint initiatives to tackle issues such as air pollution, obesity, and mental health, leveraging the unique resources and expertise of each city to develop comprehensive health policies and programs.

Educational Collaborations. Cities foster international educational collaborations to enhance learning opportunities and promote cross-cultural understanding. This can include student and academic exchanges, joint research projects, and the establishment of international campuses. For instance, a university in Boston might partner with a university in Singapore to offer dual-degree programs, facilitate faculty exchanges, and conduct collaborative research on topics like urban development or technology innovation. Cities also host international conferences and workshops that bring together scholars, students, and professionals from around the world to share knowledge and address global challenges through education.

By focusing on these aspects, city diplomacy demonstrates how urban centers can leverage their unique strengths to address global challenges, foster international cooperation, and enhance the well-being of their residents and the global community.

3. The development of Nagasaki's city diplomacy

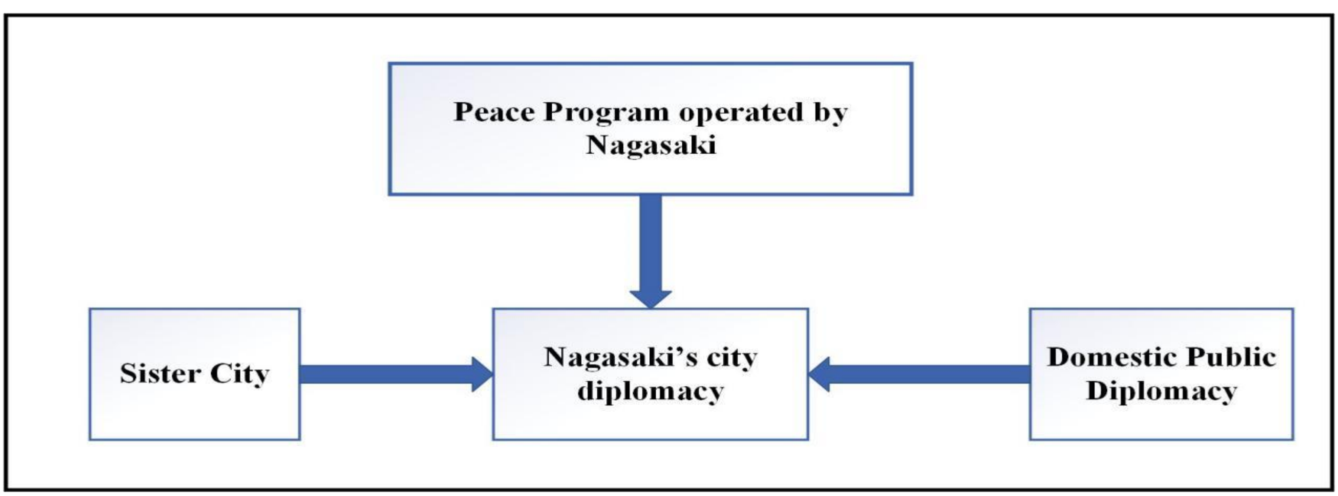

Figure2 The Nagasaki's city diplomacy

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3.1 Peace Program operated by Nagasaki

Japan's economy rebounded after the war, allowing it to re-enter the global stage and actively engage in foreign exchanges. In the 1970s, Tokyo seized the opportunity of the Olympics to establish sister city relationships with cities like Beijing and New York, making it a pioneer in Japan's city diplomacy. As globalization deepens and diplomatic forms diversify, the role and nature of city diplomacy, and its relationship with national diplomacy, keep evolving. In Japan, where central and local governments share power, Tokyo stands out as a highly autonomous city. It operates as a unique political entity, different from the state, using its economic strengths to participate in regional and international coordination, showcasing its influence on multiple levels.

Cities frequently draw upon their local histories to speak with moral authority on global issues. Nagasaki's participation in the Mayors for Peace program exemplifies this approach. As a Vice President City and a co-founder alongside Hiroshima, Nagasaki plays a crucial role in advocating for a nuclear-free world. The organization's covenant states its primary objective is to "contribute to the attainment of lasting world peace by fostering global concern for the total abolition of nuclear weapons through the solidarity of cities worldwide." In 1982, Hiroshima's mayor Takeshi Araki addressed the Second Special Session of the United Nations General Assembly Devoted to Disarmament in New York, USA, and called for "the solidarity of cities throughout the world which share a common cause with Hiroshima"[12]. As an atomic bomb survivor from the August 6, 1945 attack, he envisioned cities transcending national borders to unite in the pursuit of nuclear abolition. During the same session, Nagasaki's mayor, Hitoshi Motoshima, declared that "Nagasaki has to be the last city of the planet ever destroyed by nuclear weapons". In 1986, the organization was reconstituted as "The World Conference of Mayors for Peace through Inter-city Solidarity." It underwent another transformation in 1991, becoming "Mayors for Peace," an NGO with Special Consultative Status in the UN Economic and Social Council (ECOSOC).

On the surface, the Mayors for Peace Program aligns with two key principles of city diplomacy theory. First, it exemplifies how a city can leverage its unique history as a platform to engage with the global community and advocate for change. This mirrors initiatives in other Japanese cities that have become centers for international agreements and efforts, such as Kitakyushu's Initiative for a Clean Environment, Sendai's Framework for Disaster Risk Reduction (stemming from the March 11, 2011 triple disaster), and Minamata's Convention on Mercury (based on its experience with mercury pollution). Second, the organization aims to use networks and coalitions at various levels to maximize its influence on a single issue.

However, questions remain about how the organization operates across different levels. The Mayors for Peace program functions on multiple scales: it engages citizens through letter-writing campaigns and events, enrolls cities as members, interacts with United Nations organizations, collaborates with NGOs, and pressures national governments. Despite the extensive activity recorded on the organization's website, measuring the impact of these actions remains challenging.

A case study approach could provide valuable insights into the effectiveness of Mayors for Peace in promoting nuclear abolition beyond Japan. For instance, a case study on Mayors for Peace France would enhance our understanding of the organization's international influence. Additionally, research could be conducted to explore the motivations behind cities joining the Mayors for Peace program. In terms of global impact, it

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would be beneficial to examine how the Mayors for Peace organization has influenced ongoing multilateral negotiations regarding the Treaty on the Prohibition of nuclear weapons. This could offer a clearer picture of the organization's role in shaping global disarmament policies. Furthermore, an in-depth look at Nagasaki's domestic public diplomacy efforts would shed light on the local strategies that contribute to the broader goals of Mayors for Peace [13].

3.2 The style of transnational relationship—Sister City

There are significant advantages to studying aspects of city diplomacy often overlooked by mainstream international relations. Sister city relationships, or city twinning, have a longstanding history. While notable examples existed before World War II, the concept gained prominence post-war as a means to foster connections between former adversaries. The core idea was that strong people-to-people relationships would decrease the likelihood of future conflicts. This initiative expanded rapidly after 1956, following the establishment of a structured sister cities program initiated by U.S. President Dwight Eisenhower. This program eventually evolved into the nonprofit organization Sister Cities International [14].

Although the initial goal of sister city projects was to strengthen interpersonal ties to prevent war, these relationships now also serve to promote commerce, tourism, and cultural exchange. This evolution mirrors the dynamics of globalization and the pursuit of global competitiveness.

Nagasaki holds a unique place in the history of sister city linkages. The first sister city relationship between the United States and Japan was established on December 7, 1955, between Saint Paul, Minnesota, and Nagasaki, coinciding with the anniversary of the attack on Pearl Harbor[15]. Over the 75 years of their partnership, Saint Paul and Nagasaki have exchanged city officials, sponsored student exchanges, and hosted public events such as concerts and cultural performances.

Currently, Nagasaki has sister city relationships with numerous cities worldwide, including Fuzhou, China; Leiden, Netherlands; Porto, Portugal; Saint Paul, United States; Santos, Brazil; and Vaux-sur-Aure, France. Additionally, Nagasaki maintains a less formal "Citizen Friendship Relationship" with Aberdeen, Scotland, dating back to the time of Scottish merchant Thomas Glover in the Meiji period. Each of these partnerships has fostered numerous connections that have strengthened ties between peoples across nations.

The study of sister city relationships has often been overshadowed by the exploration of more recent phenomena such as city networks and coalitions. However, the longevity and consistency of sister city relationships warrant renewed attention, particularly for their potential to address twenty-first-century challenges. The widespread nature of sister-city relations presents ample opportunities for primary data collection through surveys and semi-structured interviews for an example of using semi-structured interviews in studying sister city relationships [16]. Within the geographical boundaries of Nagasaki Prefecture alone, there are numerous opportunities to explore how sister city relationships benefit and internationalize medium, small, and very small cities.

3.3 Nagasaki's Domestic Public Diplomacy

A relatively new field of practice and study is domestic public diplomacy, which can be described as

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encompassing "a series of initiatives which serve to inform, and acquire the assistance of, citizens within a nation. It is these citizens who play a powerful participatory role in the formulation of their nation's foreign policy and its interests overseas"[17]. Nagasaki, with its cosmopolitan history, is uniquely positioned to leverage domestic public diplomacy to promote local tourism, advance research on nuclear abolition, and highlight its historical openness to the world. Examples of domestic public diplomacy in action include Peace Boat's Hibakusha Project and the efforts of Nagasaki University's Research Center for Nuclear Weapons Abolition.

An important avenue of domestic public diplomacy is Peace Boat's Hibakusha Project. Peace Boat, a Japan-based NGO founded in 1983, travels the world with a crew of volunteers dedicated to promoting peace, advocating for human rights, and fostering sustainability in partnership with the United Nations Sustainable Development Goals campaign. In the context of Nagasaki, Peace Boat's activities center on highlighting the city's unique history and promoting its message of nuclear abolition and peace. This initiative serves not only to educate international audiences but also to engage and inform local citizens, reinforcing their role in the formulation and support of Japan's foreign policy objectives.

Another significant form of public diplomacy is undertaken by Nagasaki University's Research Center for Nuclear Weapons Abolition (RECNA). Established in 2012, RECNA operates as both an extension of Nagasaki's official diplomacy and an independent entity. The center conducts extensive research on nuclear disarmament and disseminates its findings through newsletters, policy papers, and educational pamphlets that simplify complex issues related to nuclear weapons. Describing itself as a Think tank of citizens. RECNA emphasizes its position outside traditional public policy channels [18].

Located in a medium-sized city outside the Tokyo metropolitan area, RECNA offers a unique contrast to the more established think tanks in Tokyo's Kasumigaseki district, such as the Japan Institute of International Affairs (JIIA). Historically, these Tokyo-based think tanks have maintained close relationships with Japan's Ministry of Foreign Affairs, often staffed by former bureaucrats[19]. While these think tanks provide valuable support to Japan's central government, their close ties can sometimes hinder their ability to propose innovative foreign policy alternatives. In contrast, RECNA's geographical and institutional independence allows it to formulate more diverse and potentially groundbreaking policy alternatives. However, the extent to which RECNA leverages its outsider status to its full potential remains an open question.

4.Conclusion: the profit brought by the city diplomacy in Nagasaki

Nagasaki exemplifies active city diplomacy through its global advocacy, domestic public diplomacy, and various initiatives that reinforce its global identity. Nagasaki's involvement in the Mayors for Peace program highlights two key aspects of city diplomacy theory. First, cities primarily operate through networks and coalitions, partnering with other cities, intergovernmental organizations, and NGOs. Second, cities carve out essential niches by leveraging their unique experiences and local expertise[20].

While Nagasaki's role in the Mayors for Peace program is the most prominent and well-publicized element of its city diplomacy, other, less visible aspects might hold significant theoretical value. The domestic public

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diplomacy efforts of Nagasaki, although previously overlooked in scholarly literature, present a promising area for future research. Additionally, the longstanding and widespread practice of sister city relationships has not received the attention it deserves, despite its potential to offer valuable insights into city diplomacy.

The field of city diplomacy is still in its early stages, underscoring the need to expand our current understanding. By investigating beyond major urban centers, scholars can gain deeper insights into the human drive to forge connections across national borders, both for social interaction and collaborative problem-solving. As global challenges such as climate change, pandemics, and political instability persist, studying the diplomatic efforts of smaller cities can provide valuable perspectives on how local initiatives contribute to addressing these issues on a broader scale [21].

Expanding the scope of research to include diverse cities enriches the discourse on city diplomacy and highlights the multifaceted ways in which communities engage with the world. This approach not only broadens our knowledge but also underscores the importance of local actions in the global arena.

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Environmental efficiency in China’s thermal power industry: Disparity, dynamic evolution and convergence

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ABSTRACT

The thermal power generation industry plays a crucial role in China's energy conservation and emission reduction strategy. To effectively assess the environmental efficiency of this industry, we utilize a super efficiency slacks-based measure directional distance function integrated model in this study. Additionally, we employ the Dagum Gini coefficient and its decomposition method, the spatial Markov chain method, and stochastic convergence test method to empirically analyze the disparities, distributed dynamic evolution, and convergence of environmental efficiency within China's thermal power industry. The study's findings reveal several key insights. Firstly, the overall environmental efficiency of the thermal power industry is improving, although regional disparities persist. Secondly, the gap in regional spatial distribution is decreasing, with inter-regional disparities being the primary source of the environmental efficiency gap in China. Thirdly, there is a significant spatial dependence in the environmental efficiency of China's thermal power industry. Lastly, the evolution of environmental efficiency within the thermal power industry follows a pattern of stochastic convergence. These results provide a strong basis for addressing the efficiency gap and contribute to enhancing the coordinated development of China's thermal power industry.

KEYWORDS

Environmental efficiency; Thermal power industry; Data envelopment analysis; Disparity; Stochastic convergence

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1. Introduction

China's steadfast commitment to achieving high-quality development, characterized by a balanced approach to economic growth and environmental preservation, has garnered significant attention (Song et al., 2014). In pursuit of this objective, the Chinese government has implemented a comprehensive framework of laws, regulations, and strategic objectives dedicated to safeguarding the ecological environment, accompanied by a suite of incentive policies (Wang et al., 2018a; Hu, 2012). As corroborated by the BP World Energy Statistical Yearbook 2021, China's electric power system stands as the largest on the global stage, contributing to 29% of the world's total power generation in 2020 (BP, 2021). Notably, the thermal power industry holds a predominant position within China's power generation sector (Wang et al., 2018b), which, consequently, contributed to approximately 14.29% of the world's total carbon emissions resulting from fossil fuel combustion in the same year (CIEEC, 2021). Regrettably, this has led thermal power plants to emerge as the primary culprits of air pollution in the country (Huang et al., 2017). Specifically, coal power generation accounts for a substantial 89.42% of the total thermal power generation (NBSC, 2021) and, in turn, is responsible for the release of considerable amounts of harmful pollutants, including carbon dioxide (CO2) and sulfur dioxide (SO2).

Enhancing environmental efficiency within the thermal power industry has become a matter of utmost significance and urgency. In this study, we commence by assessing the environmental efficiency through the implementation of the DEA (Data Envelopment Analysis) model. The DEA method serves as a popular tool for energy and environmental efficiency evaluations (Miao et al., 2021; Lv et al., 2021b; Halkos & Bampatsou, 2022). In this study, we propose the adoption of a super-efficiency SBM-DDF integrated model, which effectively addresses undesirable outputs, to evaluate the environmental efficiency of thermal power generation in China. This model is capable of distinguishing between efficient and inefficient outcomes, ultimately deriving super-efficiency results.

As of 2020, the top 7 out of 30 provinces, municipalities, and autonomous regions in China accounted for more than 50% of the total thermal power generation (China Energy Statistical Yearbook, 2020). Nonetheless, the impact of environmental regulation varies significantly across these different regions, as highlighted by Xie and Li (2021), Xie and Zhou (2022), and Chen et al. (2021). The power industry in China possesses unique characteristics, such as an uneven distribution of natural resources and a partial mismatch between power generation and demand (Yang et al., 2015; Wang et al., 2014). By decomposing the Gini coefficient, the uneven characteristics and patterns can be revealed (Lau & Koo, 2022; Costa, 2021). Thus, the objective of our study is to explore regional disparities and the spatial pattern of environmental efficiency in the thermal power industry across China.

The Dagum Gini coefficient (Dagum, 1997) is employed to gauge the level of inequality among different groups and to discern the contributions of various factors to the overall gap (Miao et al., 2021; Wang & Xu,

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2021; Lv et al., 2021a). In order to identify the primary causes of regional disparities in the thermal power industry, we utilized the Dagum Gini Index decomposition method. Additionally, the interplay between resource allocation, economic development, and the output, technology, and pollution of thermal power plants varies across regions in China (Wang & Feng, 2013). Disparities also exist in economic, political, and thermal power generation modes across different regions (Li et al., 2017; Xie et al., 2021; Chen et al., 2021), with each region experiencing a unique combination of production factors, population migration, technology, and knowledge diffusion (Wang et al., 2014; Qin et al., 2019; Wu & Hu, 2021).

To examine the impact of adjacent regions' efficiency levels on a province's efficiency and trend (Lv et al., 2021a; Wang & Xu, 2021), we employed the Spatial Markov chain (Quah, 1996; Rey, 2001). Investigating whether the environmental efficiency of thermal power generation in China is converging or diverging and whether external factors affect the efficiency level or necessitate self-regulation by the market or national regulation is crucial. Cui et al. (2022) utilized a convergence model to analyze the spatiotemporal heterogeneity of carbon emissions among regions, while Wang & Zhang (2021) observed that China's green development performance diverged through absolute β convergence and conditional β convergence methods. The stochastic convergence test is applied to determine whether there is stochastic convergence in the evolution of the environmental efficiency of China's thermal power generation industry. Understanding the convergence or divergence of environmental efficiency in thermal power generation among regions or provinces is essential for devising relevant policies.

This study makes distinctive and valuable contributions by bridging the research gap pertaining to environmental efficiency in China's thermal power industry. We achieve this by conducting a thorough analysis of regional disparities, spatial patterns, and trend evolution. Furthermore, we introduce a comprehensive and systematic approach for measuring environmental efficiency in the industry, utilizing an innovative super efficiency SBM-DDF integration model. This model enables a more robust evaluation of the industry's environmental performance.

The remainder of this paper is organized as follows. Section 2 introduces the related methods. Section 3 presents data. Section 4 elaborates the empirical study conducted in this study. Finally, Section 5 draws the conclusion.

