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Abstract: New energy measures have been identified as a crucial strategy for most developing countries to address climate concerns and environmental risks. Despite multitude studies documenting the desirable clean air and low-carbon outcomes brought by new energy consumption, little is known about whether and how it facilitates the cost-effective collaborative emission abatement (CCEA). Therefore, we first propose a new method based on the data envelopment analysis (DEA) framework to measure the CCEA of 283 prefecture-level and above cities in China. Subsequently, we establish the causality exploiting the enforcement of the new energy model city construction program (NEMCC) as an ideal quasi-natural experiment. We find that the policy significantly alleviates the emission abatement cost burden on the real economy caused by the collaborative process of pollution mitigation and carbon reduction. Moreover, we uncover three plausible channels in which the NEMCC nudges the CCEA from the entire production process of "source prevention-process control-end treatment". Furthermore, we demonstrate that the beneficial effect is more prominent in southern cities, and cities with superior human capital and stringent environmental regulation. Additionally, we demonstrate that digital economy positively facilitates the policy effect with more complete intellectual property protection and active innovation environment within the city. Overall, the study provides fresh evidence supporting that new energy measures and initiatives could play a cost-effective hand in pursuing multi-objective climate and environmental governance.

Keywords: New energy model city construction program; Cost-effective; Collaborative emission abatement; Digital economy; China

1. Introduction

Referring to the *Global Risks Report 2025* published by the World Economic Forum, climate and environmental risks are projected to be the primary global challenges over the next decade. There is a significant threat to human society and to the global economy posed by these risks, which negatively impact residents' quality of life (Zhu et al., 2023). As a global response to environmental degradation and climate change, carbon emissions need to be reduced and air pollution needs to be controlled (Erdogan et al., 2023; Xian et al., 2024b). China is the world's second-largest economy with a long-term trend of steady growth. China's rapid economic growth has been closely linked with a heavy reliance on fossil fuels and a significant rise in greenhouse gas (GHG) emissions (Wang et al., 2020b; Dong et al., 2022), which inevitably exacerbates climate change and worsens air quality (West et al., 2013). Historically, the Chinese government has viewed air quality improvement and climate change as separate challenges, with separate action plans for each, resulting in a waste of resources and a heavy burden to reduce emissions (Xian et al., 2024b; Huang et al., 2025a). In fact, air pollutants and GHG are homologous (Rafaj et al., 2013), and their management strategies and pathways are highly consistent (Xian et al., 2024b). The Chinese government has considered the collaborative management of carbon reduction and pollution mitigation as an essential environmental issue since 2022 and has issued a number of policy documents addressing these issues[1]. However, some regulatory initiatives or measures often induce serious transition risks and social cost issues (Huang et al., 2025a). For instance, terminating or reducing the production of energy-intensive and carbon-heavy firms is likely to lead to worker unemployment, fixed asset impairment, and supply chain instability. To this end, it is crucial to develop cost-effective collaborative emission abatement programs tailored to China's national conditions.

"Co-benefits" of climate action and pollution control are typically understood as the unintended positive outcomes of GHG emission reduction strategies that were not the primary focus of the original policy design (IPCC, 2022). The cost-effective collaborative emission abatement (CCEA) assesses the non-climate benefits of environmental policies based on representative indicators such as reductions in air pollutants and CO_2 emissions (Ramanathan and Feng, 2009; Smith and Haigler, 2009). In environmental science, existing studies have used scenario modeling techniques to predict CCEA of various environmental policies (Mir et al., 2022; Xing et al., 2020). However, scenario simulation techniques involve complex parameters, which weaken estimation accuracy and prevent the assessment of the current status of CCEA. In

[1] In June 2022, the joint issuance by multiple departments of the *Implementation Plan for Pollution Reduction and Carbon Synergy* marked the official launch of China's CO_2 and pollution cooperative control efforts. In December 2023, several Chinese government departments jointly issued the *Implementation Opinions on Promoting Pollutant Reduction, Carbon Reduction and Synergistic Efficiency of Wastewater Treatment*, emphasizing the synergistic promotion of pollutant reduction and greenhouse gas emission reduction in wastewater treatment processes in general. In March 2025, the *Report on the Work of the Government of China* at the two sessions of the Chinese People's Political Consultative Conference explicitly proposed to "synergize the promotion of carbon reduction, pollution reduction and green growth, and accelerate the overall green transformation of economic and social development".

environmental economics, CCEA's quantitative assessment is dominated by econometric estimates of the influence of policies on air pollutant emissions and GHG emissions (Hu et al., 2022; Dong et al., 2022; Xian et al., 2024a). Some studies have measured CCEA applying the DEA model (Yang et al., 2023), coupled coordination degree model (Liu et al., 2021), and logarithmic mean Divisia index (Qian et al., 2021). The DEA method improves the estimation accuracy of CCEA by integrating the effects of various economic, social, and environmental factors, whereas other methods focus on the relevance between GHGs and air pollution. Under the DEA framework, existing studies have mainly used the non-radial directional distance function (Liu et al., 2023a) and the super-efficient SBM model (Yang et al., 2023) to measure CCEA. Regarding environmental policies affecting CCEA, current researches have addressed low-carbon city pilots (LCP), carbon emissions trading (CET), and the atmosphere ten articles (ATA) related to air quality (Yang et al., 2023; Xian et al., 2024a; Yang et al., 2022). One strand of these studies have confirmed the positive synergistic emission reduction impacts of environmental policies; however, the other strand of studies have identified a "green paradox" in some inefficient environmental policies, which tends to exacerbate environmental pollution and GHG emissions (Zhang et al., 2017).