2. Methods

2.1 Super efficiency SBM-DDF integration model

Charnes et al. (1978) introduced DEA with the assumption of constant returns to scale, while Banker et al. (1984) proposed a novel model, assuming variable returns to scale. However, these traditional DEA models have limitations as they overlook the slackness of variables and fail to account for all invalid DMUs. To address these shortcomings, Tone (2003) incorporated slack variables into the objective function, presenting

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a non-radial, non-directed SBM model that considered undesired outputs. Nonetheless, this model had the drawback of being unable to distinguish the effective decision-making units (DMUs) accurately, resulting in imprecise evaluation outcomes. Subsequently, Tran et al. (2019) introduced the OneSupSBM model to address this concern effectively. Nevertheless, the OneSupSBM model had two disadvantages: it did not consider undesirable outputs and solely focused on constant returns to scale (CRS) models. To overcome these limitations, this paper proposes an improved integration model that enhances the OneSupSBM model. The newly developed integrated model combines SBM-DDF with a super-efficiency SBM-DDF, offering a comprehensive and refined estimation of the thermal power industry's environmental efficiency across the 30 provinces under study.

2.1.1 SBM-DDF model

DMU_j is used to represent the set of decision-making units. The input and output elements of the set decision-making units are expressed as follows. The input N is $x=(x_1^t,x_2^t,\cdots,x_N^t)\in R_+^N$; the desirable output M is $y=(y_1^t,y_2^t,\cdots,y_M^t)\in R_+^M$; and the undesirable output K is $b=(b_1^t,b_2^t,\cdots,b_K^t)\in R_+^K$. The parameter (x_j^t,y_j^t,b_j^t) is the input-output data for the t period of the j^{th} region. The parameter (g^x,g^y,g^b) is a directional vector, with a strictly positive value. In this paper, the direction vector is set as (x,y,b) ; the parameter (s_n^x,s_m^y,s_k^b) is the slack vector of input, desirable output, and the undesirable output to reach the efficiency frontier, respectively.

$$
\begin{aligned}
&\min \delta_o = 1-\frac{1}{2N}\sum_{n=1}^{N}\frac{s_n^x}{g_n^x}-\frac{1}{2\ M+K}\left(\sum_{m=1}^{M}\frac{s_m^y}{g_m^y}+\sum_{k=1}^{K}\frac{s_k^b}{g_k^b}\right)\\
&s.t.\sum_{j=1}^{J}x_{nj}^t\lambda_j^t+s_n^x=x_{no}^t,\ \ n=1,\cdots,N\\
&\quad\ \sum_{j=1}^{J}y_{mj}^t\lambda_j^t-s_m^y=y_{mo}^t,\ \ m=1,\cdots,M\\
&\quad\ \sum_{j=1}^{J}b_{kj}^t\lambda_j^t+s_k^b=b_{ko}^t,\ \ k=1,\cdots,K\\
&\quad\ \sum_{j=1}^{J}\lambda_j^t=1\\
&\quad\ \lambda_j^t\geq 0, s_n^x\geq 0, s_m^y\geq 0, s_k^b\geq 0
\end{aligned}
\tag{1}
$$

The parameter λ_j^t is a non-negative vector. In this model, all input-output data are positive; that is,

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$x_{nj}^t > 0,\ y_{mj}^t > 0,\ b_{kj}^t > 0$. The target value is less than or equal to 1. The parameter $\delta_o^* = 1$ denotes a valid DMU; and $\delta_o^* < 1$ denotes an invalid DMU, which needs to be improved.

2.1.2 Super efficiency SBM-DDF model

$$\begin{aligned}
&\min \rho_o = 1 + \frac{1}{2N}\sum_{n=1}^{N}\frac{z_n^x}{g_n^x} + \frac{1}{2\ M+K}\left(\sum_{m=1}^{M}\frac{z_m^y}{g_m^y} + \sum_{k=1}^{K}\frac{z_k^b}{g_k^b}\right) \\
&s.t. \sum_{j=1,j\neq 0}^{J} x_{nj}^t \lambda_j^t - z_n^x \le x_{no}^t, \quad n = 1,\cdots,N \\
&\quad \sum_{j=1,j\neq 0}^{J} y_{mj}^t \lambda_j^t + z_m^y \ge y_{mo}^t, \quad m = 1,\cdots,M \\
&\quad \sum_{j=1,j\neq 0}^{J} b_{kj}^t \lambda_j^t - z_k^b \le b_{ko}^t, \quad k = 1,\cdots,K \\
&\quad \sum_{j=1,j\neq 0}^{J} \lambda_j^t = 1, \quad j = 1,\cdots,J, \quad j \neq 0 \\
&\quad \lambda_j^t \ge 0,\ z_n^x \ge 0,\ z_m^y \ge 0,\ z_k^b \ge 0
\end{aligned} \tag{2}$$

In these expressions, z_n^x, z_m^y, z_k^b are slack variables of input, desirable output, and undesirable output respectively. The parameter λ_j^t is a non-negative vector; and x_n^t, y_m^t, b_k^t represent decision variables of input, desirable output, and undesirable output, respectively.

2.1.3 Integration model

Combining our own work and the work of Tran et al. (2019), we generated the integrated model of SBM-DDF and super-efficient SBM-DDF. This model directly generates the efficiency score of invalid DMUs and the super efficiency score of effective DMUs by solving the one-stage model, as shown in Fig. 1.

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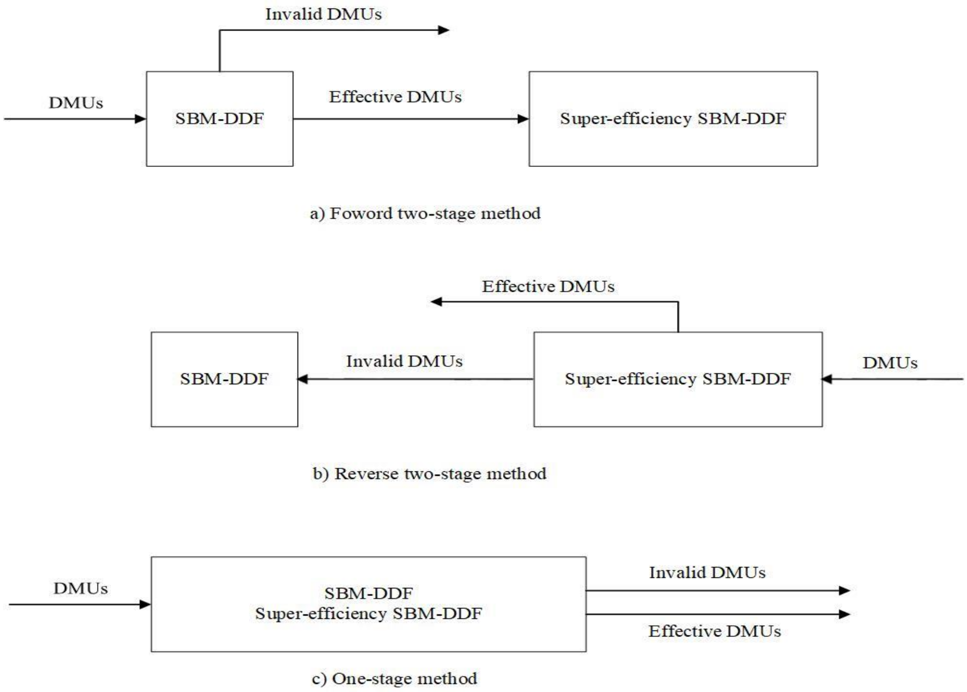

Figure 1 Explanation of the forward and reverse two-stage method and one-stage method

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The integration model is described as follows:

$$
\begin{aligned}
&\min \theta_o = \alpha\rho_0 + \ 1 - \alpha \ \ \delta_o \\
&s.t. : \frac{1}{2N}\sum_{n=1}^{N}\frac{z_n^x}{g_n^x} + \frac{1}{2 \ M+K}\left(\sum_{m=1}^{M}\frac{z_m^y}{g_m^y} + \sum_{k=1}^{K}\frac{z_k^b}{g_k^b}\right) \le \alpha\overline{M} \\
&\quad \alpha \in \ 0;1 \\
&\quad x_{no}^t = \sum_{j=1}^{J} x_{nj}^t \lambda_{1j}^t + s_n^x, \ n = 1,\cdots,N \\
&\quad y_{mo}^t = \sum_{j=1}^{J} y_{mj}^t \lambda_{1j}^t - s_m^y, \ m = 1,\cdots,M \\
&\quad b_{ko}^t = \sum_{j=1}^{J} b_{kj}^t \lambda_{1j}^t + s_k^b, \ k = 1,\cdots,K \\
&\quad \sum_{j=1}^{J}\lambda_{1j}^t = 1, \ j = 1,\cdots,J \\
&\quad \lambda_{1j}^t \ge 0, s_n^x \ge 0, s_m^y \ge 0, s_k^b \ge 0 \\
&\quad x_{no}^t \ge \sum_{j=1, j\ne 0}^{J} x_{nj}^t \lambda_{2j}^t - z_n^x, \ n = 1,\cdots,N \\
&\quad y_{mo}^t \le \sum_{j=1, j\ne 0}^{J} y_{mj}^t \lambda_{2j}^t + z_m^y, \ m = 1,\cdots,M \\
&\quad b_{ko}^t \ge \sum_{j=1, j\ne 0}^{J} b_{kj}^t \lambda_{2j}^t - z_k^b, \ k = 1,\cdots,K \\
&\quad \sum_{j=1, j\ne 0}^{J}\lambda_{2j}^t = 1, \ j = 1,\cdots,J, \ j \ne 0 \\
&\quad \lambda_{2j}^t \ge 0, z_n^x \ge 0, z_m^y \ge 0, z_k^b \ge 0
\end{aligned}
\tag{3}
$$

In these expressions, $\overline{M}$ is a large positive number; and λ_{1j}, λ_{2j} are non-negative vectors of the SBM-DDF model and super-efficient SBM-DDF model, respectively. The objective function is used to measure the efficiency score of DMU, $\rho_0 = 1 + \frac{1}{2N}\sum_{n=1}^{N}\frac{z_n^x}{g_n^x} + \frac{1}{2 \ M+K}\left(\sum_{m=1}^{M}\frac{z_m^y}{g_m^y} + \sum_{k=1}^{K}\frac{z_k^b}{g_k^b}\right)$ for the super efficiency score of valid DMU, and $\delta_0 = 1 - \frac{1}{2N}\sum_{n=1}^{N}\frac{s_n^x}{g_n^x} - \frac{1}{2 \ M+K}\left(\sum_{m=1}^{M}\frac{s_m^y}{g_m^y} + \sum_{k=1}^{K}\frac{s_k^b}{g_k^b}\right)$ for the efficiency score of invalid DMU. In the objective function, we use the binary variable $\alpha \in \ 0;1$ to transform the efficiency measurement of the SBM-DDF model and the super-efficiency SBM-DDF model. If $\alpha = 1$, the super efficiency SBM-DDF

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model is selected to calculate the super efficiency score ρ_0 of valid DMU. If $\alpha = 0$, the SBM-DDF model is selected as the calculated efficiency score δ_0 of invalid DMU. Appendix explains how the one-stage integration model can adaptively identify the SBM-DDF model or the super-efficient SBM-DDF model based on the value of α.

2.2 Dagum Gini coefficient

In this paper, the Dagum Gini coefficient and its decomposition method were used to describe the regional disparities of environmental efficiency of China's thermal power industry in the six regions. According to Dagum (1997), the Gini coefficient is defined as:

$$G = \frac{\Delta}{2\bar{Y}} = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|y_{ji} - y_{hr}\right|}{2n^2\bar{y}} \tag{4}$$

where G is the total Gini ratio; and Δ is the total Gini mean difference. For example, with respect to the environmental efficiency of thermal power generation, Δ is the mean value of the absolute value of every two levels of efficiency difference. Assume there are n provinces, divided into k subgroups (regions). Then, n_j (n_h) is the number of provinces in the $j^{th}(h^{th})$ subgroup (region). The parameter y_{ji} (y_{hr}) is the environmental efficiency of thermal power generation in $i^{th}(r^{th})$ province (or municipalities, autonomous regions) of the $j^{th}(h^{th})$ subgroup (region), $j = 1,2,...,k$, $h = 1,2,...,k$, $i = 1,2,...,n_j$, $r = 1,2,...,n_h$. The parameter $\bar{y}$ is the average value of environmental efficiency for the thermal power generation in all provinces of China.

Dagum (1997) described a new method for decomposing the Gini ratio, decomposing the ratio into three parts: the contribution of the gap within the subgroup G_w, the contribution of the gap between subgroups G_{nb}, and the contribution of hyper-variable density G_t. The relationship of the three parts satisfies $G = G_w + G_{nb} + G_t$. Before decomposing the Gini ratio, the first step is to rank the regions according to the mean environmental efficiency of thermal power generation in each subgroup (region): $\bar{Y}_h \le \cdots \bar{Y}_j \le \cdots \le \bar{Y}_k$.

In this expression, $\bar{Y}_j, \bar{Y}_h$ represent the mean environmental efficiency of thermal power generation of the

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j^{th}, h^{th} subgroup (region), respectively.

Eq. (5) describes the Dagum decomposition method and calculation method in detail. The parameters G_{jj} and G_{jh} represent the Gini ratio within a subgroup and the Gini ratio between subgroups, respectively; and $\triangle_{jj}$ defines the mean difference of Gini ratio within j^{th} subgroup. Similarly, $\triangle_{jh}$ defines the mean difference of Gini ratio between j^{th} and h^{th} subgroups. According to Dagum (1997), the concept of economic prosperity, D_{jh} can be defined as the relative effectivity degree of thermal power environmental efficiency between j^{th} and h^{th} subgroups. The parameter d_{jh} is defined as the disparity of efficiency level between subgroups; it is the mathematical expectation of the sum of all $y_{ji} - y_{hr} > 0$ sample values between subgroups j^{th} and h^{th}. The parameter p_{jh} is defined as the super variable first-order distance, which is the mathematical expectation of the sum of all $y_{hi} - y_{jr} > 0$ sample values between subgroups j^{th} and h^{th}.

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$$
\begin{aligned}
& p_j = \frac{n_j}{n_J},\; s_j = \frac{n_j Y_j}{nY},\; j,h = 1,2,\ldots,k \\
& G_w = \sum_{j=1} G_{jj} p_j s_j \\
& G_{jj} = \frac{\Delta_{jj}}{2\overline{Y}_j} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|y_{ji}-y_{jr}\right|}{n_j^2} \\
& G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j\text{-}1} G_{jh}(p_j s_h + p_h s_j) D_{jh} \\
& G_t = \sum_{j=2}^{k}\sum_{h=1}^{j\text{-}1} G_{jh}(p_j s_h + p_h s_j)(1 - D_{jh}) \\
& G_{jh} = \frac{\Delta_{jh}}{\overline{Y}_j + \overline{Y}_h} \\
& \Delta_{jh} = d_{jh} + p_{jh} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|y_{ji}-y_{hr}\right|}{n_j n_h} \\
& D_{jh} = \frac{d_{jh} - p_{jh}}{d_{jh} + p_{jh}} \\
& d_{jh} = \int_0^{\infty} dF_j(y) \int_0^{y} (y-x)\, dF_h(x) \\
& p_{jh} = \int_0^{\infty} dF_h(y) \int_0^{y} (y-x)\, dF_j(y)
\end{aligned}
\tag{5}
$$

2.3 Spatial Markov chain

The Markov chain is mainly used to analyze the internal dynamics and evolution process of variables (Quah, 1996). In this study, a Markov transfer matrix was constructed to describe the dynamic evolution of the environmental efficiency level of thermal power generation in each region. The Markov chain is the state space of a random process $(X\ \ t\ ,t \in T)$. We assume the random variable $X_t = j$; in other words, the system state in t period is j. Its value is a finite set; its spatial state is $I\{i, j, \cdots\}$; and the Markov chain of the system satisfies Eq. (6). This indicates that the probability that random variable X is in state j in period $t+1$ only depends on its state in period t.

$$
\begin{aligned}
& P\ \ X_{t+1} = j \mid X_0 = i_0, X_1 = i_1, X_2 = i_2, \cdots, X_{t\text{-}1} = i_{t\text{-}1}, X_t = i \\
& = P\ \ X_{t+1} = j \mid X_t = i \\
& = P_{ij}
\end{aligned}
\tag{6}
$$

We assume that P_{ij} is the transfer probability of the environmental efficiency of thermal power generation in a province from state i in year t to state j in year $t+1$. Using the maximum likelihood estimation

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method:

$$P_{ij} = \frac{n_{ij}}{n_i} \tag{7}$$

where n_{ij} refers to the number of all provinces in the sample period that are transferred from state i in year t to state j in year $t+1$; and n_i refers to the number of all provinces in state i throughout the sample period.

The transition of random variables from one state to another is called state transition. Assuming there is a total of k states, then we can construct a transition probability matrix of $k \times k$. Then, the state transition probability P_{ij} refers to the probability of transition from state i to state j. The $k \times k$ matrix of all P_{ij} is the state transition probability matrix P. The transition probability matrix is then used to determine the distribution dynamic evolution trend of each region in the economic system. The efficiency level of a region is affected by the efficiency level of neighboring regions, that is, the approximate values of random variables have an aggregation effect in space.

In this study, we applied the spatial Markov chain method, introducing the concept of spatial lag, to consider the spatial and geographical interaction effect of environmental efficiency of thermal power generation in China (Rey, 2001). The spatial lag value is the spatial weighting of the surrounding efficiency level of each province. We calculate the lag value based on the following equation:

$$F_r = \sum w_{sr} y_s \quad (s \neq r) \tag{8}$$

where F_r is the spatial lag value of province r; y_s is the efficiency value of province s; and W_{sr} is a spatial weight matrix. If other provinces border province r, then $w_{sr} = 1$; otherwise, $w_{sr} = 0$. The Spatial Markov chain decomposes the traditional $k \times k$ transfer probability matrix into the $k \times k \times k$ matrix. Therefore, P_{ij} becomes the probability of a province changing from t year state i to $t+1$ year state j in the case of spatial lag type k. This can reveal the impact of the space effect on the regional thermal power environmental efficiency gap.

2.4 Stochastic convergence test

China's thermal power generation industry is categorized as a traditional high-energy consumption sector, leading to the production of polluting gases such as carbon dioxide and sulfur dioxide. Prolonged and large-scale emissions of these pollutants exacerbate the greenhouse effect. The conventional development approach has inflicted significant environmental damage and deviates from the principles of sustainable development. Therefore, it is imperative to enhance the environmental efficiency of thermal power

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generation, curtail carbon emissions, and steer it towards a more sustainable trajectory that aligns with economic development, social stability, and environmental protection. However, achieving this convergence is challenging due to economic disparities among regions, varying resource endowments, and different economic development models, resulting in imbalanced environmental efficiency levels in thermal power generation across regions.

To evaluate the potential of long-term convergence and non-convergence in environmental efficiency, we employ the stochastic convergence method. The unit root test, initially proposed by Carlino et al. (1996) and Evans et al. (1996), serves as the primary methodology for examining the overall convergence of China's thermal power generation environmental efficiency at both national and regional levels.

The stochastic convergence needs to meet the following equation:

$$\lim_{k\to\infty} E_t \left(y_{i,t+k} - \overline{y}_{t+k} \right) = \mu_i - \frac{1}{n}\sum_{i=1}^{n}\mu_i , \quad i = 1,2,\cdots,n \tag{9}$$

In this study, two panel unit root test methods were utilized: the IPS test (IM, 2003) and the Hadri test (Hadri, 2000). The IPS test assumes that all series have unit roots, whereas the Hadri test presumes that all series are stationary. However, it is crucial to note that rejecting the original hypothesis based on the IPS test does not necessarily mean that all series are stable, and vice versa, rejecting the original hypothesis using the Hadri test does not imply that all series have unit roots. Relying solely on a single criterion as the test standard can jeopardize the reliability of empirical findings. To address this concern, Choi (2002) proposed the use of the confirmatory analysis (CA) method, which allows for a more robust conclusion by comparing results from various types of panel unit root tests. This approach can result in four potential situations, as outlined in Table 1, thereby enhancing the accuracy and credibility of our empirical findings.

Table 1 Situation and conclusions associated with the confirmatory analysis method

Situation	Test for rejection of assumptions	Conclusion
I	IPS test and Hadri test failed to reject the original hypothesis.	We cannot judge the stability of the sequence.
II	The IPS test rejects the hypothesis that the sequence possesses a unit root, while the Hadri test does not provide sufficient evidence to reject the original hypothesis that the sequence is stable.	Time series are stationary stochastic processes; that is, there is stochastic convergence among variables.
III	IPS test does not reject the possibility of a unit root for all series, while the Hadri test significantly rejects the original hypothesis of	All series have unit roots and there is random divergence among variables.

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	stationarity.	
IV	The IPS test and Hadri test both reject the original hypothesis.	This may be due to the random divergence or convergence of some series. The conclusion is not clear.

3. Data

In this study, we categorized the 30 provinces of China into six regions using the geographical divisions defined by the National Bureau of Statistics of the People's Republic of China in 2011 (see Fig. 2). The regions are as follows: North China, Northeast China, East China, Central China, Northwest China, and South China. The data used for analysis spanned from 2006 to 2015. However, due to missing data, we excluded Taiwan, Hong Kong, Macao, and Tibet from the study. The data were collected from the China Statistical Yearbook as our primary source.

Figure 2 China is divided into six areas for this study

The input, desirable output, and undesirable output were defined as follows:

(1) Input: Input variables include the labor force, installed capacity of thermal power generation, and energy consumption. Due to the unavailability of labor input data in the thermal power industry, labor in the power, heat, and supply industries, published in the 2007-2016 China Statistical Yearbook, were used in place of labor in the thermal power industry. Data on installed capacity of thermal power generation were collected

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from the China Power Yearbook. Fuels include coal, oil, and natural gas. Total energy consumption data were converted to standard coal. Data on coal, oil, and gas were collected from the China Energy Statistics Yearbook.

(2) Desirable output: The desirable output was thermal power generation. Power generation is the most important indicator of the power industry and reflects the operation efficiency of the power industry (Lam et al., 2001). This paper set the provincial thermal power generation as the expected output, and the data were collected from the China Energy Statistics Yearbook.

(3) Undesirable output: Undesired outputs included CO_2 and SO_2 emissions. The SO_2 emission data for the thermal power industry were collected from the annual report of China's environmental statistics[1]. There is no direct statistical monitoring data source on CO_2 emissions, so this paper used three kinds of fossil fuel (coal, oil and natural gas) consumption to calculate regional CO_2 emissions. The equation is as follows:

$$C_{it} = \sum E_{ijt} \times CEF_j \times COR_j \times \frac{44}{12} \quad (10)$$

where C_{it} represents the CO_2 emissions generated by the fuel required by the region i thermal power industry in year t. The parameter E_{ijt} represents the fuel consumption j of region i thermal power industry in year t. The parameter CEF_j is the carbon emission factor of fuel j; and COR_j is the carbon oxidation rate of fuel j. The data related to CEF_j and COR_j are shown in Table 2, which is consistent with Liu et al. (2016). Table 3 shows the descriptive statistics of input-output variables of China's thermal power industry from 2006 to 2015.

Table 2 Carbon emission factors and carbon oxidation rate associated with the consumption of three energy types

Type of energy consumption	Coal	Petroleum	Natural gas
Carbon emission factors (CEF)	0.75	0.58	0.44
Carbon oxidation rate (COR)	0.90	0.98	0.99

Note: the unit is 10000 tons of carbon / 10000 tons of standard coal.

[1] From 2016, the annual report of China's environmental statistics does not provide the data of SO_2 emission.

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Table 3 Descriptive statistics of input and output in 2006-2015

Variable	Input			Desirable Output	Undesirable Output	
	Labor	Installed capacity	Energy consumption	Thermal power generation	CO_2 Emissions	SO_2 Emissions
Mean	11.35	2466.04	3851.10	114.85	9462.96	27.81
Max	32.18	8754.00	14461.26	450.21	35822.20	93.31
Min	1.20	152.00	285.82	7.20	618.81	0.10
S.D.	6.05	1909.43	3053.32	92.86	7519.70	20.94

Note: the unit of installed capacity is 10,000 kW, the unit of labor force of thermal power is 10,000 persons, the energy consumption is expressed in 10000 tons of standard coal, the unit of power generation is TWH, and the unit of SO_2, CO_2 emissions is 10000 tons.

4. Empirical study

4.1 Environmental efficiency evaluation results

We applied the super efficiency SBM-DDF integration model to measure the environmental efficiency of China's thermal power industry in 2006-2015. We also analyzed the environmental efficiency levels and their changing trends in the six regions.

The box diagram in Fig. 3 displays the environmental efficiencies of thermal power industry in China's provinces from 2006 to 2015. Overall, the environmental efficiency levels were high for Shanghai (0.9264), Ningxia (0.9548), Beijing (0.9612), Tianjin (0.9632), Qinghai (0.9944) and Hainan (1.0000). This may be because there were fewer thermal power plants in these areas and the pollution caused by thermal power generation was small, or because the energy conservation and environmental protection measures taken in these areas were better. Therefore, with the same expected output, undesired output was less and efficiency was higher. These results closely relate to their significant development levels in the categories of the economy, society, technology and environmental protection. The environmental efficiency levels were lower for (0.5865), Liaoning (0.5806), Sichuan (0.4975), Inner Mongolia (0.3966), Guizhou (0.5068), Shandong (0.4504) and Henan (0.3847). This may be due to the early development of the thermal power industry in these regions, which mainly relied on traditional high-polluting power generation methods, resulting in excessive carbon dioxide and sulfur dioxide emissions and low environmental efficiency.

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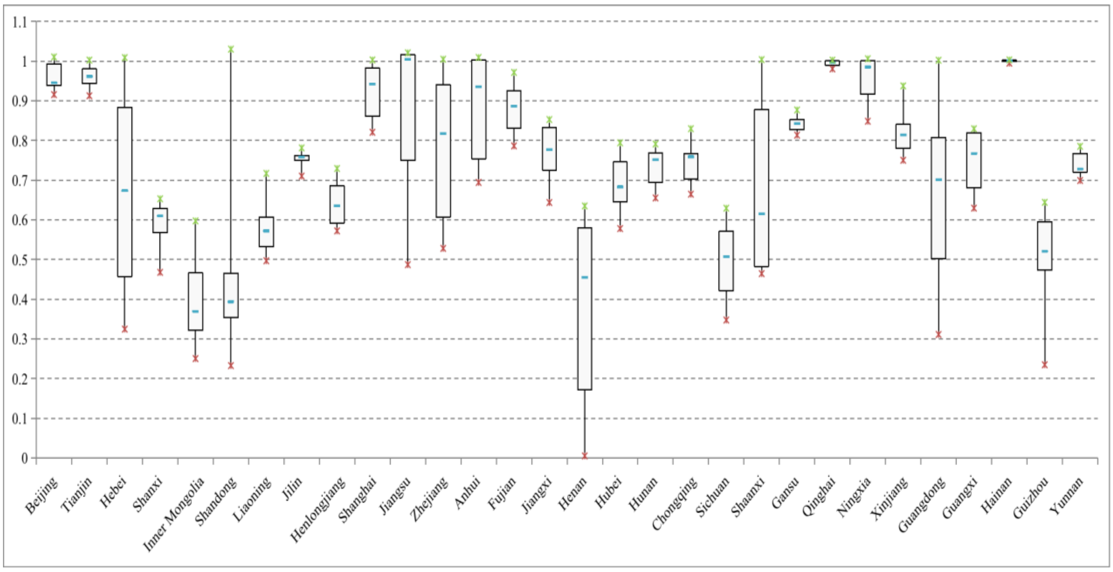

Figure 3 Environmental efficiency box diagram of the thermal power industry in the 30 provinces of China

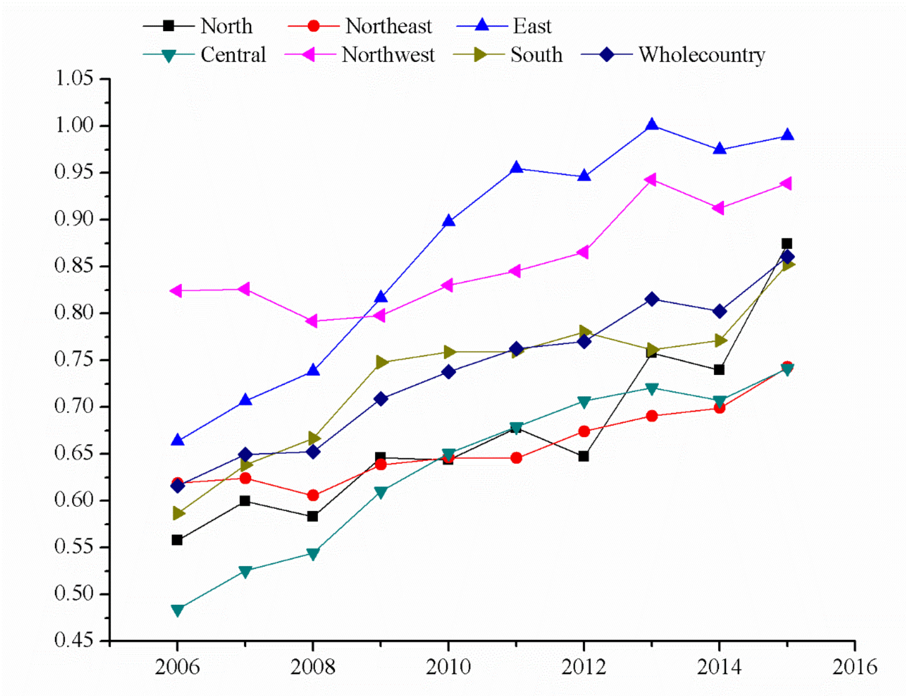

Figure 1 The changing trend in the environmental efficiency of the thermal power industry in the six regions of China from 2006 to 2015

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Fig. 4 shows the changing trend of environmental efficiency for the thermal power industry in six regions of China from 2006 to 2015. The overall environmental efficiency of the six regions showed an upward trend from 2006 to 2015, with as national average environmental efficiency value of 0.7376. From a regional perspective, the environmental efficiency value of the eastern region was the highest, at 0.8689, followed by the northwest region (0.8576), and the south region (0.7323). The indices for North China (0.6727), Northeast China (0.6585), and Central China (0.6370) were all lower than 0.7. The central region had the lowest index of all regions.

4.2 Regional disparity results

To identify the main sources of regional disparities, the Gini coefficient and decomposition method proposed by Dagum (1998) was used to calculate the environmental efficiency of thermal power generation in China from 2006 to 2015. The decomposition was done for six regions: North, Northeast, East, Central, Northwest, and South China. The calculation results are shown in Table 4.

Table 4 Dagum Gini coefficient and decomposition results of environmental efficiency

		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Total		0.191	0.175	0.165	0.139	0.141	0.153	0.138	0.132	0.127	0.111
Intra- group disparities	North	0.225	0.237	0.221	0.192	0.192	0.239	0.209	0.168	0.167	0.141
	Northeast	0.047	0.079	0.079	0.071	0.060	0.081	0.056	0.048	0.042	0.022
	East	0.085	0.071	0.058	0.044	0.049	0.035	0.032	0.009	0.019	0.019
	Central	0.189	0.156	0.168	0.138	0.118	0.079	0.095	0.102	0.088	0.081
	Northwest	0.117	0.117	0.107	0.097	0.089	0.072	0.071	0.043	0.064	0.035
	South	0.212	0.166	0.147	0.101	0.090	0.134	0.116	0.119	0.107	0.102
Inter-group disparities	N/NE	0.200	0.203	0.198	0.163	0.166	0.222	0.174	0.150	0.149	0.172
	N/E	0.188	0.188	0.189	0.168	0.197	0.203	0.204	0.160	0.156	0.097
	N/C	0.241	0.231	0.227	0.192	0.187	0.225	0.184	0.160	0.156	0.176
	N/NW	0.236	0.223	0.212	0.176	0.186	0.196	0.185	0.148	0.153	0.107
	N/S	0.230	0.211	0.210	0.176	0.183	0.214	0.191	0.154	0.153	0.137
	NE/E	0.089	0.091	0.103	0.122	0.165	0.203	0.178	0.203	0.181	0.162
	NE/C	0.149	0.145	0.143	0.128	0.107	0.085	0.084	0.092	0.077	0.068
	NE/NW	0.175	0.175	0.160	0.135	0.141	0.141	0.131	0.166	0.142	0.129
	NE/S	0.180	0.144	0.128	0.109	0.102	0.140	0.125	0.106	0.097	0.107
	E/C	0.165	0.149	0.148	0.142	0.164	0.183	0.159	0.186	0.178	0.165
	E/NW	0.138	0.126	0.099	0.078	0.077	0.076	0.067	0.038	0.055	0.038
	E/S	0.171	0.137	0.123	0.093	0.112	0.134	0.117	0.151	0.134	0.094
	C/NW	0.257	0.236	0.205	0.163	0.152	0.125	0.123	0.149	0.143	0.132
	C/S	0.225	0.184	0.177	0.146	0.121	0.131	0.122	0.119	0.108	0.118
	NW/S	0.217	0.183	0.157	0.115	0.113	0.114	0.105	0.129	0.116	0.086
Contributio n rate	G_w	14.45	14.56	14.58	14.30	13.17	12.68	12.97	11.45	11.94	11.45
	G_{nb}	41.81	41.19	41.38	44.36	51.65	51.13	58.49	61.61	59.37	61.34
	G_t	43.74	44.25	44.04	41.34	35.18	36.19	28.54	26.94	28.68	27.22

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Note: “N” “NE” “E” “C” “NW” “S” refers to North China, Northeast China, East China, Central China, Northwest China, and South China, respectively. The unit of contribution rate is %.

4.2.1 Result of the overall regional gap

The data presented in Table 4 demonstrate a descending fluctuating trend in the overall Gini coefficient of China's thermal power generation environmental efficiency throughout the study period, with an average value of 0.147. Analyzing the changing trend, it is observed that from 2006 to 2009, the overall gap in China's thermal power generation environmental efficiency experienced a downward movement, particularly during 2008-2009, resulting in a decreased value of 0.026. Subsequently, from 2009 to 2010, there was an upward trend in the environmental efficiency of thermal power generation in China, followed by a year-to-year decrease in 2011 and 2015.

Fig. 5 provides a visual representation of the ten-year period from 2006 to 2015, illustrating that the maximum overall disparity in environmental efficiency of thermal power generation in China was recorded in 2006 with a value of 0.191, while the minimum value of 0.111 was observed in 2015. This indicates a substantial reduction of 72.2% in the overall disparity compared to 2006, highlighting a significant decline in regional disparities by the end of the study period.

The findings suggest that the overall disparity in environmental efficiency related to thermal power generation in China witnessed a considerable decrease over the course of the decade. Notably, the reduction in regional disparities became more pronounced in the later years, reflecting increased national attention to the environmental impact of thermal power generation.

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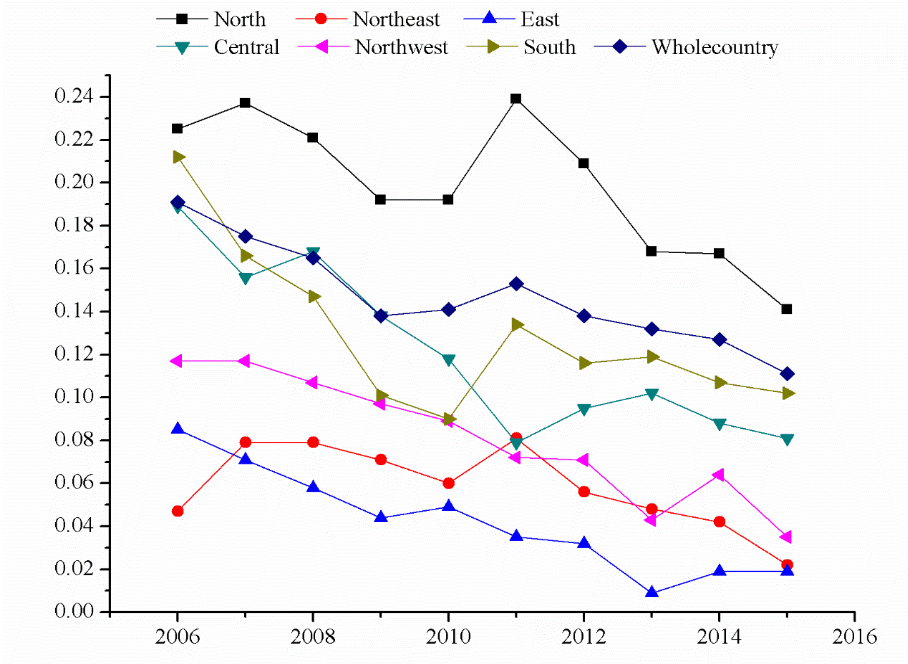

Figure 2 Intra-group disparities in emission efficiency

4.2.2 Results of intra-group disparity

Fig. 5 provides an overview of the trends in intra-group disparities among the six regions in China, revealing a general downward trend. Over the ten-year period from 2006 to 2015, eastern China exhibited the smallest gap in thermal power generation environmental efficiency, with an average value of only 0.042. This represents a substantial reduction of 77.7% and an annual decrease of 8.6%. In contrast, North China displayed the largest intra-group disparity, with an average value of 0.199. Although this region experienced a reduction of 37.3% in the gap and an annual decrease of 4.1%, it still maintained a higher average intra-group disparity compared to the national average of 0.147. This highlights the persistent issue of unbalanced development in North China. The low environmental efficiency of thermal power generation in Shanxi and Inner Mongolia in North China could be attributed to excessive emissions or underdeveloped thermal power generation technology.