Traditional energy sources are prone to resource depletion and environmental pollution, while new energy sources are characterized by low pollution, renewability, and high-power generation potential (Ai et al., 2025). In many countries, new energy sources are therefore considered a key component of energy policy and sustainable development (Weng et al., 2025). The Chinese government has enacted many official documents, such as the *Renewable Energy Law*, the *Medium and Long-Term Development Plan for Renewable Energy*, and the *14th*

Five-Year Plan for Renewable Energy Development[2]. **Figure 1** demonstrates that while China still uses non-clean energy power as its primary power source, the scale and share of clean energy power production has grown significantly over the long term. In 2014, China launched the NEMCC, which aims to reduce urban economic growth's dependence on fossil fuels and maximize the proportion of new energy production and consumption (Cheng et al., 2023). There has been evidence that NEMCC boosts green economic growth (Wang and Yi, 2021), eco-efficiency improvement (Zhang et al., 2023a), and industrial structure transformation (Liu et al., 2024b), resulting in both economic and environmental welfare effects. Remarkably, these studies do not consider the potential social costs of new energy consumption. Specifically, the transition from traditional fossil fuels to new energy sources through changes in energy consumption patterns in order to achieve green development is clearly not without social cost (Alpino et al., 2023). Fossil fuels can achieve higher economic growth rates than new energy sources, but tend to emit greenhouse gases and pollutants that adversely affect the environment (Farhidi, 2023; Andrew, 2020; Lelieveld et al., 2023). Therefore, increasing the proportion of new energy sources and reducing the proportion of fossil fuels in energy consumption to achieve green development and carbon emission reduction comes at the cost of sacrificing economic growth. Under China's "dual carbon" goals, there are socioeconomic costs (especially carbon costs) associated with achieving green transformation and carbon emission reductions through new energy development. To bridge the research gap, the paper aims to reveal whether and how the NEMCC facilitates the CCEA, which is of significant importance for China to deepen the

[2] The *Renewable Energy Law* is derived from the Chinese National Regulations Database. The *Medium and Long-Term Development Plan for Renewable Energy* and the *14th Five-Year Plan for Renewable Energy Development* are derived from the official website of China's National Development and Reform Commission.

energy revolution and the realization of sustainable and low-carbon progress with minimum economic losses.

The digital economy (DE) is a novel economic model that uses digital technology to spur economic growth and social development (Don, 1996; Mesenbourg, 2001; Carlsson, 2004). The DE is transforming economic and social processes in new ways. The DE has clearly enhanced information transparency for governments, businesses, and environmental social organizations by reducing the cost of data gathering and dissemination (Matheus et al., 2021; Li et al., 2020). Undoubtedly, the DE has become a key catalyst for promoting China's green and sustainable development by deeply integrating with the real economy and enabling innovation and production to flourish (Ma et al., 2024; Song et al., 2023a; Lin and Xie, 2024; Sun et al., 2024). Hence, it is necessary to assess the influence of the DE on the synergistic emission reduction of NEMCC, which provides essential practical insights for promoting the role of DE in achieving green development.

Taken together, the following issues need to be resolved: Does NEMCC significantly impact CCEA? What is the direction and mechanism of this impact? Is there heterogeneity in its effects across cities with different characteristics? Does DE facilitate the impact of NEMCC on CCEA? To answer the above questions, we first measure the CCEA in 283 prefecture-level cities and above in China from 2009 to 2021 using the augmented DEA method developed by Liu et al. (2023a). Then, we build a DID model to estimate the real impact of NEMCC on CCEA and verify the robustness of the main conclusions by a series of tests. Next, we explore the internal mechanism through which the NEMCC policy impacts the CCEA across the three stages of the environmental management cycle: source prevention, process control, and end-of-pipe treatment.

Further, we explore the heterogeneity of NEMCC's impact on pollution and carbon reduction synergies across geographic distribution, human capital, and environmental regulation. Finally, we analyze the moderating role of the DE on NEMCC's impact on synergistic emission reduction effects.

This paper makes a threefold contribution to research. First, by examining the theoretical mechanism by which NEMCC affects CCEA from the entire production process, this paper reconciles the current debate over whether new energy consumption should be aggressively expanded to achieve synergistic emission reductions. Currently, there is little literature exploring the relationship between new energy consumption policies and synergistic emission reductions (Ding et al., 2024; Xian et al., 2024a; Liu et al., 2024b), resulting in an unclear theoretical influence mechanism of NEMCC on CCEA. Therefore, we expand and enrich the scope of existing research by analyzing the impact of NEMCC on CCEA from a cost-benefit perspective. On this basis, we comprehensively analyzed the theoretical mechanism of NEMCC influencing CCEA in three production stages: source prevention, process control, and end treatment. Based on these theoretical analyses, we propose research hypotheses and conduct rigorous empirical studies to verify them.

Second, our study extends the relevant literature about CCEA accounting framework by augmenting a new non-parametric method to measure synergistic emission reduction effect from a cost-effective perspective based on the DEA framework. Regarding the measurement of CCEA, most studies independently assessed reductions in air pollution and GHG emissions (Hu et al., 2022; Dong et al., 2022; Xian et al., 2024a) or measured in terms of the relevance of the emissions (Qian et al., 2021; Liu et al., 2021). None of the existing literature has provided an accurate measurement of CCEA from a cost-effective perspective. The approach of Liu et al. (2023a) provided inspiration for us to measure CCEA. Liu et al. (2023a) estimated CCEA by calculating the marginal abatement cost based on non-radial directional distance function. However, Liu et al. (2023a) omitted the effect of slack vectors in deriving marginal abatement costs, leading to biased final calculations of CCEA. We refined the method of Liu et al. (2023a) by deriving the Lagrange equation to obtain the correct formula for the marginal abatement cost, which accurately calculates CCEA from a cost-effective perspective.

Finally, our study has extended the relevant literature by discussing the topical issue of urban DE development's economic, social, and environmental impacts. Current literature gives poor attention to how DE influences environmental regulatory policy effectiveness (Wang et al., 2024b). Notably, in the literature exploring the policy effectiveness of NEMCC (Wang and Yi, 2021; Liu et al., 2024b; Zhang et al., 2023a), the DE is lacking. Therefore, we incorporate the DE as a moderating variable in our framework. On this basis, we thoroughly analyze the impact of two factors—intellectual property protection and the innovation environment—on the moderating role of the DE. Our study elucidates how the DE influences the relationship between NEMCC and CCEA, addressing a research gap.

The remainder of this paper is organized as follows: Section 2 introduces the institutional background of NEMCC; Section 3 presents the theoretical analysis and research hypotheses; Section 4 explains the model construction process, indicator measurement method, and data sources; Section 5 analyzes empirical results in detail; and Section 6 presents the conclusions, recommendations, and limitations.

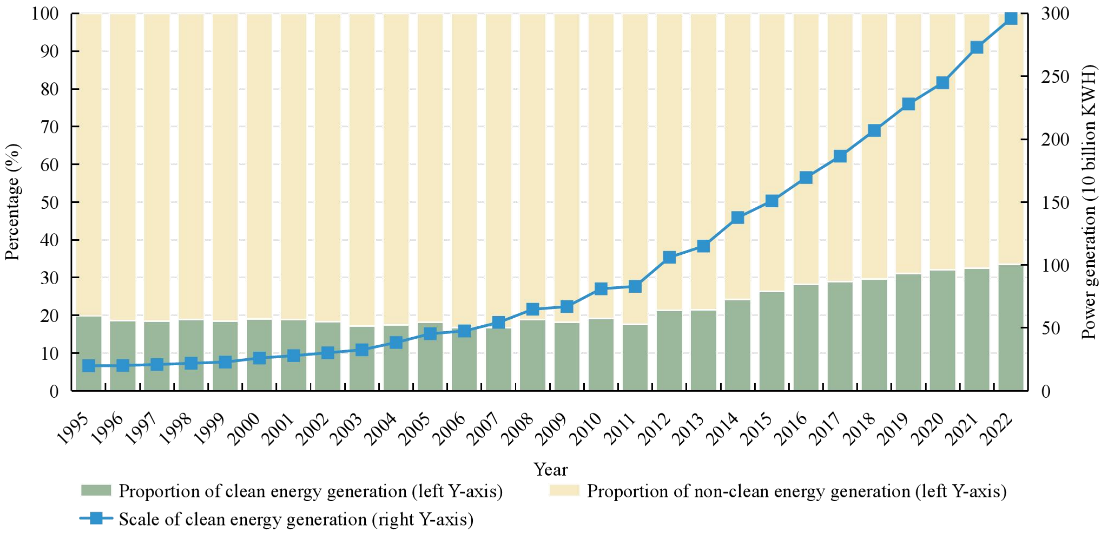

Fig. 1 Clean energy and non-clean energy power production in China.

2. Institutional background of NEMCC in China

Sustainable urban development requires efficient and clean energy utilization. To promote an environmentally friendly and resource-efficient society, the Chinese government has emphasized renewable energy as a key strategy for emission reductions and energy conservation. In 2012, the National Energy Administration of China (NEA) initiated the process of establishing new energy model cities as part of the NEMCC. Based on principles of efficiency, comprehensive coordination, distributed utilization, and multi-energy complementarity, NEMCC promotes the deployment of renewable energy sources and technologies in cities. These include biomass, solar, geothermal energy, and wind. A key priority of the NEMCC is to integrate energy supply and consumption into urban planning in order to reduce air pollution and excessive GHG emissions. In May 2012, NEA released the *New Energy Model City Development Planning Outline* (hereinafter the Outline), and the *Evaluation Indicator System and Instructions for New Energy Model Cities (Trial)* (hereinafter the Instructions). A development plan, basic conditions, and evaluation indicators are described in these two documents. A list of 81 pilot cities was officially announced by the NEA in January 2014 (see **Figure 2** for a geographical distribution).

The declaration process requires that new energy model cities meet two basic requirements: their comprehensive capacity and their new energy utilization base. Comprehensive urban capacity includes both pollutant emission reduction and energy conservation, as well as building energy efficiency and comprehensive environmental remediation. The basic indicator of urban new energy utilization is the proportion of new energy to urban energy consumption in the base year. Moreover, the NEMCC provides detailed explanations of renewable energy innovation, market incentives, infrastructure systems, financial services innovation, organization and regulation, statistics, monitoring, and assessment. **Figure 3** illustrates the overall institutional framework of the NEMCC.