The gaps in environmental efficiency of thermal power generation in Central China exhibited significant fluctuations, but the intra-group gap within this region experienced a total reduction of 57.4% and an annual decrease of 6.4%. Southern China saw a 52% overall reduction in the intra-group gap, with an annual decrease of 5.8%. Notably, the gap reached its minimum value of 0.09 in 2010.

In contrast, the intra-group gaps in thermal power generation environmental efficiency remained relatively

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stable in Northeast China and Northwest China. The gaps in these regions decreased by 53.4% and 70.1%, respectively, with an average annual decrease of 5.9% and 7.8%, respectively. Specifically, notable improvements were observed in the environmental efficiency of thermal power generation in provinces such as Liaoning, Heilongjiang, Shaanxi, Guangdong, Guangxi, and Guizhou. The disparities in efficiency levels can be attributed to differences in the scale of thermal power generation, varying policies for the adoption and promotion of new technologies in thermal power generation, and the level of attention given to environmental pollution caused by thermal power generation by the public and regional governments.

4.2.3 Results of inter-group disparity results

The environmental efficiency of thermal power generation in China exhibited a general downward trend during the study period, with an average value of 0.151. Among the regions, the inter-group disparity between Eastern and Northwest China was the lowest, with an average value of 0.079. The regional gap in environmental efficiency of thermal power generation in Eastern China experienced a significant downward trend throughout the study period, with a maximum average annual decrease of 8.1% and a total decrease of 72.5% over ten years. This can be attributed to the implementation of emission reduction policies, the development of green financial policies, and the adoption of clean energy sources, which led to the transformation and upgrading of the thermal power industry in the region and a reduction in the undesired outputs of thermal power generation, ultimately improving environmental efficiency.

Except for Shaanxi Province, the efficiency levels of other regions in Northwest China remained above 0.8, and Shaanxi Province witnessed a significant improvement in environmental efficiency over the study decade. Fig. 6 provides further insight into the regional gap and its evolutionary trend in thermal power generation environmental efficiency. The disparities in environmental efficiency between the listed regions exhibited a downward trend with fluctuations throughout the study period, except for the gap between the northeast and eastern regions. The data presented in Table 4 indicate that the regional disparity in thermal power generation environmental efficiency increased by 82% over the study decade, with an average value of 0.150 between Northeast and Eastern China, and an annual increase in the regional gap by 9.1%.

This result may be attributed to the implementation of emission reduction policies in the eastern region over the ten-year study period, resulting in a significant increase in environmental efficiency within the region. Throughout the study decade, the efficiency levels of Liaoning Province and Heilongjiang Province improved, except for Jilin Province. However, the rate of improvement was not as fast as in the eastern region, leading to an increasingly significant gap with the eastern region. Fig. 6 illustrates the disparity in the inter-group gap in environmental efficiency of thermal power generation, highlighting the uneven development levels between regions.

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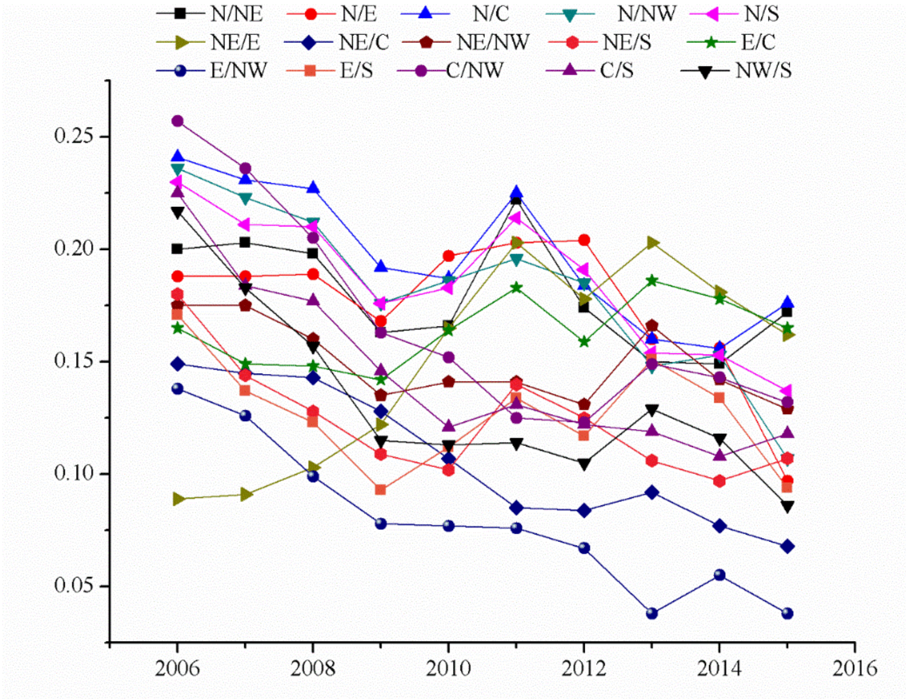

Figure 3 Inter-group disparities of environmental efficiency

4.2.4 Contribution analysis of regional disparity

Fig. 7 presents the sources of regional disparities in environmental efficiency regarding thermal power generation in China and the evolution of their contribution rates over the study period. The analysis reveals that the main driver of the gap is the inter-group disparity, accounting for an average contribution rate of 51.23%, which is more than three times higher than the contribution rate of the intra-group disparity at 13.15%. The contribution rate of the inter-group disparity exhibits a fluctuating upward trend, with an average annual growth of 5.19%. In contrast, the intra-group disparity and hyper-variable density display a downward trend. The contribution rate of the intra-group disparity decreases by 2.31% annually, while the contribution rate of the hyper-variable density decreases by 4.2% annually.

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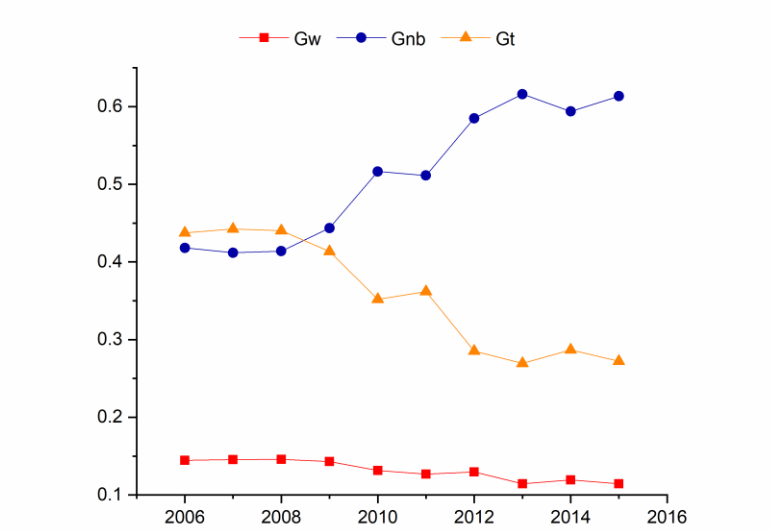

Figure 4. Contribution of regional disparities in environmental efficiency

Note: the contribution of the intra-group disparity G_w, the contribution of the inter-group disparity G_{nb}, and the contribution of hyper-variable density G_t.

These findings highlight that the disparity between groups is the primary driver of the overall regional disparity in environmental efficiency regarding thermal power generation in China. Therefore, reducing disparities between different groups is crucial for addressing regional imbalances. Moreover, the contribution rate of the hyper-variable density represents the impact of cross-term statistics on the overall efficiency disparity among the six subgroups (regions) in China. It reflects the contribution of the interaction between the disparity between groups and the disparity within groups to the overall efficiency disparities. The declining trend of the contribution rate of the hyper-variable density indicates that the interaction of disparities within and between groups gradually weakened over the study period.

4.3 Dynamic evolution results

4.3.1 Results of traditional Markov chain

We investigate the use of the traditional Markov chain and spatial Markov chain method to study the internal dynamics of environmental efficiency distribution of thermal power generation in China, and analyze the dynamic transfer characteristics of those efficiency levels. The study refers to the research ideas of Pu Ying-Xia, combined with the level of environmental efficiency of thermal power generation in China. The provinces in the previously defined six regions were divided into five types, listed in Table 5, according to their respective efficiency values (Qin et al., 2020): (1) lower than 0.50 (low efficiency level provinces – VL); (2) between 0.50 and 0.65 (low to medium efficiency level provinces - L); (3) between 0.65 and 0.80

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(medium efficiency level provinces - M); (4) between 0.80 and 0.95 (high efficiency level provinces - H); (5) greater than or equal to 0.95 (very high efficiency level provinces - VH).

Table 5 Classification of environmental efficiency

	VL	L	M	H	VH
Environmental efficiency of thermal power generation in China	<=0.50	0.50~0.65	0.65~0.80	0.80~0.95	>=0.95
Number of provinces met condition	42	54	80	62	62

Table 6 Markov chain transfer probability matrix of environmental efficiency

t/t+1	n_i	VL	L	M	H	VH
VL	42	0.667	0.310	0.000	0.000	0.024
L	49	0.082	0.694	0.204	0.000	0.020
M	74	0.014	0.014	0.770	0.176	0.027
H	55	0.000	0.000	0.091	0.709	0.200
VH	50	0.000	0.000	0.020	0.100	0.880

Table 6 presents the maximum likelihood estimation of the transfer probability of environmental efficiency in thermal power generation across different regions in China. The transfer stability and transfer path exhibit certain patterns. The elements on the main diagonal indicate the probability of a province maintaining its current efficiency level without any increase or decrease in the next period. The elements outside the main diagonal represent the probability of a province transitioning from its current state to another state. The findings from the Markov chain analysis in Table 6 yield the following results:

(1) The transfer probability on the main diagonal is relatively high. Provinces with medium and high environmental efficiency levels in thermal power generation have the highest probability of maintaining their previous efficiency levels, at 77% and 88% respectively. Provinces with other efficiency levels also have a probability of more than 65% of maintaining their previous levels. As a result, the overall distribution of environmental efficiency in thermal power generation across different regions remains relatively stable, with most provinces staying at their previous efficiency levels.

(2) Non-diagonal transfer probabilities are not all zero. Some probabilities are distributed on both sides of the diagonal, indicating that certain provinces may experience a transfer of environmental efficiency in thermal power generation to an adjacent level in two consecutive years.

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(3) Some off-diagonal transfer probabilities are scattered and not concentrated around the diagonal. This suggests significant changes in environmental efficiency of thermal power generation in certain provinces, indicating the possibility of multilevel transitions in environmental efficiency. For instance, 2.4% of provinces with a low efficiency level rapidly improve to a high efficiency level, 2% of provinces at the middle and low efficiency level quickly increase to a high efficiency level, 1.4% of provinces at the middle efficiency level drop to a low efficiency level, and 2.7% rapidly increase to a high efficiency level, while 2% of provinces at a high efficiency level decrease to a medium efficiency level.

(4) The probabilities of upward and downward non-diagonal transfers are asymmetric. In other words, the probability of an efficiency level improvement in the next year is significantly higher than the probability of a decline, particularly in the middle efficiency level, where the probability of upward transfer is more than 12 times higher than the probability of downward transfer.

These results indicate that in the later years of the study period, provinces in China made efforts to improve the environmental efficiency of thermal power generation, yielding some positive outcomes. However, the traditional Markov chain analysis does not consider the spatial interaction between regions and does not explain the spatial mechanism of regional efficiency convergence or divergence.

4.3.2 Result of spatial Markov chain

Table 7 presents a spatial Markov chain transfer matrix that incorporates the spatial lag effect, allowing for an exploration of the influence of neighboring provinces' efficiency environment on the environmental efficiency level of regional thermal power generation. The specific features observed are as follows:

(1) The neighboring environment significantly impacts the environmental efficiency of regional thermal power generation. In the spatial Markov matrix, the probabilities on the main diagonal are notably higher than those in other positions. This suggests that, when considering the neighbor environment, the environmental efficiency of thermal power generation in China demonstrates a high level of club stability throughout the research period. This matrix differs significantly from the traditional Markov matrix, further confirming the substantial influence of the neighbor environment on regional economic development. Table 7 reveals that neighbors have the most significant impact on a specific region when the efficiency level is high. When neighboring regions exhibit high efficiency levels, samples tend to remain at medium or high efficiency levels without transitioning. When the neighbor has a low efficiency level, there is a 22.2% probability of an upward transfer from a low efficiency level and a 28.6% probability from a low-middle efficiency level. The probability of upward and downward transfers from the medium efficiency level is 7.1%, suggesting the occurrence of cross-regional transfers. Furthermore, there is a 20% probability of a downward jump from the high efficiency level.

(2) Spatial correlation plays a crucial role in the environmental efficiency of thermal power generation. The probability of an upward transfer from a low efficiency level to adjacent regions with low or low-middle efficiency levels is 22.2% and 35.7%, respectively. When neighboring regions exhibit a high level of

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environmental efficiency in thermal power generation, the probability of an upward transfer from a low efficiency level region is highest, reaching 60%. In the traditional Markov chain, the maximum probability of an upward transfer from a low-efficiency area is 31%, significantly lower than in the spatial Markov chain. This highlights the important role of spatial correlation in the environmental efficiency of regional thermal power generation. Regions with low environmental efficiency in thermal power generation can enhance their efficiency more effectively when surrounded by a more developed regional environment.

(3) The neighbor environment also exerts some influence on regions with a high level of efficiency in thermal power generation. Table 7 reveals that, when adjacent regions have a low or medium-low efficiency environment, the region with a high efficiency level experiences the largest probability (20%) of a downward transfer compared to other neighbor environments. This value is also higher than the probability of a high efficiency level transitioning to a low efficiency level or a low-medium efficiency level in the traditional Markov matrix. This indicates that the neighbor environment also impacts regions with a high efficiency level.

Overall, these findings demonstrate that the neighbor environment significantly affects the environmental efficiency of thermal power generation in regions. Spatial correlation and the efficiency levels of neighboring regions play important roles in determining the upward or downward transfers of efficiency levels.

Table 7 Transfer probability matrix of the spatial Markov chain for environmental efficiency

Lag value	t/t+1	n_i	VL	L	M	H	VH
VL	VL	9	0.778	0.222	0	0	0
	L	7	0	0.714	0.286	0	0
	M	14	0.071	0.071	0.714	0.071	0.071
	H	0	0	0	0	0	0
	VH	5	0	0	0	0.200	0.800
L	VL	14	0.643	0.357	0	0	0
	L	18	0.056	0.611	0.278	0	0.056
	M	30	0	0	0.900	0.100	0
	H	12	0	0	0	0.833	0.167
	VH	5	0	0	0.200	0.200	0.600
M	VL	14	0.786	0.214	0	0	0
	L	19	0.105	0.789	0.105	0	0
	M	18	0	0	0.833	0.167	0
	H	23	0	0	0.043	0.739	0.217
	VH	21	0	0	0	0.095	0.905
H	VL	5	0.200	0.600	0	0	0.200

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	L	5	0.200	0.600	0.200	0	0
	M	12	0	0	0.417	0.500	0.083
	H	19	0	0	0.211	0.579	0.211
	VH	15	0	0	0.000	0.067	0.933
	VL	0	0	0	0	0	0
	L	0	0	0	0	0	0
VH	M	0	0	0	0	0	0
	H	1	0	0	0	1	0
	VH	4	0	0	0	0	1

4.4 Stochastic convergence test

The confirmatory analysis provides a more cautious explanation for the panel unit root test results, and generates a more robust conclusion. Therefore, Stata 15 was used for the analysis, using the confirmatory analysis method to assess whether there is stochastic convergence in the environmental efficiency with respect to thermal power generation in China.

4.4.1 Global random convergence test

Rejection of the null hypothesis of convergence for the whole panel does not rule out the existence of convergence in subgroups of the panel (Du, 2017). Table 8 shows that, even at the 10% significance level, the IPS test still rejects the original hypothesis of the unit root, and Hadri test significantly rejects the original hypothesis of stationarity. This belongs to the fourth case in confirmatory analysis, which indicates that the confirmatory analysis does not prove the existence of global random convergence trend and divergence trend, relative to the national average. This may be due to the random divergence of partial series and the random convergence of partial series.

Table 8 Confirmatory analysis results

Region	IPS	Prob	Hadri	Prob	CA result
All of China	-8.2159	0	7.2445	0	IV
North	-4.4665	0	0.9859	0.1621	II
Northeast	-2.3513	0.0094	1.3173	0.0939	IV
East	-2.8382	0.0023	3.4968	0.0002	IV

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Central	-4.8473	0	3.9030	0	IV
Northwest	-3.0905	0.0010	1.8437	0.0326	IV
South	-2.1712	0.0150	3.6282	0.0001	IV

We further applied the ADF, PP, and KPSS univariate unit root test methods to determine whether there is a convergence trend with respect to thermal power environmental efficiency in some provinces. Table 9 indicates that, according to the ADF test results, among the 30 provinces investigated, data for only 7 provinces reject the original hypothesis of the unit root. Of these, Shandong, Henan, Gansu, Qinghai Ningxia and Guangdong show significant results at a 1% significance level; and Xinjiang shows significant results at a 10% significance level. The environmental efficiency sequence of thermal power generation in the other 23 provinces do not reject the original hypothesis of the unit root.