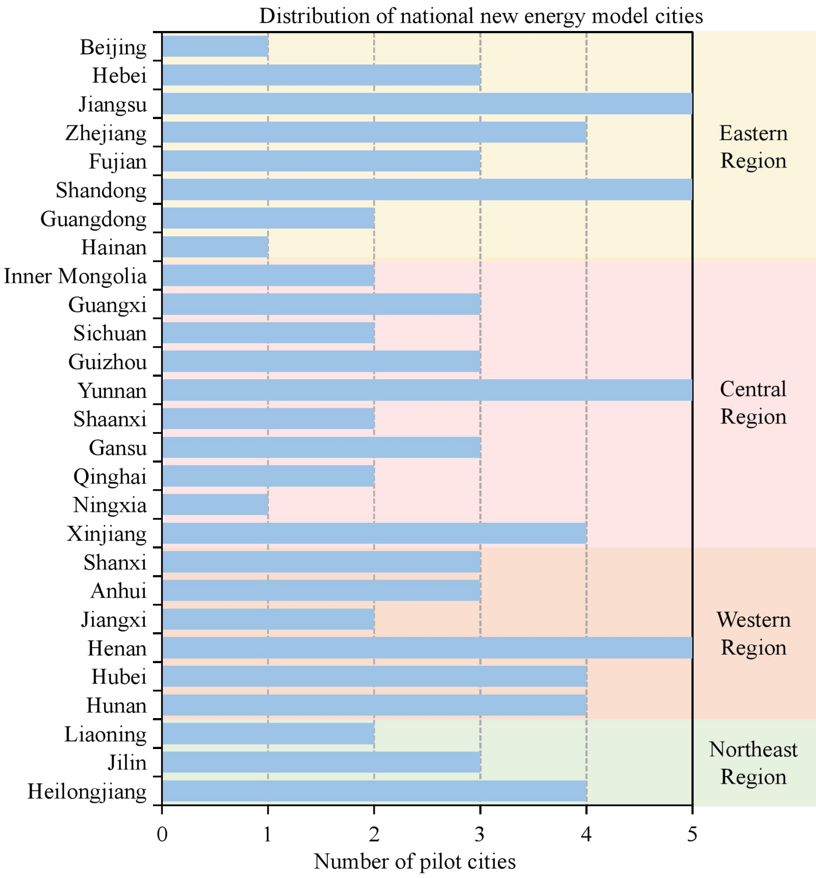

Fig. 2 Geographic distribution of NEMCC.

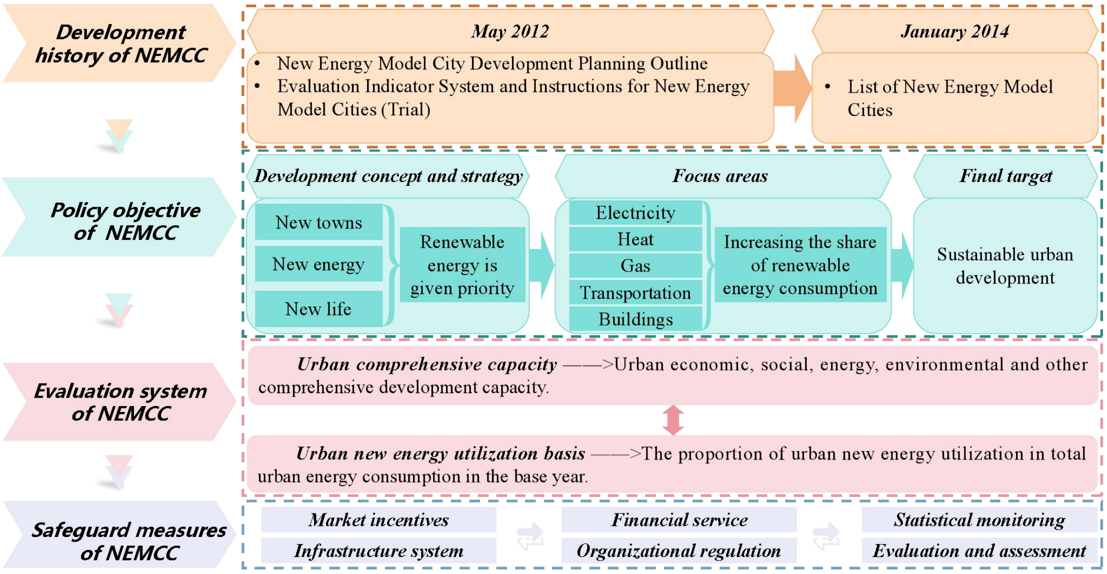

Fig. 3 General institutional framework of NEMCC.

3. Theoretical analysis and research hypotheses

3.1 Mechanisms of NEMCC's impact on CCEA

By promoting new energy, cities will be able to reduce GHG and pollutant emissions in a synergistic manner. With its innovative development model, NEMCC offers a feasible path towards building a system that combines economic development, energy consumption, resource supply, and environmental protection. In contrast to other mandatory environmental regulations, the NEMCC emphasizes the role that new energy plays in reshaping the energy mix and improving the environment. The NEMCC encourages cities to explore comprehensive utilization models that integrate renewable and conventional energy sources in a way that maximizes their efficiency. Building on this, the NEMCC promotes renewable energy as a direct alternative to fossil fuels and optimizes the way energy is produced and consumed (Chai et al., 2023), achieving cost-effective synergistic emissions reduction.

Studies have demonstrated that the NEMCC is able to decline urban GHG emissions and advance green economic development (Chai et al., 2023; Wang et al., 2024c); likewise, it is effective in reducing environmental pollution, including $PM_{2.5}$ and SO_2, and fostering local environmental governance (Guo et al., 2024; Yang et al., 2021). First, NEMCC declines the reliance on fossil fuels in urban development. In these circumstances, local governments have actively explored the use of new energy sources for urban power supply, heating, gas, transportation, and construction. This will help increase new energy utilization efficiency and its consumption proportion, promoting pollution control and GHG emission reduction. From the perspective of institutional economics, CCEA is inextricably linked to system design (North, 1990). NEMCC facilitates the dismantling of traditional energy dependence models and promotes positive institutional change. Second, NEMCC can promote new energy technology industrialization and industry clustering. Through NEMCC, new energy technologies can be integrated into traditional industries, including construction, manufacturing, and power generation (Yang et al., 2021). This will help establish a green development chain of "new energy technology - new energy industry - new energy city", achieving energy savings and emissions reduction. According to the economies of scale theory, NEMCC links investment and demand entities through new energy projects, enabling economies of scale by sharing costs and increasing efficiency. Third, due to the interconnected nature of GHGs and environmental pollutants (Rafaj et al., 2013), GHGs and pollutants reduction may be integrated at multiple levels, including coordinated planning, policy implementation, and effect evaluation, resulting in synergies (Xian et al., 2024b). Therefore, NEMCC can promote CCEA. In light of this, we formulate Hypothesis 1.

Hypothesis 1. NEMCC can improve CCEA.

As stated in the Outline, new energy sources should be assessed in terms of their environmental impact and benefit, including their ability to reduce fossil fuel consumption, pollutants, and greenhouse gas emissions, as well as the conservation of energy and water. The Instructions also state that the criteria for declaring a "New Energy Model City" include energy savings and emission reduction, energy efficiency, environmental governance, and new energy consumption. To this end, local governments have taken a number of measures to improve their environmental performance in response to NEMCC's environmental regulatory pressures, which may affect the CCEA. To excavate the intrinsic mechanism of NEMCC's impact on CCEA, we examine each phase of the local environmental management cycle: source prevention and control, process control, and end-of-pipe treatment.