Table 9 Univariate unit root test

Province	ADF	PP	KPSS	Province	ADF	PP	KPSS
Beijing	-0.168	-2.069	0.133*	Henan	-4.819***	-7.648***	0.148**
Tianjin	-1.847	-2.496	0.115	Hubei	-1.986	-2.672	0.0805
Hebei	-1.543	-2.611	0.116	Hunan	-0.183	-1.300	0.140*
Shanxi	-1.428	-1.700	0.0914	Chongqing	-2.196	-2.646	0.0967
Inner Mongolia	-0.921	-2.019	0.101	Sichuan	-0.841	0.7451	0.120*
Shandong	-5.601***	-2.871	0.0842	Shaanxi	-2.211	-2.345	0.102
Liaoning	-0.147	-2.707	0.145*	Gansu	-4.163***	-2.625	0.089
Jilin	-2.279	-10.954***	0.0576	Qinghai	-8.841***	-2.634	0.058
Heilong-jiang	-2.239	-3.749**	0.0807	Ningxia	-7.157***	-1.798	0.123*
Shanghai	-0.465	-1.677	0.123*	Xinjiang	-3.354*	-4.373***	0.0736
Jiangsu	-2.180	-1.088	0.139*	Guangdong	-8.083***	-2.242	0.124*
Zhejiang	-0.230	-1.326	0.130*	Guangxi	-0.144	-1.809	0.111
Anhui	-0.523	-1.162	0.126*	Hainan	-0.445	-2.888	0.117
Fujian	-1.852	-1.422	0.114	Guizhou	-2.890	-3.074	0.118
Jiangxi	-0.441	-0.627	0.142*	Yunnan	-1.178	-1.623	0.107

For the PP test, among the 30 provinces investigated, only 4 provinces rejected the original hypothesis of the existence of the unit root. Of these, the results for Jilin, Henan and Xinjiang show significance at a 1%

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significance level; and Heilongjiang shows significance at a 5% significance level. However, the environmental efficiency series of thermal power generation in other 25 provinces do not reject the original hypothesis of unit root.

For the KPSS test, of the 30 provinces investigated, 12 provinces did not meet the original hypothesis of stationarity; 18 provinces met the original hypothesis of stationarity, including Anhui, Beijing, Chongqing, Guangdong, Henan, Hunan, Jiangsu, Jiangxi, Liaoning, Ningxia, Shanghai and Zhejiang. These tests indicate that if the global random divergence of regions given in the confirmatory analysis is not determined, there may still be stochastic convergence of environmental efficiency with respect to thermal power generation in some provinces. In other words, global random divergence cannot negate the possibility of convergence subset.

4.4.2 Club identification based on stochastic convergence

In this study, the regional means of the six regions were used as benchmarks to assess the random convergence of each region. Table 8 presents the results, indicating that, at a 10% statistical significance level, the IPS test did not reject the possibility of unit roots in all series. Conversely, the Hadri test rejected the original hypothesis of stationarity, falling into the third case of confirmatory analysis. This implies that provinces exhibit random divergence in relation to their regional means. For North China, the IPS test rejected the original hypothesis of unit roots, while the Hadri test did not reject the hypothesis of stationarity for all series. This falls under the second case of confirmatory analysis, suggesting that all time series are stationary random processes, and the regional mean value of each province reflects stochastic convergence.

However, both the IPS test and Hadri test in the northeast, eastern, central, northwest, and southern regions rejected the original hypothesis, placing them in the fourth case of confirmatory analysis. This suggests the possibility of random divergence and convergence in some series. In the evolutionary process of environmental efficiency in thermal power generation in China, it is possible to form random convergence clubs. The convergence clubs within other regions require further identification.

The sequential analysis method used by Choi (2002) for identifying random convergence subsets has certain limitations. For instance, the selection of the initial prior information set is subjective. To address these limitations, a full subset analysis path is employed to identify the convergence clubs of environmental efficiency in thermal power generation within each region. The subsequent tables present the identification results of random convergence clubs at a 10% statistical significance level in five regions.

Table 10 reveals that the subset consisting of Shanghai, Zhejiang, and Anhui in the eastern region tends to converge towards its regional mean. The addition of other provinces to this subset would disrupt its convergence. Table 11 shows that Jiangxi, Hubei, Hunan, Chongqing, and Sichuan constitute a random convergence subset within the central region. Table 12 demonstrates that Gansu, Qinghai, and Xinjiang form a random convergence subset within the northwest region. Table 13 highlights that Guangdong and Hainan form a random convergence subset within the southern region. Lastly, Table 14 indicates that Jilin and

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Heilongjiang form a random convergence subset within the Southeast region.

In conclusion, the evolutionary process of environmental efficiency in thermal power generation in China exhibits a stochastic convergence club, and there may be convergence subsets within regions that experience random divergence.

Table 10 Results of random convergence club test in Eastern China

Region	P-IPS	P-Hadri	CA	Region	P-IPS	P-Hadri	CA
E1	0.0023	0.0002	IV	E6=E1-Shanghai	0.2002	0.0003	III
E2=E1-Fujian	0.2374	0.0002	III	E7=E2-Anhui	0.5062	0.0000	III
E3=E1-Anhui	0.5311	0.0000	III	E8=E3-Fujian	0.5062	0.0000	III
E4=E1-Zhejian	0.4195	0.0000	III	E9=E4-Fujian	0.7192	0.0000	III
E5=E1-Jiangsu	0.1491	0.0719	III	E10=E5-Fujian	0.0399	0.4678	II

Note: E1 includes Shanghai, Jiangsu, Zhejiang, Anhui and Fujian

Table 11 Results of random convergence club test in Central China

Region	P-IPS	P-Hadri	CA	Region	P-IPS	P-Hadri	CA
C1	0.0000	0.0000	IV	C5=C1-Hubei	0.0000	0.0002	IV
C2=C1-Sichuan	0.0005	0.0000	IV	C6=C1-Hunan	0.0000	0.0002	IV
C3=C1-Chongqing	0.0000	0.0002	IV	C7=C1-Henan	0.0004	0.2246	II
C4=C1-Jiangxi	0.0000	0.0001	IV				

Note: C1 includes Jiangxi, Henan, Hubei, Hunan, Chongqing and Sichuan

Table 12 Results of random convergence club test in Northwest China

Region	P-IPS	P-Hadri	CA	Region	P-IPS	P-Hadri	CA
W1	0.0010	0.0326	IV	W5=W1-Shaanxi	0.0087	0.0457	IV
W2=W1-Xinjiang	0.0169	0.0168	IV	W6=W5-Xinjiang	0.0033	0.0024	IV
W3=W1-Ningxia	0.1551	0.1566	I	W7=W5-Ningxia	0.0087	0.5056	II
W4=W1-Qinghai	0.1492	0.0103	III				

Note: W1 includes Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang

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Table 13 Results of random convergence club test in Southern China

Region	P-IPS	P-Hadri	CA	Region	P-IPS	P-Hadri	CA
N1	0.0150	0.0001	IV	N6=N1-Guangdong	0.0796	0.0004	IV
N2=N1-Yunnan	0.0013	0.0037	IV	N7=N4-Yunnan	0.0043	0.0052	IV
N3=N1-Guizhou	0.0000	0.0023	IV	N8=N4-Guangxi	0.1405	0.0020	III
N4=N1-Hainan	0.0244	0.0021	IV	N9=N8-Guizhou	0.0000	0.0053	IV
N5=N1-Guangxi	0.0011	0.0005	IV	N10=N8-Yunnan	0.0000	0.3847	II

Note: N1 includes Guangdong, Guangxi, Hainan, Guizhou and Yunnan

Table 14 Results of random convergence club test in Southeast China

Region	P-IPS	P-Hadri	CA	Region	P-IPS	P-Hadri	CA
S1	0.0094	0.0939	IV	S6=S1-Jilin	0.1232	0.2131	I
S5=S1-Heilongjiang	0.0655	0.0336	IV	S10=S8-Liaoning	0.0251	0.4220	II

Note: S1 includes Liaoning, Jilin and Heilongjiang

5. Conclusions and policy implication

This study presents a novel approach by introducing a super efficiency SBM-DDF integrated model to accurately distinguish decision-making units and calculate the environmental efficiency of thermal power generation in 30 provinces of China from 2006 to 2015. The analysis utilizes various methods such as the Dagum Gini coefficient and its decomposition method, spatial Markov chain, and a stochastic convergence test to examine efficiency levels, spatial dynamics, convergence patterns, and regional disparities in China's thermal power industry.

The key findings of the study are as follows. Firstly, the environmental efficiency of thermal power generation across the six regions of China exhibited steady growth over the study period, with the eastern region being the most efficient. Secondly, the overall Gini ratio of China's thermal power generation environmental efficiency demonstrated a general downward trend with slight fluctuations, averaging at 0.147. Notably, the intra-group disparity in the eastern region experienced the most significant decline, with an average annual rate of 8.6%. On the other hand, the intra-group disparity in North China showed the least reduction, with an average annual rate of 4.1%. The main driver of regional disparities in environmental efficiency was the inter-group disparity. Thirdly, the analysis of the spatial dynamic evolution pattern using the spatial Markov chain revealed a significant spatial dependence and notable spatial imbalance in the environmental efficiency of thermal power generation in China. Lastly, the study identified the existence of

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a stochastic convergence club in the evolution of environmental efficiency, particularly in North China where the efficiency tended to converge towards a common mean value. Convergence subsets were also observed in other regions characterized by random divergence or where convergence or divergence could not be definitively determined.

To promote balanced regional development in thermal power generation environmental efficiency, it is crucial to consider the unique characteristics and circumstances of each region. Strengthening multilateral technical cooperation and exploring the full potential of thermal power generation environmental efficiency in each region are essential. Regions should leverage their specific industry and resource advantages while fostering cooperation and exchanging technological innovations with neighboring provinces. By doing so, the overall growth of thermal power environmental efficiency can be facilitated.

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Is the Low-carbon Economy Efficient in China?

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ABSTRACT

China has been actively advancing towards a low-carbon economy (LCE), emphasizing the importance of evaluating its efficiency. This study utilizes panel data from 30 regions in China spanning 2005 to 2021. It integrates economic scale and carbon emissions in assessing low-carbon economy efficiency (LCEE) through the Super-slack-based Measure model and analyzes the evolving LCEE dynamics across these regions using the Malmquist Productivity Index. The findings reveal widespread low-carbon economic inefficiencies in these regions, with notable performance disparities in LCEE. Particularly, high-performing regions are predominantly situated in eastern China. Additionally, China has made significant strides in enhancing LCEE performance.

KEYWORDS

LCEE; Super-SBM; China; Malmquist; Productivity Index

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1. Introduction

Energy has always been a pivotal factor in competitiveness. The concept of "a low-carbon economy" first emerged in an energy white paper published by the government of the United Kingdom. It advocates for the establishment of a low-energy-consumption, low-pollution, and low-emission economic system, emphasizing the need for all economies to strive for maximizing output while minimizing energy consumption. With the increasing concern over the anthropogenic effects of rising greenhouse gas emissions on climate change (European Parliament, 2007) [1], more economies are intensifying their efforts to achieve decarbonization. As a developing country with substantial energy consumption, China must intensify its actions. Recognizing that enhanced feedback on low-carbon economic efficiency can enable better control over energy consumption and lead to increased efficiency, the establishment of a scientific and rational standard for low-carbon economic efficiency is now imperative. This paper primarily aims to achieve greater output with less input in low-economy activities. Through our empirical investigation, we seek to conduct a comparative efficiency analysis using the super-SBM model and Malmquist index. Upon reviewing existing literature on low-carbon economic efficiency, we noted a limited number of empirical studies that compare efficiency within China. Given China's critical role in the energy sector, we also intend to identify the most significant variables to provide policy recommendations.

2. Literature review

Supporting research on a low-carbon economy has been undertaken from various disciplinary perspectives. A typical method for assessing the efficiency of a system is data envelopment analysis (DEA) (Beltrán-Esteve,etc., 2017[2]; Gémar, Gómez, etc., 2018[3]; Marcelo Furlan,2021[4];) Data Envelopment Analysis (DEA) has been proposed by American operations researchers A. Charnes and W. W. Cooper since 1978[5], and is mainly used to evaluate the relative effectiveness of the same type of units (decision- making units, DMUs) with comparability, which is based on a number of input indexes and a number of output indexes, and is analyzed in-depth by using the method of linear programming.

Besides, fuzzy comprehensive evaluation and multi-criteria evaluation methods have been commonly utilized in various research studies. Sadia Samar Ali et al. (2020) used a hybrid approach of SEM/PLS machine learning and IRT to validate the positive relationship between sustainable practices and low carbon performance, which is ultimately the responsibility of a sustainable society[6].Rajesh Kumar Mishra et al. (2022) [7]explored an optimal sustainable inventory model that attempts to maximize profits with non-instantaneous deterioration and sub-standard quality products in the presence of carbon emissions and complete stock-outs, providing a solution to obtain a joint optimal strategy for inventory cycle time, inventory consumption time, order quantity and backorder quantity.

Moreover, Super-SBM model is a special kind of efficiency evaluation model, which is extended and optimized based on the SBM (Slacks-Based Measure) model. The SBM model itself is a non-radial and non-angle efficiency evaluation method, which can solve the problems that cannot be solved by the radial model and the angle model, such as the slackness of inputs or outputs. Data Envelopment Analysis (DEA) is a commonly used efficiency assessment method to evaluate the relative efficiency of a set of decision units with multiple inputs and multiple outputs, but the DEA model does not satisfy

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the monotonic linear relationship requirement, and then it is necessary to use the non-expected SBM model proposed by Tone (2001) [8]. However, the traditional SBM model cannot differentiate and rank these decision units while they are all efficiency. Super-SBM model would be the best choice among them without these defects.

In order to study the development status of low-carbon economy more deeply, Zhou Zejiong et al. (2013)[9]used the Super-SBM model and drew on the output-oriented Malmquist productivity index to select corresponding indicators from multiple perspectives (e.g., energy, R&D, industrial structure, urbanization level, etc.) to measure regional inputs, and selected the GDP and CO2 emissions per unit of GDP of each region as the desired and non-desired outputs to measure the development of low-carbon economy in the Central Plains Economic Zone, based on the Central Plains panel data of 15 cities in the economic zone from to 2011, the empirical study was conducted, and the results of the study showed that the backward carbon technology and the scale of development are not the main factors restricting the development of low-carbon economy; in addition, Li Qiaochu et al. (2022) [10] also adopted a super-efficiency SBM model that includes non-desired outputs to incorporate energy, economic and environmental factors into the low-carbon economic efficiency assessment system. They measured the low-carbon economic efficiency of China's energy sector from 2000 to 2018 and concluded that the overall low-carbon economic efficiency of China's energy sector is on an upward trend.

In terms of the factors influencing the development of a low carbon economy, Muhammad Yousaf Raza et al. (2023) Decomposing the main two dimensions such as changes in carbon sources and carbon damages from 1986 to 2020 into eight factors, the results of the study showed that the main influencing factors are economic development, population and land, while energy intensity and emission factors are the main forces in the reduction of CO2 emissions[11].Ghosh Subrata et al. (2023) Adopted an integrated evaluation methodology to assess spatial carbon emissions, carbon sink capacity, carbon sink balance and carbon resilience of Himalayan cities using ecological support coefficients, which showed that population size, household size and concentration of built-up land are the main causes of carbon emissions[12].

3. Research methodology

3.1 The principle of the Super-SBM model with undesirable outputs

In this paper, we use the Super-SBM model based on the structural form of the efficiency model CCR with the variable returns to scale (VRS) condition.

First, it is assumed that there are n DMUs has q input factors to produce s1 desirable outputs and s2 undesirable outputs, represented by three vectors,$x \in R^m, y^d \in R^{s_1}, and y^{ud} \in R^{s_2}$,respectively.The three matrices,$X, Y^d and\ Y^{ud}$,can be formed when n DMUs are considered:

$$X = [x1, x2, \dots, xn] \in R^{m*n} > 0$$

$$Y^d = [y_1^d, y_2^d, \dots, y_n^d] \in R^{s1*n} > 0$$

$$Y^{ud} = [y_1^{ud}, y_2^{ud}, \dots, y_n^{ud}] \in R^{s2*n} > 0$$

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The base model is specified as follows:

$$\rho^* = min\frac{\frac{1}{q}\sum_{i=1}^{q}\frac{x_i}{x_{i0}}}{\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{\bar{y}_r^d}{y_{r0}^d}+\sum_{r=1}^{s_2}\frac{\bar{y}_l^{ud}}{y_{l0}^{ud}}\right)}$$

$$Subject\ to\ \bar{x} \geq \sum_{j=1,\ \neq 0}^{n}\lambda_j\, x_j,\ \ \bar{y}^d \leq \sum_{j=1,\ \neq 0}^{n}\lambda_j\, y_j^d, \bar{y}^{ud} \geq \sum_{j=1,\neq 0}^{n}\lambda_j\, y_j^{ud}$$

$$\bar{x} \geq x_0,\ \ \bar{y}^d \leq y_0^d,\ \ \bar{y}^{ud} \geq y_0^{ud}$$

$$\sum_{i=1}^{n}\lambda_i = 1,\ \ \bar{y}^{ud} \geq 0,\ \ \lambda \geq 0$$

Where $\rho^*$is an objective function, whose value can be larger than 1. In using the Super-SBM model, it is requested that the inputs (x) and outputs (y_g, y_b) are correlated (Li & Shi, 2014[13]; López, Ho, & Ruiz-Torres, 2016[14]). λ is the weight vector.

3.2 The principle of the Malmquist Productivity Index

In fact, it is important to understand the dynamic changes among different regions over a period. Thus, the Malmquist Productivity Index (MPI)is introduced. Fare et al. (1997) [15] defined MPI as follows:

Let t and s (t<s)refer to two observed time points. Assuming that$\rho^t(x_j^t, y_j^{td}, y_j^{tud})$ *and* $\rho^s(x_j^t, y_j^{td}, y_j^{tud})$ are the efficiency values of DMUj based on the data measured in the time t under the technological condition in the time t and s, respectively. Also,$\rho^t(x_j^s, y_j^{sd}, y_j^{sud})$ *and* $\rho^s(x_j^s, y_j^{sd}, y_j^{sud})$ are the efficiency value of DMUj based on the data measured in the time s. The value of MPI is defined as follows:

$$MPI_j(t,s) = \left[\left(\frac{\rho^t(x_j^s, y_j^{sd}, y_j^{sud})}{\rho^t(x_j^t, y_j^{td}, y_j^{tud})}\right)\left(\frac{\rho^s(x_j^s, y_j^{sd}, y_j^{sud})}{\rho^s(x_j^t, y_j^{td}, y_j^{tud})}\right)\right]^{1/2}$$

where $MPI_j(t,s) > 1$ represents an increase in total factor productivity compared to the previous period and vice versa; $MPI_j(t,s)$= 1or <1, which means that productivity remains the same, or even deteriorated from t to

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4. Indicator Selection and Data Sources

4.1 Selection of indicators

Based on an extensive literature review, decision-making criteria, sub-criteria, tertiary criteria, and indicators of low-carbon economic efficiency have been identified. Initially, a comprehensive list of criteria was compiled, followed by the categorization of decision-making factors into two groups, as illustrated in Table 1. The sub-criteria encompass four categories: non-energy inputs, energy inputs, desired outputs, and non-desired outputs. Non-energy inputs primarily comprise production factors excluding energy consumption in the production or service process, such as X1 transportation (TRA), X2 greening (GRE), X3 total labor force (TLF), and X4 capital (CAP) inputs. Specifically, TRA represents the number of resident-owned cars, GRE signifies forest coverage, TLF denotes the total labor force, and CAP indicates the growth rate of fixed asset investments. Energy inputs refer to the total natural gas consumption resources expressed as X5 total energy use (TEU). Output indicators are essential metrics that quantify the outcomes and benefits of production activities, encompassing both desired and undesired outputs. Desired outputs reflect the maximum expected outputs of the decision-making unit (DMU), directly showcasing the positive effects of production activities, represented in this study by Yd Gross Domestic Product (GDP). Conversely, non-desired outputs signify negative effects typically linked to environmental pollution, represented by Yud total CO2 emissions.

Table1 List of Decision Criteria

	Sub- criteria	Indicators
Input	Non-energy inputs	X1(Transportation)
		X2(Greening)
		X3(Labor)
		X4(Capital)
	Energy inputs	X5(Total energy use)
Output	Desired outputs	Y^{d} (Gross Domestic Product)
	Non-desired outputs	Y^{ud} (CO2)

4.2 Data sources

The data collected from 30 sample regions for the period 2005 to 2021are available from China Carbon Accounting Databases (CEADs)， China Statistical Yearbook and China Environmental Yearbook. The

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volume of the data is too large to be included in this paper. Instead, the main features of the data are presented in Table 2.

Table 2 Main features of the data collected for analysis

Indicator	unit	Minimum	Maximum	Median	Mean	Std.dev.
X1(TRA)	10^4	12.18	2740.07	314.405	467.7813	481.2306
X2(GRE)	%	4	66.8	36.45	33.47314	17.95096
X3(TLF)	10^4	543	12684	3850	4518.959	2770.612
X4(CAP)	%	-56.6	41.3	14.3	14.33843	11.46547
X5(TEU)	10^8m^3	0.01	192.43	16.975	29.72994	35.62254
Yd(GDP)	10^8Yuan	499.4	124719.5	13848.5	20305.32	19825.07
Yud(CO2)	10^4tonnes	1633.32	104528.9	24438.87	31043.5	21017.4

Data source: China Carbon Accounting Databases (CEADs)， China Statistical Yearbook and China Environmental Yearbook

According to the result, the differences in inputs and outputs among the regions are very significant， which shows the irrationality of resource allocation.

In order to eliminate the quantitative outline between the data, the data would be standardized through the following method.

$$Z_{ij} = 0.9 * \frac{P_{ij} - min(P_{ij})}{max(P_{ij}) - min(P_{ij})} + 0.1$$

Where P_{ij} represents the i indicator of the j province or city, max(P_{ij}) and min(P_{ij}) denotes the maximum and minimum， i=1,2,…,n； j=1, 2,…,m

5. Results and Discussion

5.1 Results

By applying the data to the Super-SBM model, the results of ρ (LCEE performance) from 2005 to 2021 are calculated in Table 3.

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Table 3 The 30 regions in LCEE performance from 2005 to 2021

		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Average
Eastern Area	Beijing	0.61	0.59	0.59	0.62	0.56	0.56	0.61	0.60	0.62	0.65	0.66	0.71	0.76	1.00	1.00	0.93	1.04	0.71
	Tianjin	0.86	0.78	0.74	0.72	0.70	0.71	0.78	0.73	0.73	0.71	0.73	0.69	0.72	0.74	0.69	0.71	0.72	0.73
	Hebei	0.65	0.65	0.67	0.68	0.63	0.66	0.61	0.62	0.61	0.58	0.57	0.56	0.51	0.49	0.48	0.48	0.51	0.59
	Shanghai	1.00	0.86	0.92	1.01	1.01	1.01	1.00	0.96	0.89	0.93	0.88	0.86	0.86	0.92	1.00	1.01	1.04	0.95
	Jiangsu	1.04	1.00	0.93	1.03	0.94	1.00	1.01	0.89	0.87	0.87	0.86	0.97	1.00	0.93	0.92	0.94	1.06	0.96
	Zhejiang	0.86	0.86	0.85	0.86	0.80	0.79	0.78	0.74	0.72	0.69	0.73	0.76	0.77	0.77	0.81	0.81	0.78	0.79
	Fujian	1.01	1.00	1.00	1.01	1.00	0.92	1.00	0.91	0.89	0.87	0.87	0.94	0.93	0.92	0.96	1.02	1.03	0.96
	Shandong	0.68	0.74	0.77	0.72	0.76	0.73	0.68	0.66	0.65	0.68	0.75	0.77	0.71	0.61	0.64	0.61	0.64	0.69
	Guangdong	0.78	1.00	1.02	1.01	0.96	1.03	0.55	0.58	0.59	0.61	0.66	0.69	0.78	0.82	0.88	1.02	1.04	0.83
	Hainan	1.02	0.98	0.96	0.92	0.91	1.00	1.00	1.00	0.91	0.92	0.93	1.00	1.00	1.02	1.01	1.00	1.01	0.98
Central Area	Shanxi	0.77	0.68	0.67	0.65	0.57	0.58	0.57	0.55	0.54	0.59	0.53	0.53	0.52	0.51	0.50	0.55	0.61	0.58
	Anhui	0.80	0.73	0.72	0.72	0.67	0.67	0.67	0.67	0.68	0.69	0.70	0.69	0.73	0.78	0.79	0.79	0.84	0.73
	Jiangxi	1.00	0.90	0.89	1.00	0.87	0.89	0.88	0.86	0.85	0.82	0.82	0.79	0.76	0.75	0.74	0.73	0.76	0.84
	Henan	0.67	0.66	0.71	0.76	0.73	0.76	0.76	0.78	0.76	0.75	0.80	0.84	0.83	0.83	0.85	0.84	0.85	0.78
	Hubei	0.80	0.76	0.73	0.76	0.71	0.73	0.73	0.73	0.72	0.71	0.73	0.75	0.78	0.82	0.81	1.00	0.83	0.77
	Hunan	0.79	0.76	0.76	0.77	0.71	0.75	0.75	0.73	0.67	0.69	0.71	0.72	0.75	0.77	0.84	0.92	1.01	0.77
Western Area	Inner Mongolia	1.00	0.77	0.73	0.73	0.70	0.68	0.59	0.63	0.66	0.66	0.70	0.64	0.68	1.02	0.62	0.65	0.66	0.71
	Guangxi	1.00	0.92	0.87	0.87	0.82	0.83	0.86	0.87	0.87	0.87	0.87	0.84	0.80	0.81	0.80	0.69	0.67	0.84
	Chongqing	0.60	0.59	0.60	0.59	0.58	0.58	0.59	0.61	0.65	0.65	0.66	0.67	0.67	0.69	0.71	0.74	0.76	0.64

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	Sichuan	0.43	0.45	0.45	0.46	0.45	0.49	0.50	0.52	0.53	0.55	0.56	0.57	0.63	0.66	0.67	0.78	1.00	0.57
	Guizhou	0.76	1.01	0.92	1.00	0.80	0.77	0.74	0.75	0.75	0.73	0.74	0.73	0.70	0.71	0.74	0.70	0.71	0.78
	Yunnan	0.67	0.89	0.89	0.93	1.00	1.00	1.00	1.00	1.00	1.00	1.01	0.97	0.96	0.97	0.97	0.93	1.03	0.96
	Shanxi	0.60	0.58	0.57	0.58	0.56	0.57	0.57	0.57	0.59	0.59	0.58	0.60	0.60	0.60	0.61	0.58	0.63	0.59
	Gansu	1.04	0.84	0.82	0.78	0.75	0.71	0.68	0.66	0.65	0.64	0.65	0.65	1.11	0.67	0.64	0.63	0.63	0.74
	Qinghai	1.05	1.00	1.00	1.00	0.87	1.01	1.00	0.90	0.90	0.88	0.90	0.90	0.91	0.95	0.96	1.05	1.00	0.96
	Ningxia	0.80	0.78	0.77	0.73	0.75	0.71	0.67	0.65	0.64	0.64	0.66	0.66	0.68	1.02	0.68	0.66	1.00	0.74
	Xinjiang	1.01	1.00	1.00	1.00	0.88	0.90	0.92	1.00	1.00	0.67	0.70	0.79	0.67	1.10	0.84	0.75	1.01	0.90
Northeastern Area	Liaoning	0.65	0.64	0.68	0.70	0.69	0.67	0.68	0.71	0.71	0.68	0.79	1.52	0.57	0.57	0.58	0.57	0.60	0.71
	Jilin	0.72	0.69	0.72	0.73	0.73	0.72	0.71	0.69	0.67	0.63	0.65	0.65	0.64	0.63	0.69	0.61	0.61	0.68
	Heilongjiang	0.75	0.73	0.75	0.75	0.68	0.64	0.64	0.65	0.63	0.65	0.64	0.62	0.60	0.63	0.59	0.60	0.59	0.66

Meanwhile, this paper presents the dynamic changes of LCEE among 30 regions from2005 to 2021 by using the MPI model. The results of MPI(DLCEE)are showed in Table 4. It shows that China has been experiencing an improvement in terms of LCEE performance, as evidenced by the overall average DLCEE value of 1.0062 during the surveyed period. Sichuan is the best performer, with an average DLCEE value of 1.06, while Guangxi is the worst.

Table 4 The DLECC values of the 30 regions from2005/2006 to 2020/2021

regions	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019	2019-2020	2020-2021	Average
Sichuan	1.04	0.99	1.03	0.97	1.09	1.03	1.03	1.03	1.03	1.03	1.01	1.10	1.05	1.02	1.17	1.28	1.06
Beijing	0.97	1.00	1.05	0.91	1.00	1.09	0.98	1.04	1.04	1.01	1.07	1.08	1.31	1.00	0.93	1.12	1.04

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Liaoning	0.98	1.06	1.04	0.98	0.98	1.02	1.03	1.01	0.95	1.16	1.92	0.38	1.00	1.02	0.98	1.04	1.03
Guangdong	1.28	1.02	0.99	0.95	1.06	0.54	1.05	1.03	1.03	1.08	1.04	1.13	1.05	1.07	1.15	1.03	1.03
Ningxia	0.99	0.98	0.95	1.02	0.94	0.94	0.98	0.98	1.00	1.03	1.01	1.02	1.50	0.67	0.97	1.52	1.03
Yunnan	1.33	1.00	1.04	1.08	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.99	1.01	1.00	0.96	1.11	1.03
Xinjiang	0.99	1.00	1.00	0.88	1.02	1.02	1.09	1.00	0.67	1.04	1.13	0.85	1.64	0.77	0.89	1.34	1.02
Hunan	0.96	1.00	1.01	0.93	1.06	1.00	0.97	0.92	1.02	1.03	1.02	1.04	1.02	1.09	1.10	1.09	1.02
Chongqing	0.99	1.01	1.00	0.98	1.00	1.01	1.03	1.06	1.01	1.00	1.03	0.99	1.04	1.02	1.05	1.02	1.02
Henan	0.98	1.07	1.06	0.96	1.04	1.00	1.02	0.98	0.99	1.06	1.05	0.99	1.01	1.02	0.99	1.01	1.02
Hubei	0.95	0.96	1.05	0.93	1.02	1.01	1.00	0.98	0.99	1.03	1.03	1.04	1.06	0.99	1.24	0.82	1.01
Shanghai	0.86	1.07	1.09	1.00	1.00	1.00	0.96	0.93	1.04	0.95	0.98	1.00	1.07	1.09	1.01	1.03	1.00
Jiangsu	0.97	0.93	1.11	0.91	1.07	1.01	0.88	0.98	1.00	0.99	1.14	1.03	0.93	0.99	1.02	1.12	1.00
Shaanxi	0.97	1.00	1.01	0.96	1.02	1.01	1.00	1.03	1.00	0.97	1.05	0.99	1.00	1.01	0.96	1.08	1.00
Anhui	0.91	0.99	1.00	0.93	1.00	1.01	1.00	1.02	1.01	1.01	0.99	1.05	1.07	1.01	1.00	1.06	1.00
Fujian	0.99	1.00	1.01	0.99	0.92	1.09	0.91	0.98	0.98	1.00	1.08	0.98	0.99	1.05	1.06	1.01	1.00
Guizhou	1.33	0.92	1.09	0.80	0.96	0.97	1.01	1.00	0.97	1.02	0.99	0.95	1.02	1.04	0.95	1.01	1.00
Hainan	0.96	0.98	0.96	0.99	1.09	1.00	1.00	0.91	1.01	1.01	1.08	1.00	1.02	0.98	1.00	1.01	1.00
Qinghai	0.95	1.00	1.00	0.87	1.15	1.00	0.89	1.00	0.98	1.02	1.00	1.01	1.05	1.01	1.10	0.95	1.00
Shandong	1.08	1.05	0.93	1.06	0.95	0.94	0.96	0.98	1.05	1.11	1.03	0.91	0.86	1.05	0.95	1.05	1.00
Zhejiang	1.00	0.99	1.01	0.93	0.99	0.98	0.95	0.98	0.96	1.06	1.03	1.01	1.01	1.05	0.99	0.97	0.99
Inner Mongolia	0.77	0.95	0.99	0.97	0.97	0.86	1.07	1.06	0.99	1.06	0.92	1.06	1.50	0.60	1.06	1.02	0.99

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Jilin	0.95	1.05	1.01	1.01	0.98	0.99	0.97	0.98	0.94	1.03	1.01	0.98	0.98	1.11	0.87	1.00	0.99
Tianjin	0.91	0.95	0.98	0.97	1.02	1.10	0.94	0.99	0.97	1.03	0.95	1.05	1.03	0.93	1.02	1.02	0.99
Gansu	0.81	0.97	0.96	0.96	0.95	0.96	0.98	0.98	0.99	1.02	1.00	1.70	0.61	0.96	0.98	1.00	0.99
Shanxi	0.89	0.99	0.96	0.88	1.01	0.98	0.97	0.98	1.10	0.90	1.00	0.98	0.99	0.98	1.10	1.10	0.99
Heilongjiang	0.98	1.02	1.00	0.90	0.94	1.00	1.02	0.97	1.04	0.98	0.97	0.97	1.04	0.93	1.03	0.99	0.99
Hebei	1.00	1.03	1.01	0.92	1.05	0.93	1.01	0.98	0.96	0.97	0.98	0.91	0.97	0.98	1.00	1.06	0.99
Jiangxi	0.90	0.98	1.13	0.87	1.02	1.00	0.98	0.98	0.97	0.99	0.97	0.95	0.99	0.99	0.98	1.04	0.98
Guangxi	0.92	0.95	1.00	0.95	1.01	1.03	1.01	1.00	1.00	1.00	0.97	0.95	1.00	0.99	0.86	0.98	0.98

5.2 Discussion

5.2.1 the best and worst performers

According to the results of LCEE performance the 30 selected regions can be classified into some groups by their average values in terms of LECC performance in Table 5.

Table 5 LCEE performance classification for the surveyed regions

Performance group	LCEE scale(ρ)	Regions
Best	>1	None
Excellent	0.9-1	Hainan Fujian Qinghai Jiangsu Yunnan Shanghai
Better	0.8-0.9	Xinjiang， Jiangxi， Guangxi， Guangdong
Good	0.7-0.8	Zhejiang, Guizhou, Henan, Hunan, Hubei, Gansu, Ningxia, Tianjin, Anhui
Poor	0.6-0.7	Shandong, Jilin, Heilongjiang, Chongqing
Very Poor	0.5-0.6	Shaanxi, Hebei, Shanxi, Sichuan

As Table 5 shows, Hainan, Fujian and Qinghai are the top three performers. Their LCEE values are all >0.9 during the surveyed period. They are the pioneering regions in promoting LCE with various measures. Such as, Hainan Province Government has been developing a green transportation system based on electric

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vehicles, public transportation and non-motorized vehicles to reduce carbon emissions in the transportation sector. Besides, it implements a series of energy-saving and carbon-reducing special actions to strengthen publicity and education on the construction of a low-carbon society, and raise the awareness and recognition of carbon peaking and carbon neutrality throughout society. Fujian Province also has carried out a great deal of work to promote the pilot construction of national low-carbon cities and practice the concept of green and low-carbon development.

On the other hand, the data shows that Hebei, Shanxi and Sichuan are the three worst performers. In fact, Shanxi is poor at developing economy which is evidenced from its GDP. Although GDP of Hebei Province is relatively large, its carbon emissions per unit of GDP times higher than the global average value. Thus, it can be found that regions like Hebei and Hunan with similar scales of economy can be very different in LCEE performance. The poor performance of Hebei mainly results from its inefficient industrial structure. The secondary industry in Hebei Province is dominated by heavy industries that consume high amounts of energy and emit high levels of emissions, which has led to high energy consumption and carbon emission intensity.

5.2.2 A regional perspective of LCEE performance

Table 3 demonstrates that China's low carbon economic efficiency presents the overall distribution characteristics of higher efficiency in the eastern regions and lower low-carbon economic efficiency in the central, western and northeastern regions. The average value of the efficiency in the eastern region is 0.82, while that in the central, western and northeastern regions is 0.74, 0.77 and 0.68 respectively. From the perspective of the provinces, Shanghai, Jiangsu, Fujian and Hainan, which belong to the eastern region, have higher low-carbon economic efficiency, with an average value of 0.9 or above. The reason for this is that these regions are ahead of the rest of the country in terms of investment and technological development in economic development and environmental protection, and therefore have remarkable results in the development of low-carbon economy. However, Shandong, Hebei and other regions have low values of low carbon economic efficiency, with average values of 0.69 and 0.59 respectively, which is closely related to their high carbon emissions caused by the industrial structure with a high proportion of heavy industry. The regions with low LCE values are mainly concentrated in the central-western and northeastern regions, such as Shanxi, Sichuan, Heilongjiang and other provinces. Most of these regions are backward in the development of various industries due to the lack of optimization of the energy structure.