Source prevention and control focuses on "prevention as the mainstay", with the aim of reducing pollution and GHG emissions directly at the source. NEMCC internalizes the negative externalities of emissions, aligns the costs and benefits of emissions with the protection of the environment, enables an effective allocation of resources, as well as an effective management of abatement at the regional level (Shin, 2018). NEMCC presents a series of binding development targets regarding energy consumption, pollutants, and GHG emissions. The local governments allocate targets to companies within their jurisdictions in order to meet the emission requirements of binding targets (Liu et al., 2023b). According to the compliance cost hypothesis, firms in pilot areas must incur additional costs in order to meet emission standards (Huang et al., 2025b). In general, firms will not invest in green technologies if the costs are perceived to be higher than their benefits, or if the technologies are complex and time-consuming. In such a scenario, a firm may reduce energy consumption, lower production, or even cease operations in order to meet emission targets. The NEMCC improves regional energy efficiency through clear regulations on limiting fossil energy consumption and promoting new energy development. Due to environmental regulations, enterprises in pilot regions are compelled to maximize energy value in order not to be excluded from the market (Cheng et al., 2023). The measures include optimizing energy management, increasing renewable energy use, and coordinating multipurpose use patterns that combine renewable and conventional energy sources. As a result, the pilot city can effectively reduce dependence on fossil energy and energy waste, thereby achieving cost-effective synergistic emission reduction. Therefore, we formulate Hypothesis 2.

Hypothesis 2. At the source prevention and control stage, the NEMCC improves CCEA by promoting energy and production reduction and energy efficiency.

Through the process control stage, pollution and carbon emissions are reduced during production by optimizing management models and continuously updating technologies. NEMCC introduces new energy technologies that may contribute to cost-effective synergistic emissions reduction. Researchers have shown that promoting green technology innovation is able to reduce environmental pollution and GHG emissions (Zhang et al., 2023b; Habiba et al., 2022). Two factors determine how NEMCC impacts green tech innovation: the “compliance cost effect” and the “innovation compensation effect”. According to the compliance cost effect, strict environmental regulatory policies increase emissions reduction costs, which may “crowd out” corporate green technology innovation (Zhang et al., 2024; Ouyang et al., 2020). Nevertheless, the innovation compensation effect indicates that well-designed environmental policies motivate businesses to internalize external costs and improve competitiveness through green innovation, resulting in a win-win situation for the environment and the economy, according to Porter hypothesis (Porter and Linde, 1995). Although both effects may coexist, this paper argues that NEMCC's intervention into urban new energy technology innovation generates a more substantial compensation effect than the cost effect. NEMCC achieves compliance costs offset by innovation compensation effects, in accordance with Porter hypothesis (Zhang et al., 2024). According to the Outline and Description, NEMCC requires pilot cities to develop local energy focus areas and utilization methods. Furthermore, NEMCC introduces regulations covering management systems, organizational safeguards, and information monitoring. Additionally, it facilitates and supports new energy technology innovation in pilot areas by setting emission targets, evaluating environmental data, and introducing subsidies. As a result, NEMCC endogenously drives green development (Yang et al., 2021), helping achieve emission reduction targets. In light of this, we formulate Hypothesis 3.

Hypothesis 3. At the process control stage, NEMCC improves CCEA by promoting green technology innovation.

The Outline and the Instructions specify that NEMCC requires pilot cities to comply with national and provincial emission reduction targets on time and to propose countermeasures for potential adverse environmental effects. NEMCC requires pilot cities to evaluate and monitor the environmental impacts and benefits of new energy development, including pollution and GHG emissions. If emissions in the pilot cities are at risk of exceeding or have already exceeded the environmental risk threshold, interventions should be made promptly to address risks at the production process's end. To protect and manage potential environmental risks, NEMCC will increase local government budgets for pollutant and greenhouse gas management, such as purchasing exhaust treatment and decarbonization devices (Deschenes et al., 2017). Additionally, new energy development is crucial for achieving the dual-carbon goal, and NEMCC has made reducing CO_2 emissions a priority (Zhao and You, 2020). On the one hand, a key measure of the NEMCC is to raise the share of new energy while declining fossil fuels consumption; on the other hand, the NEMCC encourages pilot regions to adopt low-carbon production technologies in main sectors such as, construction, transportation, and industry in order to reduce urban GHG emissions (Wang et al., 2024c; Chai et al., 2023). Since environmental pollutants and greenhouse gases are homologous, improving carbon emission efficiency aids not only carbon reduction but also pollution control, thus achieving cost-effective synergistic emission reductions (Xian et al., 2024b). Therefore, we formulate Hypothesis 4.

Hypothesis 4. At the end-of-pipe treatment stage, NEMCC improves CCEA by promoting increased investment in emissions reduction and pollution control, as well as reducing carbon emissions intensity.

3.2 Moderating role of the digital economy

The digital economy (DE) encompasses a wide range of technologies, such as cloud computing, artificial intelligence, big data, blockchain, and the Internet of Things (IoT). It is characterized by high innovation, wide penetration, and broad coverage (Li et al., 2024; Song et al., 2023b). As a result of the DE, NEMCC has a more positive effect on CCEA. First, the data assets are non-exclusive and non-rivalrous, and the DE reduces the marginal cost of disseminating knowledge and experience (Colombelli et al., 2024). Due to the DE, new energy and energy-saving technologies are rapidly disseminated across firms and regions, amplifying the impact of NEMCC. Second, the DE connects multiple stakeholders and builds a digital ecosystem. For example, online trading platforms enable financial payments and deliveries between trading parties (Carballo et al., 2022), facilitating the exchange of renewable energy products and technologies. Blockchain platforms create trust mechanisms through decentralized technology, which mitigates financing risks associated with green technology innovation (Babich and Hilary, 2020). Industrial Internet platforms integrate R&D, production, and sales, advancing the innovation and dissemination of renewable energy technologies and products (Wang et al., 2020a). Third, the DE enhances information transparency and reduces information asymmetry. On the one hand, by making government data available to the public, NEMCC improves government transparency (Matheus et al., 2021). This promotes openness, accountability, and social trust in NEMCC, enhancing disclosure and regulation. On the other hand, smart devices and IoT enable enterprises in pilot areas to monitor, collect, and disclose their environmental performance more easily (Li et al., 2020). This eliminates information asymmetry between external investors and firms (Li et al., 2022), thus preventing investment difficulties in new energy projects. Fourth, the DE provides technical support for the NEMCC environmental database and statistical evaluation process. NEMCC requires pilot cities to establish information monitoring and statistical systems for new and renewable energy use and to furnish relevant data on a regular basis to provincial energy authorities. The digital technology facilitates the collection, storage, monitoring, and evaluation of environmental data. Hence, we formulate Hypothesis 5.

Hypothesis 5. The DE enhances the positive effect of NEMCC on CCEA.

Figure 4 illustrates the mechanism by which NEMCC affects CCEA.

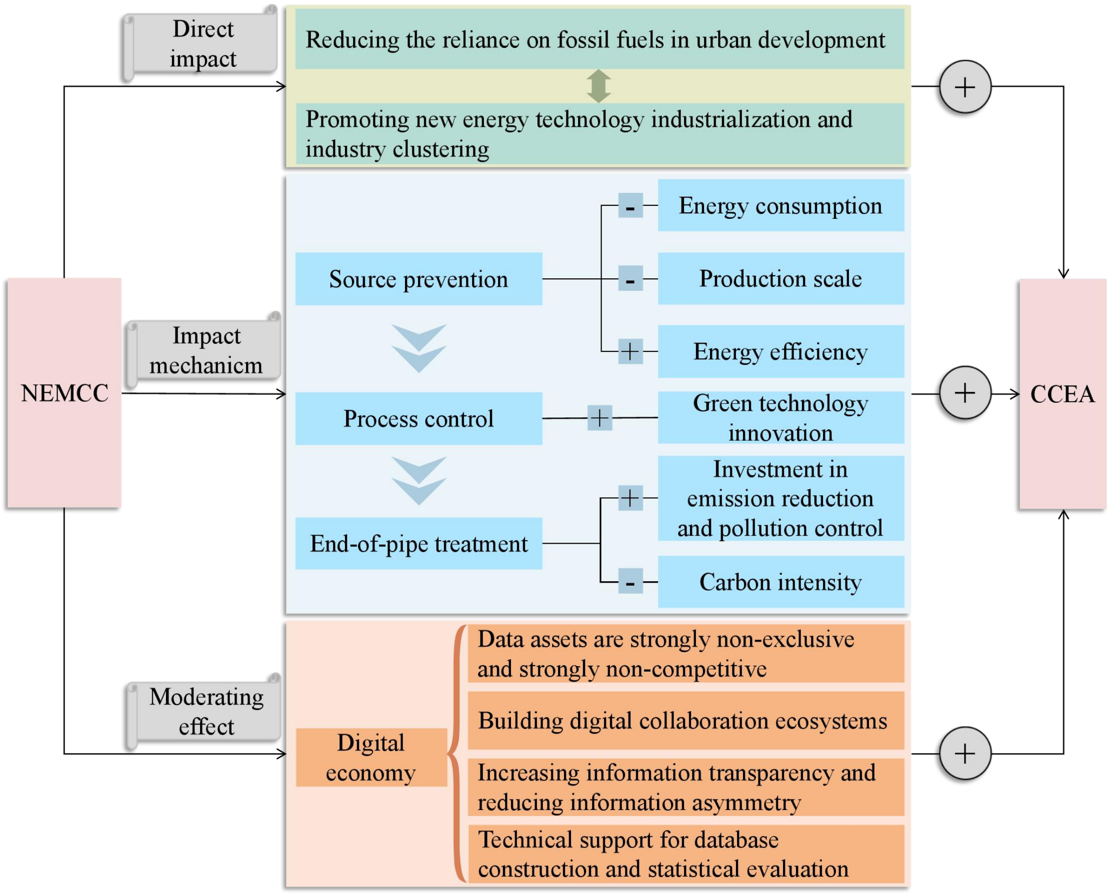

Fig. 4 Theoretical mechanisms by which NEMCC affects CCEA.

4. Research design

4.1 Econometric modeling

Our study belongs to the research topic of policy evaluation and applies to the scope of application of the DID method (Zhang and Wang, 2024; Wang et al., 2024a; Pan and Lin, 2025). Therefore, we develop a DID model to examine the differences in urban CCEA between experimental and control groups before and after NEMCC execution. This paper constructs the following formula:

$$CCEA_{it} = \alpha_0 + \alpha_1 NEMCC_{it} + \sum \alpha W_{it} + \eta_i + \theta_t + \varepsilon_{it} \tag{1}$$

In formula (1), i denotes city, t denotes year. $CCEA_{it}$ is the CCEA of city i in year t.

$NEMCC_{it}$ is a policy dummy variable. ε_{it} is the random error term. The set of control variables is denoted as W_{it}. η_i denotes individual fixed effect, and θ_t denotes the year fixed effect. α_1 measures the effect of NEMCC on CCEA.

To test the mechanism of the effect of NEMCC on CCEA, this paper builds the following formula reference to Chen et al. (2020b):

$$M_{it} = \beta_0 + \beta_1 NEMCC_{it} + \sum \beta W_{it} + \eta_i + \theta_t + \varepsilon_{it} \tag{2}$$

Where M_{it} represents the mechanism variable. The significance of the influence mechanism is jointly determined by the theoretical analysis and the significance of β_1.