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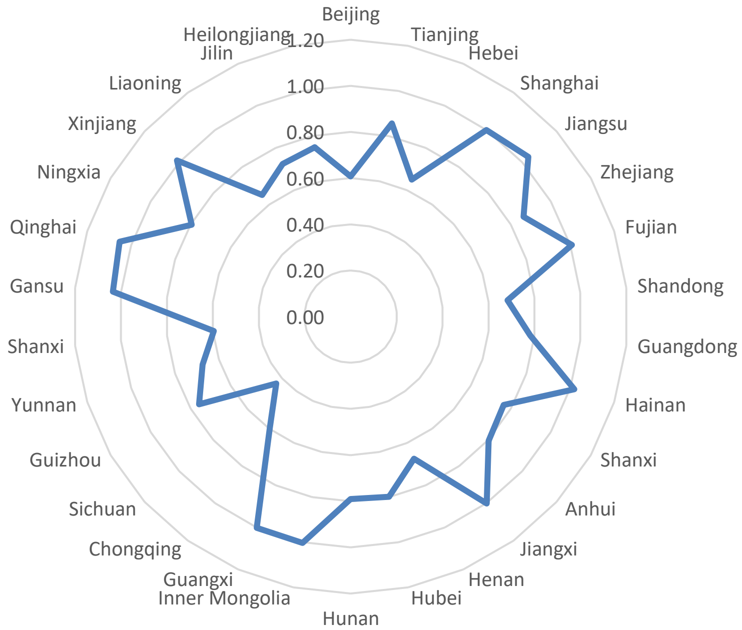

Figure 1 The LCEE value of 30 regions in 2005

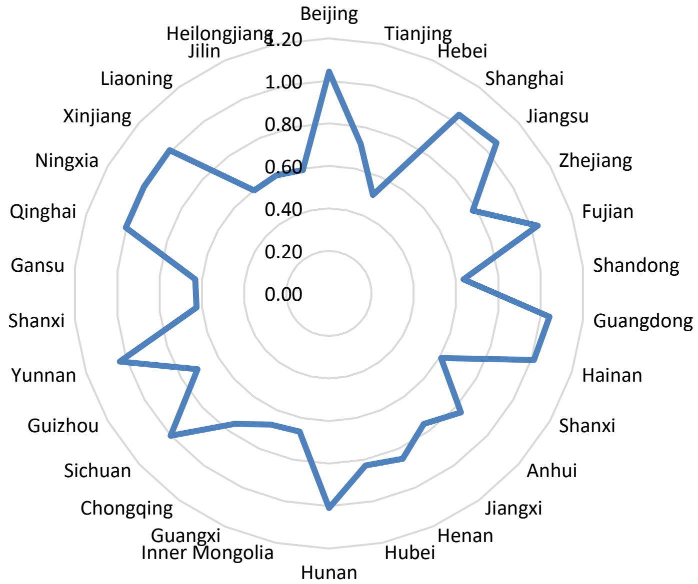

Figure 2 The LCEE value of 30 regions in 2021

The average LCEE value among these regions is 0.822, indicating that the LCEE performance of China is

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still inefficient. According to Figure 1 and 2, the low-carbon economic efficiency of all regions in China is continuously improving, and gradually approaching the efficient state. However, there are still large differences in the changes of low-carbon economic efficiency among regions. As Figure 1 shows, in 2021, the ρ values in Beijing, Shanghai, Fujian, Guangdong, Hainan, Hunan, Sichuan, Yunnan, Qinghai, Ningxia and Xinjiang are larger than 1, which means their low-carbon economy are efficient. However, Residual areas behave inefficiently.

5.2.3 The dynamic perspective of LCEE

As Table 4 shows, China has experienced an improvement in their LCEE performance, with an average value of MPI=1.0062 during the surveyed period, indicating that LCEE has improved by 0.62% annually since 2005.During this period,18 of 30 regions achieved average DLCEE values>1, while the residual regions had a value of DLCEE<1. Therefore, the 30 regions can be divided into two groups as progression group and deterioration group.

We find an interesting phenomenon. According to the results showed in Figure 3, Sichuan Province ranked at the bottom of the list in terms of low-carbon economic efficiency, but it did have the highest MPI value. This means that Sichuan's low-carbon economic efficiency grew significantly faster than other regions during this period. This is due to a series of low-carbon development and emission reduction policies it has put in place. Sichuan is rich in hydropower, wind and solar energy resources, and it has vigorously developed its clean energy industry. Moreover, it supports the R&D and innovation of low-carbon technologies, promotes the transformation of scientific and technological achievements, and improves the market competitiveness of low-carbon technologies. In addition, according to its GDP value, its economy has developed rapidly during this period.

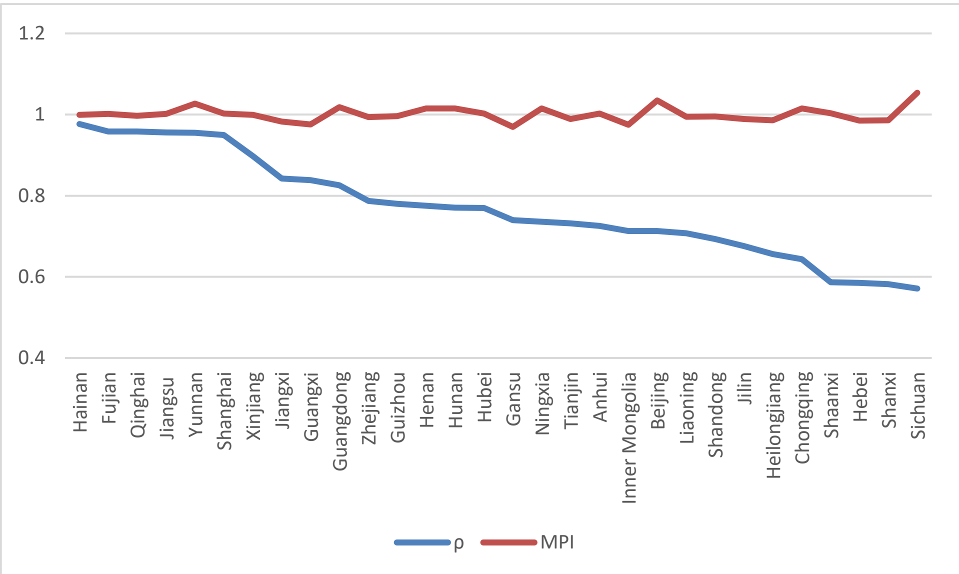

Figure 3 A comparison of LCEE Value(ρ) with MPI among 30 regions

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6. Conclusion

Overall, China's low-carbon economy demonstrates subpar efficiency levels. Hainan, Fujian, and Qinghai provinces emerge as the top performers in average low-carbon economic efficiency, while Hebei, Shanxi, and Sichuan lag behind. The regions excelling in performance are predominantly situated in the eastern part of the country, characterized by robust economic development. Conversely, the underperforming regions are clustered in central, western, and northeastern China, often adopting less sophisticated economic development models, resulting in heightened carbon emissions and undermining low-carbon economy efficiency. However, the study reveals a positive trend, with 60% of regions showing improved low-carbon economic efficiency from 2005 to 2021, although many still fall below average efficiency benchmarks. Notably, Sichuan Province ranks lowest in low-carbon economic efficiency but has witnessed significant growth due to effective policies, achieving efficient status by 2021. This comprehensive evaluation of 30 regions in China provides valuable insights for low-carbon economic development, highlighting the need for diverse economic, technological, and human resource policies. Tailored analyses for different regions and stakeholders can enhance understanding of their successes and challenges in low-carbon economic development. By fostering knowledge exchange on regional development strategies, China can advance towards efficient low-carbon practices. This study lays the groundwork for further research on influencing factors and development trajectories in the low-carbon economy.

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Does Environmental Governance Performance Have a Positive Influence on Regional Economic Growth?

——Evidence from Guangdong Province, China

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ABSTRACT

This study examines the influence of environmental governance efficiency on regional economic growth in Guangdong Province, China. By employing the Data Envelopment Analysis (DEA) method, we evaluate the environmental governance efficiency of 21 cities, considering both expected outputs and unexpected outputs. The findings reveal a significant positive relationship between environmental governance efficiency and regional economic growth, highlighting the role of effective environmental policies in promoting sustainable economic development. Our research underscores the importance of integrating environmental strategies into economic planning, suggesting that robust environmental governance can enhance economic performance by fostering innovation, attracting investments, and reducing health costs. This study contributes to the broader discourse on sustainable development, providing policymakers with actionable insights to balance economic growth and environmental sustainability effectively.

KEYWORDS

Environmental governance, Economic growth, DEA, Guangdong, China

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1.Introduction

Environmental governance has become an integral aspect of sustainable development, particularly in rapidly industrializing regions where the balance between economic growth and environmental sustainability is critical. This study aims to explore the relationship between environmental governance efficiency and regional economic growth in Guangdong Province, China, by focusing on per capita Gross Domestic Product (GDPpc) as a measure of economic performance. The central question addressed in this research is whether effective environmental governance can positively influence regional economic growth.

Guangdong Province, known as the powerhouse of China's economic development, offers a unique context for this study. Over the past few decades, Guangdong has experienced unprecedented economic expansion, becoming one of the most economically advanced regions in China. However, this rapid growth has also led to significant environmental challenges, including air and water pollution, resource depletion, and ecological degradation. Recognizing these challenges, the provincial government has implemented a series of environmental policies aimed at promoting sustainable development. These initiatives include stringent pollution control measures, investment in green technologies, and policies to enhance resource efficiency.

The theoretical framework underpinning this study is based on the concept of sustainable development, which posits that long-term economic growth can be achieved without compromising environmental integrity. According to this framework, environmental governance plays a crucial role in ensuring that economic activities do not exceed the carrying capacity of the environment. Effective environmental governance can lead to improved environmental quality, which in turn can enhance the attractiveness of a region for investment, reduce health costs, and foster innovation in green technologies. Consequently, this study hypothesizes that higher environmental governance efficiency is associated with higher regional economic growth.

To empirically test this hypothesis, this study employs the Data Envelopment Analysis (DEA) method to estimate the environmental governance efficiency scores for 21 cities in Guangdong Province. DEA is a non-parametric method used to evaluate the efficiency of decision-making units (DMUs) by considering multiple inputs and outputs. This approach is particularly suitable for this study as it allows for the inclusion of both expected outputs, such as reductions in pollution levels and improvements in resource efficiency, and unexpected outputs, such as economic costs and compliance burdens associated with environmental regulations.

The data for this analysis is drawn from a variety of sources, including provincial statistical yearbooks, environmental reports, and economic databases. Key variables include indicators of environmental governance, such as pollution control expenditures, implementation of green technologies, and enforcement of environmental regulations, as well as economic indicators such as GDPpc, industrial output, and foreign direct investment (FDI). The inclusion of control variables, such as population density and industrial structure, ensures a robust analysis that accounts for potential confounding factors.

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A significant aspect of our research is the use of the DEA method to estimate the value of environmental governance efficiency, considering both expected and unexpected outputs, rather than merely taking fiscal expenditures as the sole indicator of environmental governance performance. By incorporating a broader range of outputs, this approach allows for a more comprehensive representation of the level of environmental governance in each city. Expected outputs include intended outcomes such as improved air and water quality, while unexpected outputs consider unintended consequences such as economic costs and regulatory compliance burdens. This comprehensive evaluation provides a nuanced understanding of how environmental governance impacts economic performance, offering a more accurate and holistic assessment than traditional methods.

The findings of this study are expected to provide valuable insights for policymakers and stakeholders. By demonstrating the positive impact of environmental governance efficiency on regional economic growth, this research underscores the importance of integrating environmental considerations into economic planning. Moreover, the study offers a methodological contribution by applying the DEA approach to the assessment of environmental governance efficiency, providing a framework that can be replicated in other regions and contexts.

In addition to its empirical contributions, this study engages with broader theoretical debates on the relationship between environmental governance and economic development. It challenges the traditional view that environmental regulations are merely a cost to businesses and economic growth, instead highlighting the potential for such regulations to drive innovation, improve public health, and enhance long-term economic performance. This perspective aligns with the growing body of literature advocating for green growth, which emphasizes the compatibility of environmental sustainability and economic prosperity.

In conclusion, this study aims to fill a critical gap in the literature by providing empirical evidence on the positive influence of environmental governance efficiency on regional economic growth in Guangdong Province. By doing so, it contributes to the ongoing dialogue on sustainable development and offers practical recommendations for policymakers seeking to foster both economic growth and environmental sustainability. The following sections will delve into the literature review, methodology, empirical results, and policy implications of the study, providing a comprehensive analysis of the nexus between environmental governance and economic performance.

2.Literature Review

The relationship between environmental governance and economic growth has been a topic of extensive academic inquiry, especially in the context of sustainable development. This literature review examines the existing body of research on environmental governance, its measurement through efficiency analysis, and its impact on regional economic growth, with a specific focus on the application of Data Envelopment Analysis (DEA) in evaluating governance efficiency.

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2.1 Environmental Governance and Economic Growth

Environmental governance refers to the policies, regulations, and practices that governments implement to manage natural resources and environmental impacts effectively. It aims to balance economic development with environmental sustainability, ensuring that economic activities do not degrade environmental quality. Numerous studies have explored the link between environmental governance and economic performance, often highlighting a complex and multifaceted relationship.

One strand of the literature argues that stringent environmental regulations can impose additional costs on businesses, potentially hindering economic growth in the short term [1,2]. These costs include compliance expenses, investments in cleaner technologies, and potential reductions in productivity. However, other studies suggest that effective environmental governance can lead to long-term economic benefits by fostering innovation, improving public health, and creating a more attractive environment for investment [3,4].

The Porter Hypothesis, proposed by Michael Porter, posits that well-designed environmental regulations can stimulate innovation and improve competitiveness, ultimately leading to economic gains. This hypothesis has been supported by empirical evidence in various contexts, indicating that environmental governance can enhance economic performance by driving technological advancements and efficiency improvements [5,6].

2.2 Measurement of Environmental Governance Efficiency

Evaluating the efficiency of environmental governance involves assessing how effectively resources are utilized to achieve desired environmental outcomes. Traditional measures often rely on fiscal expenditures on environmental protection as a proxy for governance performance. However, this approach has limitations, as it does not account for the actual environmental outcomes or the unintended consequences of regulatory measures.

Data Envelopment Analysis (DEA) has emerged as a powerful tool for measuring the efficiency of environmental governance. DEA is a non-parametric method that evaluates the relative efficiency of decision-making units (DMUs) by considering multiple inputs and outputs. It provides a more comprehensive assessment by incorporating both expected outputs and unexpected outputs [7].

Several studies have applied DEA to evaluate environmental performance. For instance, [8] used DEA to assess the environmental performance of Chinese provinces, considering both desirable and undesirable outputs. Their findings highlighted significant regional disparities in environmental efficiency and underscored the need for targeted policies to improve governance. They also employed DEA to measure the environmental efficiency of industrial sectors in China, providing insights into sector-specific challenges and opportunities for improvement.

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2.3 Environmental Governance in China

China's rapid economic growth has been accompanied by severe environmental challenges, prompting the government to implement various environmental policies and regulations. The effectiveness of these policies has been a subject of extensive research. Studies have examined the impact of China's environmental governance on air quality, water pollution, and resource management, often highlighting mixed results [9].

Guangdong Province, as one of China's most economically advanced regions, provides a unique context for studying the relationship between environmental governance and economic growth. The province has implemented a range of environmental initiatives aimed at reducing pollution and promoting sustainable development. Research on Guangdong's environmental governance has shown that while significant progress has been made, challenges remain in terms of enforcement and regional disparities [10].

2.4 Impact on Regional Economic Growth

The impact of environmental governance on regional economic growth has been a critical area of study. Empirical research has produced varied results, reflecting the complex interplay between regulatory measures and economic performance. Some studies have found a positive relationship between environmental governance and economic growth, suggesting that effective governance can enhance economic performance by improving environmental quality and fostering innovation [11].

In contrast, other studies have identified potential trade-offs, where stringent regulations may impose short-term economic costs. However, the long-term benefits, such as enhanced public health, reduced environmental degradation, and increased investment in green technologies, often outweigh these initial costs [12].

The literature on environmental governance and economic growth highlights the importance of measuring governance efficiency comprehensively. By using the DEA method to incorporate both expected and unexpected outputs, this study aims to provide a nuanced understanding of how environmental governance impacts economic performance in Guangdong Province. The findings will contribute to the ongoing debate on sustainable development and offer valuable insights for policymakers seeking to balance economic growth with environmental sustainability.

3.Data, variables and methodology

The data used in this paper are from Guangdong Provincial Statistical Yearbook, Guangdong Provincial Social Statistical Yearbook, China Statistical Yearbook and China Urban Statistical Yearbook from 2001 to 2020. There are 21 cities in Guangdong Province, China. The panel data is strongly balanced, and number of areas is more than number of years means it’s a short panel. (Table 1)

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Table 1. Descriptive Statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
GDPpc	420	47494.45	42096.89	1210.4	210931
Efficiency	420	.8878959	.512677	.006024	2.765199
Popu	420	488.6666	282.9899	128.45	1874.03
Sufficiency	420	.566762	.2510869	.1354	1.168413
FDI	420	98521.27	155847	1611	862924.8
Industry	420	3.97e+07	6.16e+07	334569	3.85e+08
Electron	420	1701199	2285434	24663	1.01e+07
Tertiary	420	41.48755	8.31252	24.44	72.50714
Ecar	420	2635.686	6207.747	43	38728
GovtSize	420	.1228089	.0331438	.0509	.2204
AVTax	420	.2111544	.0671794	.0661	.4003852
EnvInput	420	98517.71	296233.9	469	3316349
AreaDummy	419	.4295943	.49561	0	1

3.1 Independent variable

In this study, Environmental Governance Efficiency is chosen as the independent variable to explore its impact on regional economic growth, measured by GDP per capita (GDPpc), in the 21 cities of Guangdong Province, China. (Figure 1) Environmental Governance Efficiency captures the effectiveness of policies and practices aimed at managing and protecting the environment. Effective environmental governance is crucial for sustainable development, balancing economic growth with environmental preservation. By evaluating governance efficiency, the study addresses the broader goal of achieving long-term sustainability, which is essential for maintaining economic stability and quality of life. Assessing Environmental Governance Efficiency provides actionable insights for policymakers. Understanding how efficiently environmental policies are implemented can help identify areas for improvement and guide resource allocation. This is particularly relevant for Guangdong Province, where rapid industrialization necessitates effective environmental management to sustain economic growth.