To examine the moderating effect of the digital economy, we construct the following formula:

$$CCEA_{it} = \gamma_0 + \gamma_1 DI_{it} + \gamma_2 NEMCC_{it} + \gamma_3 NEMCC_{it} \times DI_{it} + \sum \gamma W_{it} + \eta_i + \theta_t + \varepsilon_{it} \tag{3}$$

Where DI_{it} means the level of development of the digital economy of city i in year t.

4.2 Indicators selection

4.2.1 Dependent variable: CCEA

Different from prior research, we attempt to assess CCEA in cities from a cost-effective perspective. According to Liu et al. (2023a), we first build a non-radial directional distance function (NDDF)[3] under the global production set. Specifically, suppose we have N city

[3] Chung et al. (1997) initially proposed the classic directional distance function (DDF) approach to capture the weakly free disposability between desired and undesired outputs. However, the DDF approach assumes that the expansion of desired output and the reduction of input factors and undesired output are strictly proportional, which may result in "slack bias" (Zhang and Choi, 2014; Huang et al., 2022). Zhou et al. (2012) proposed the non-radial directional distance function, which allows the expansion of desired output, the reduction of undesired output and input factors to be in different proportions.

production units, each of which creates economic added value (y) by absorbing three input factors (x): labor (L), capital (K), and energy (E), but it also inevitably brings some "by-products" (z). Referring to existing studies (Guan et al., 2023; Yang et al., 2023), we mainly consider two "by-products" reflecting air pollution and carbon emissions: $PM_{2.5}$ (P) and CO_2 (C). Under a single-period input-output system, we can construct the following production possibility set (PPS):

$$
\begin{aligned}
PPS^t(x^t) &= \left\{(y^t, z^t) \middle| x^t \text{ can produce } (y^t, z^t)\right\} \\
&= \left\{(x^t, y^t, z^t) \middle| \sum_{j=1}^{N} \lambda_j^t x_j^t \le x; \sum_{j=1}^{N} \lambda_j^t y_j^t \ge y; \right. \\
&\left. \sum_{j=1}^{J} \lambda_j^t z_j^t = z\ i;\ \sum_{j=1}^{J} \lambda_j^t = 1, \lambda_j^t \ge 0; j = 1, \dots, J \right\}
\end{aligned}
\tag{4}
$$

Although the single-period production possibility set can assure the comparability of the performance evaluation results of decision-making units (DMU) in the cross section; however, it cannot assure the comparability of the performance evaluation results of DMU across periods. To address this concern, we refer to Oh (2010) and construct the following global production possibility set:

$$
\begin{aligned}
PPS^G(x) &= \text{convexhull}\left\{PPS^t(x^t), PPS^{t+1}(x^{t+1}), \dots, PPS^T(x^T)\right\} \\
&= \left\{(x^t, y^t, z^t) \middle| \sum_{t=1}^{T} \sum_{j=1}^{N} \lambda_j^t x_j^t \le x; \sum_{t=1}^{T} \sum_{j=1}^{N} \lambda_j^t y_j^t \ge y; \right. \\
&\left. \sum_{t=1}^{T} \sum_{j=1}^{N} \lambda_j^t z_j^t = z; \sum_{t=1}^{T} \sum_{j=1}^{N} \lambda_j^t = 1, \lambda_j^t \ge 0; j = 1, \dots, J;\ t = 1, \dots, T \right\}
\end{aligned}
\tag{5}
$$

Where, $\text{convexhull}\{\cdot\}$ means to calculate the convex set of all contemporaneous benchmark technologies. On this basis, we can express the non-radial directional distance function under the global production possibility set as follows:

$$
\begin{aligned}
&\overrightarrow{ND}(x,y,z;g)=\max\left\{w_L\beta_L+w_K\beta_K+w_E\beta_E+w_Y\beta_Y+w_L\beta_L+w_P\beta_P+w_C\beta_C\right\}\\
&s.t.\sum_{t=1}^{T}\sum_{j=1}^{N}\lambda_j^tL_j^t\le L-\beta_Lg_L,\sum_{t=1}^{T}\sum_{j=1}^{N}\lambda_j^tL_j^t\le K-\beta_Kg_K,\sum_{t=1}^{T}\sum_{j=1}^{N}\lambda_j^tE_j^t\le E-\beta_Eg_E;\\
&\quad\sum_{t=1}^{T}\sum_{j=1}^{N}\lambda_j^tY_j^t\ge Y+\beta_Yg_Y,\sum_{t=1}^{T}\sum_{j=1}^{N}\lambda_j^tP_j^t=P-\beta_Pg_P,\sum_{t=1}^{T}\sum_{j=1}^{N}\lambda_j^tC_j^t=C-\beta_Cg_C;\\
&\quad\sum_{t=1}^{T}\sum_{j=1}^{N}\lambda_j^t=1,\ \lambda_j^t\ge0;\ j=1,2,\cdots,N;t=1,2,\ldots,T;\beta_L,\beta_K,\beta_E,\beta_Y,\beta_P,\beta_C\ge0
\end{aligned}
\tag{6}
$$

Where, $\beta=(\beta_L,\beta_K,\beta_E,\beta_Y,\beta_P,\beta_C)^{\mathrm{T}}$ represents a set of slack variables, which reflects the proportion of inputs and non-desirable outputs that can be reduced, and the proportion of expected output that can be expanded. $w=(w_L,w_K,w_E,w_Y,w_P,w_C)^{\mathrm{T}}$ represents a set of weight vectors, which reflects the importance of various input and output factors. $g=(g_L,g_K,g_E,g_Y,g_P,g_C)^{\mathrm{T}}$ represents a set of direction vectors, indicating the direction of change of various input shrinkage or output rise. Following Liu et al. (2023a), we assume that the input system is equally important as the output system, that is, the weights of input and output are both $1/2$. The input system includes three variables: labor, capital, and energy, so the weight corresponding to each input variable is $1/6$ (i.e., $1/2\times1/3$). In the scenario of single emission abatement, the output system includes one expected output and one undesired output, so the weight corresponding to each output variable is $1/4$ (i.e., $1/2\times1/2$). In the scenario of joint emission abatement, the output system includes one expected output and two undesired outputs, so the weight corresponding to each output variable is $1/6$ (i.e., $1/2\times1/3$). For the sake of clarity, we summarize the weight vectors and direction vectors in the three abatement scenarios into **Table 1**.