The Data Envelopment Analysis (DEA) method used to estimate Environmental Governance Efficiency allows for a nuanced evaluation by incorporating multiple inputs and outputs. This method captures the complexity of environmental governance, providing a detailed understanding of its efficiency and impact on economic growth. We estimate regional environmental governance efficiency based on super-efficiency SBM method (Tone, 2001、2010). Suppose the total number of decision units (DMU) in period T is K, and each DMU uses M input factors and produces I desired outputs and R undesired outputs, $x_k \in \mathrm{R}^M, y_k \in R^I$

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and $b_k \in R^R$ respectively represent the input vector, expected output vector and unexpected output vector of the k DMU, then, the input-output of the k DMU in period t is expressed as (x_k^t, y_k^t, b_k^t). Define the production possibility set constructed by other DMU other than DMU_k as follows:

$$P^t = \{(x^t, y^t, b^t) \mid x^t \geq \sum_{j=1, j\neq k}^{K} x_j^t \lambda_j,\ y^t \leq \sum_{j=1, j\neq k}^{K} y_j^t \lambda_j,\ b^t \geq \sum_{j=1, j\neq k}^{K} b_j^t \lambda_j,\ \lambda_j \geq 0\} \tag{1}$$

Where, λ_j is the weight coefficient vector (intensity vector), here we assume that scale returns are variable (i.e. VRS), so the sum of weight coefficients of all decision making units is equal to 1, i.e $\sum_{j=1, j\neq k}^{K} \lambda_j = 1$. Here, DMU is each district in Guangdong Province, and the input variable of each area is environmental input. The expected output variable is waste water utilization rate and solid waste treatment rate, and the unexpected output variable is sulfur dioxide and nitrogen oxide. Therefore, M=1, *I*=2, R=2.

The super-efficiency SBM efficiency value of decision unit K $k \in \{1, 2, \cdots, K\}$ can be obtained by solving the following programming problem:

$$IE_{SuperSBM}^t(x_k^t, y_k^t, b_k^t, \lambda) = \min \frac{1 + (1/M)\sum_{m=1}^{M}(s_m^{x,-} / x_{m,k}^t)}{1 - [1/(I+R)][\sum_{i=1}^{I}(s_i^{y,+} / y_{i,k}^t) + \sum_{r=1}^{R}(s_r^{b,-} / b_{r,k}^t)]} \tag{2}$$

$$\begin{aligned}
s.t.\quad & \sum_{j=1, j\neq k}^{K} x_{m,j}^t \lambda_j - s_m^{x,-} \leq x_{m,k}^t \\
& \sum_{j=1, j\neq k}^{K} y_j^t \lambda_j + s_i^{y,+} \geq y_{i,k}^t \\
& \sum_{j=1, j\neq k}^{K} b_j^t \lambda_j - s_{r,k}^{b,-} \leq b_{r,k}^t \\
& s^{x,-} \geq 0,\ s^{y,+} \geq 0,\ s^{b,-} \geq 0,\ \lambda \geq 0,\ \sum_{j=1, j\neq k}^{K} \lambda_j = 1 \\
& m = 1, 2, \cdots, M;\quad i = 1, 2, \cdots, I;\quad r = 1, 2, \cdots, R
\end{aligned}$$

Among them, $IE_{SuperSBM}$ stands for regional efficiency and its value is between [0,1]. The larger the value is,

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the higher the regional efficiency is. When $IE_{SuperSBM}=1$, it means that the decision-making unit is an effective unit, that is, it is located on the production frontier. $s_m^{x,-}$, $s_i^{y,+}$, $s_r^{b,-}$ respectively represent the relaxation variables corresponding to input variables, expected output variables and non-expected output variables. To solve Equation (2), we use the method of Charnes and Cooper (1978) to convert the equation into the following linear programming problem.

$$IE^t_{SuperSBM\_L}(x_k^t, y_k^t, b_k^t, \lambda) = \min \tau + (1/M)\sum_{m=1}^{M}(S_m^{x,-}/x_{m,k}^t) \tag{3}$$

$$\begin{aligned} s.t.\quad & 1 = \tau - [1/(I+R)][\sum_{i=1}^{I}(S_i^{y,+}/y_{i,k}^t) + \sum_{r=1}^{R}(S_r^{b,-}/b_{r,k}^t)] \\ & \sum_{j=1, j\neq k}^{K} x_{m,j}^t \Lambda_j - S_m^{x,-} \le \tau x_{m,k}^t \\ & \sum_{j=1, j\neq k}^{K} y_j^t \Lambda_j + S_i^{y,+} \ge \tau y_{i,k}^t \\ & \sum_{j=1, j\neq k}^{K} b_j^t \Lambda_j - S_{r,k}^{b,-} \le \tau b_{r,k}^t \\ & S^{x,-} \ge 0, S^{y,+} \ge 0, S^{b,-} \ge 0, \Lambda \ge 0, \tau > 0, \sum_{j=1, j\neq k}^{K} \Lambda_j = \tau \\ & m = 1,2,\cdots,M;\quad i = 1,2,\cdots,I;\quad r = 1,2,\cdots,R \end{aligned}$$

Let the optimal solution of equation (3) of linear programming be $(IE^*_{SuperSBM\_L}, S^{x,-,*}, S^{y,+,*}, S^{b,-,*}, \tau^*, \Lambda^*)$, then the optimal solution of the original nonlinear programming problem (2) is:

$$IE^*_{SuperSBM} = IE^*_{SuperSBM\_L},\quad \lambda^* = \Lambda^*/\tau^* \tag{4}$$

$$s^{x,-,*} = S^{x,-,*}/\tau^*,\quad s^{y,+,*} = S^{y,+,*}/\tau^*,\quad s^{b,-,*} = S^{b,-,*}/\tau^*$$

Accordingly, we can also get the efficiency of each input-output variable:

$$DE_{k,t}^{in} = (x_{k,t}^{in} - s_{k,t}^{in})/x_{k,t}^{in} \tag{5}$$

$$DE_{k,t}^{uo} = (b_{k,t}^{uo} - s_{k,t}^{uo})/b_{k,t}^{uo}$$

$$DE_{k,t}^{do} = y_{k,t}^{do}/(y_{k,t}^{do} + s_{k,t}^{do})$$

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Among them, $DE_{k,t}^{in}$, $DE_{k,t}^{uo}$, $DE_{k,t}^{do}$ respectively represents the efficiency of input variable, expected output variable and unexpected output variable, and its value is between [0,1]. The larger the value is, the higher the efficiency of the input or output factor is.

3.2 Dependent variable

In this study, GDP per capita (GDPpc) is selected as the dependent variable to represent each city's economic growth level in Guangdong Province. it encapsulates the overall economic activity within a city, providing a clear picture of economic health and prosperity. It takes into account the total output of goods and services, thereby reflecting the productivity and economic efficiency of the region. GDPpc allows for standardized comparisons across different cities and regions, enabling a consistent and uniform assessment of economic performance. This is crucial for a comparative analysis across the 21 cities in Guangdong Province, ensuring that variations in economic growth are accurately captured. Policymakers often use GDPpc as a key indicator to formulate and evaluate economic policies. By focusing on it, this study aligns its findings with policy frameworks and discussions, providing actionable insights that can directly influence economic planning and policy decisions.

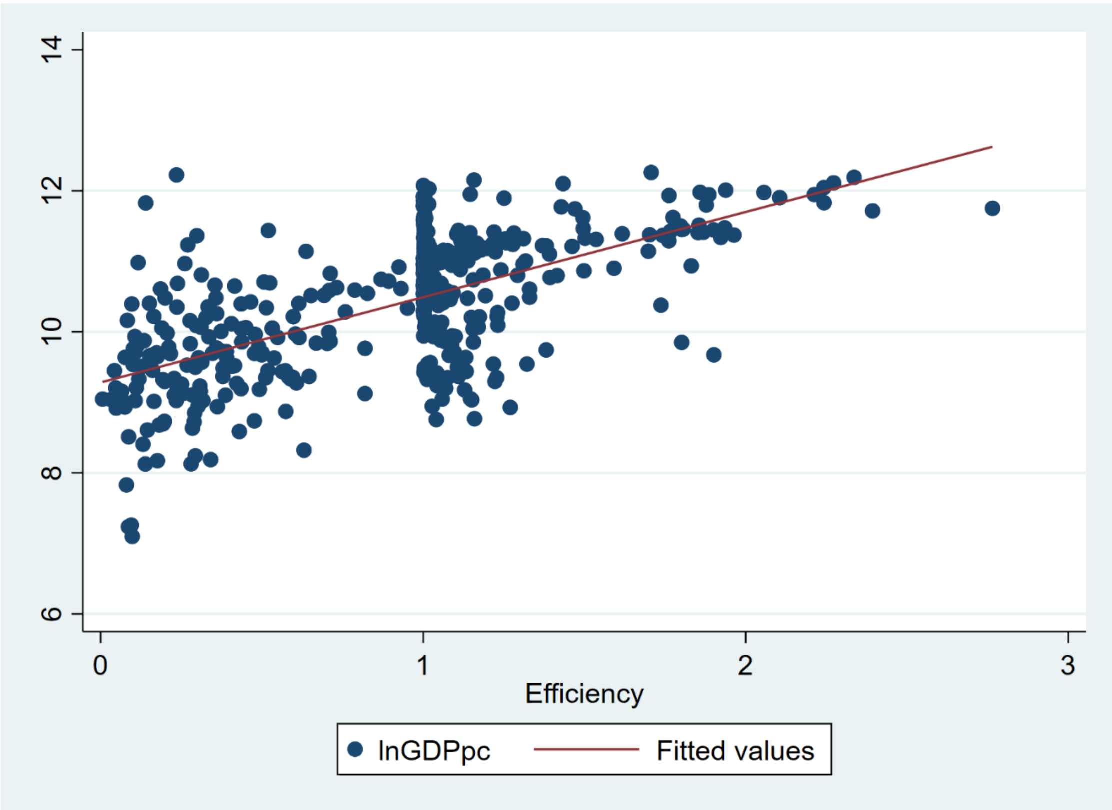

Figure 1. Partial correlation graph between the core variable and the explained variable

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3.3 Controlling Variables

In the process of regression analysis, it is crucial to control for several variables to ensure the robustness of the results. First and foremost, we must control for the population base (Popu), as it is the most fundamental variable. Additionally, indicators that have a direct relationship with economic growth, such as total industrial output (Industry), overall electricity consumption (Electron), and total value-added tax (AVTax), must also be controlled. Guangdong Province is one of the fastest-growing economic regions in China and attracts substantial foreign direct investment (FDI). The developed service industry further drives the rapid economic and social growth of the province. Hence, FDI and the proportion of the tertiary industry (Tertiary) are essential control variables to consider.

In recent years, Guangdong Province has emphasized the integration of industrial development and carbon emission reduction, vigorously promoting the adoption of electric vehicles. Shenzhen, located in Guangdong, is home to China's largest electric vehicle manufacturer. Therefore, we include the number of electric buses (ECar) in each city as a control variable to represent the local government's environmental awareness. Furthermore, local governments in Guangdong invest significant financial resources annually to improve the ecological environment (EnvInput), and this variable is controlled in some regression analyses.

Local governments in China often play a leading role in economic development. In this study, it is necessary to control for the financial scale of urban governments (GovtSize), which serves as a basic variable for government size, and the impact of financial self-sufficiency (Sufficiency), which measures the actual wealth of local governments, on the dependent variable. Finally, the economic development levels across different regions in Guangdong Province vary significantly. To account for this, we include regional dummy variable (AreaDummy) to differentiate between the Pearl River Delta region and other cities, thereby testing the impact of regional differences on economic development.

4.Results

As each city in the province is different, there may be omitted variables that do not vary over time, and there may be time effects that do not vary geographically. Based on the above reasons, we adopted the two-way fixed effects model:

$$\ln GDPpc_{it} = \beta_0 + \beta_1 Efficiency_{it} + \delta Controls_{it} + \mu_i + \gamma_t + \varepsilon_{it}$$
$$(i = 1, \cdots, 21; t = 1, \cdots 20)$$

We estimate the two-way fixed effects model with the null hypothesis $H_0\colon all\ \mu_i = 0$. The P-value corresponding to the F-test result is 0, which is much less than 0.01, indicating that we reject the null hypothesis and should choose the fixed effects model. Next, we conducted an F-test of the regional dummy

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variable, and the P-value was less than 0.1, suggesting we can reject the null hypothesis and that individual effects exist. Finally, the model passes the Hausman test, which strongly rejects the null hypothesis, confirming our choice of the fixed effects model. To ensure the robustness of the model, we conducted three additional regression analyses, controlling for different important variables (Table 2).

Table 2. Regression Results.

	(1)	(2)	(3)	(4)	(5)
	OLS	FE	FE	FE	FE
Efficiency	6.7955**	11.537***	9.107**	8.4376***	11.7705***
	(2.28)	(3.15)	(3.03)	(2.12)	(2.95)
Popu	-0.5148*	0.0511	-0.112	0.8358*	0.102
	(0.26)	(0.12)	(0.37)	(0.41)	(0.35)
Sufficiency	-0.473	2.1768	-3.9597*		2.117
	(1.56)	(1.88)	(2.01)		(1.98)
FDI	-0.1711	-3.0302**		-2.5807*	1.055
	(1.24)	(1.09)		(1.31)	(1.86)
Industry	3.0432	-4.3778*	5.0213	8.3398*	
	(2.78)	(2.12)	(4.21)	(4.15)	
Electron	0.0290	0.0184	-1.5381*		-0.1267
	(1.39)	(0.67)	(0.73)		(0.98)
Tertiary	1.1789	1.3235*		0.2971	3.1459*
	(0.98)	(0.66)		(0.25)	(1.59)
ECar	0.1488	0.6304*	1.1147*	0.9718	
	(0.15)	(0.32)	(0.51)	(0.88)	
GovtSize	-2.3471*	0.9881	-2.6837*		-1.063
	(1.19)	(0.77)	(1.23)		(0.82)
AVTax	-4.1976*	6.3347**		3.2202	7.1198
	(2.05)	(2.12)		(6.48)	(11.23)
EnvInput	1.34876	-2.4789	2.9963*	-1.773	
	(1.03)	(1.98)	(1.31)	(1.26)	
AreaDummy	1.3486	2.7685	1.5653	2.9918	3.0121
	(1.26)	(2.12)	(1.37)	(2.01)	(3.35)
_cons	4.713**	7.026**	6.175*	1.383	2.279
	(1.04)	(1.97)	(3.16)	(1.32)	(2.87)
N	420	420	420	420	420

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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In the results of regression analysis, we can see that the environmental governance efficiency of the explanatory variable has a significant positive impact on the per capita economic growth of the explained variable, which is in line with the significance of this study. The effect of population size is not uniform, while the effect of government size is more negative, indicating that the government should maintain a moderate size. The effect of government financial adequacy ratio on economic growth is also not obvious, but there is a significant negative effect in the result. We see a relatively negative impact of FDI, which is surprising in an export-oriented economy like Guangdong. Reflecting the economic fundamentals of the total industrial output value, the whole society electricity consumption is not consistent performance, but the total value-added tax situation has a more positive impact. It is also surprising that electric bus use has a consistent positive effect on economic growth across regions. Also uniformly positive are the regional dummy variables, which may be consistent with Guangdong's basic economic outlook. The impact of local government environmental spending is inconsistent.

5.Policy Suggestions

Strengthening Environmental Governance Infrastructure. Guangdong Province should continue to invest in robust environmental governance infrastructure. This includes enhancing monitoring systems for pollution control, implementing advanced waste management technologies, and upgrading water treatment facilities. Effective infrastructure is crucial for ensuring that environmental policies are enforced efficiently and sustainably.

Promoting Green Technologies. Encouraging the development and adoption of green technologies can drive both environmental and economic benefits. Policies should support research and development in renewable energy, electric vehicles, and energy-efficient industrial processes. Incentives such as tax breaks, grants, and subsidies for businesses that invest in green technologies can accelerate this transition.

Enhancing Regulatory Frameworks. Strengthening regulatory frameworks to ensure compliance with environmental standards is essential. This includes setting clear, achievable targets for pollution reduction and resource efficiency, as well as establishing stringent penalties for non-compliance. Transparent and consistent enforcement of regulations will help build trust and accountability.

Encouraging Public Participation. Fostering greater public participation in environmental governance can lead to more effective and accepted policies. Mechanisms such as public consultations, community-based monitoring, and environmental education programs can empower citizens to contribute to environmental protection efforts. Engaging the public also helps raise awareness about the importance of sustainability and fosters a culture of environmental stewardship.

Integrating Environmental and Economic Planning. Policymakers should integrate environmental

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considerations into economic planning processes. This involves conducting environmental impact assessments for major economic projects and ensuring that economic policies support sustainable development goals. By aligning economic and environmental objectives, Guangdong can achieve balanced and sustainable growth.

Addressing Regional Disparities. Given the significant regional disparities in economic development and environmental governance within Guangdong, targeted policies are needed to support less developed areas. Investments in environmental infrastructure, capacity building, and economic incentives for green development should be prioritized in these regions to promote equitable growth and environmental sustainability.

6.Conclusion

This study has empirically examined the positive influence of environmental governance efficiency on regional economic growth in Guangdong Province, China, using the Data Envelopment Analysis (DEA) method. The findings underscore the critical role that effective environmental governance plays in enhancing economic performance. By integrating environmental considerations into economic planning, fostering innovation in green technologies, and ensuring robust regulatory frameworks, Guangdong can achieve sustainable development that balances economic growth with environmental preservation.

The results of this study provide valuable insights for policymakers not only in Guangdong but also in other regions facing similar challenges. The comprehensive evaluation approach adopted in this research can be replicated in different contexts to assess the impact of environmental governance on economic growth. By demonstrating the long-term economic benefits of effective environmental governance, this study contributes to the broader discourse on sustainable development and offers practical recommendations for achieving both economic and environmental objectives.

In conclusion, enhancing environmental governance efficiency is essential for promoting sustainable economic growth. Policymakers should prioritize investments in green technologies, strengthen regulatory frameworks, encourage public participation, and address regional disparities to ensure that economic development does not come at the expense of environmental health. By doing so, Guangdong Province can continue to lead as a model for sustainable development in China and beyond.

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