Table 1. Weight vectors and direction vectors corresponding to three abatement scenarios

Scenarios	Direction vectors	Weight vectors
Abating $PM_{2.5}$ alone	$g=(-L,-K,-E,Y,0,-P)$	$w^{\mathrm{T}}=(\frac{1}{6},\frac{1}{6},\frac{1}{6},\frac{1}{4},0,\frac{1}{4})$

Abating CO_2 alone	$g=(-L,-K,-E,Y,-C,0)$	$w^{T}=(\frac{1}{6},\frac{1}{6},\frac{1}{6},\frac{1}{4},\frac{1}{4},0)$
Abating $PM_{2.5}$ and CO_2	$g=(-L,-K,-E,Y,-C,-P)$	$w^{T}=(\frac{1}{6},\frac{1}{6},\frac{1}{6},\frac{1}{6},\frac{1}{6},\frac{1}{6})$

According to Färe et al. (1993), the relationship between the profit function and the distance function allows us to derive the shadow prices of desired and undesired outputs since the ratio of the shadow prices of the two outputs is equal to the marginal rate of substitution of the two outputs on the production frontier. We assume that $v^{x}=[v^{L},v^{K},v^{E}]$ represents the prices of three input factors, v^{y} is the price of the desired output, and $v^{z}=[v^{P},v^{C}]$ is the prices of two undesired outputs. Then the profit function can be written as: $R=v^{Y}Y-v^{L}L-v^{K}K-v^{E}E-v^{P}P-v^{C}C$. For each DMU, to maximize profits along the direction vector:

$$\begin{aligned}&\max\ v^{Y}Y-v^{L}L-v^{K}K-v^{E}E-v^{P}P-v^{C}C\\&\text{s.t. } \overrightarrow{ND}_{0}\left[(1-\beta_{L})L,(1-\beta_{K})K,(1-\beta_{E})E,(1+\beta_{Y})Y,(1-\beta_{P})P,(1-\beta_{C})C\right]\leq 1\end{aligned} \tag{7}$$

We construct the following Lagrangian function to solve the above optimization issue:

$$\begin{aligned}H=\ &v^{Y}Y-v^{L}L-v^{K}K-v^{E}E-v^{P}P-v^{C}C-\gamma\{\\&\overrightarrow{ND}_{0}\left[(1-\beta_{L})L,(1-\beta_{K})K,(1-\beta_{E})E,(1+\beta_{Y})Y,(1-\beta_{P})P,(1-\beta_{C})C\right]-1\}\end{aligned} \tag{8}$$

Where, γ is the Lagrange multiplier. From this, we can obtain three first-order necessary conditions to meet profit maximization:

$$\frac{\partial H}{\partial Y}=v^{Y}-\gamma\frac{\partial\overrightarrow{ND}_{0}[\cdot]}{\partial(1+\beta_{Y})Y}(1+\beta_{Y})=0 \tag{9}$$

$$\frac{\partial H}{\partial P}=v^{P}-\gamma\frac{\partial\overrightarrow{ND}_{0}[\cdot]}{\partial(1+\beta_{P})P}(1-\beta_{P})=0 \tag{10}$$

$$\frac{\partial H}{\partial C}=v^{C}-\gamma\frac{\partial\overrightarrow{ND}_{0}[\cdot]}{\partial(1+\beta_{C})C}(1-\beta_{C})=0 \tag{11}$$

By combining formula (9) and formula (10), as well as formula (9) and formula (11), we can obtain:

$$\frac{v^{Y}}{v^{P}}=\frac{\dfrac{\partial \overrightarrow{ND}_{0}[\cdot]}{\partial\left(1+\beta_{Y}\right)Y}}{\dfrac{\partial \overrightarrow{ND}_{0}[\cdot]}{\partial\left(1-\beta_{P}\right)P}}\frac{1+\beta_{Y}}{1-\beta_{P}},\frac{v^{Y}}{v^{C}}=\frac{\dfrac{\partial \overrightarrow{ND}_{0}[\cdot]}{\partial\left(1+\beta_{Y}\right)Y}}{\dfrac{\partial \overrightarrow{ND}_{0}[\cdot]}{\partial\left(1-\beta_{C}\right)C}}\frac{1+\beta_{Y}}{1-\beta_{C}} \tag{12}$$

Let t_Y, t_P, t_C represent the Lagrange multipliers of the desired output and undesired output constraints respectively, and satisfy:

$$\frac{t_{Y}}{t_{P}}=\frac{\dfrac{\partial \overrightarrow{ND}_{0}[\cdot]}{\partial\left(1+\beta_{Y}\right)Y}}{\dfrac{\partial \overrightarrow{ND}_{0}[\cdot]}{\partial\left(1-\beta_{P}\right)P}},\quad \frac{t_{Y}}{t_{C}}=\frac{\dfrac{\partial \overrightarrow{ND}_{0}[\cdot]}{\partial\left(1+\beta_{Y}\right)Y}}{\dfrac{\partial \overrightarrow{ND}_{0}[\cdot]}{\partial\left(1-\beta_{C}\right)C}} \tag{13}$$

Then, we can get the marginal abatement cost (or shadow price) expression of the two undesired outputs:

$$v^{P}=v^{Y}\frac{t_{P}}{t_{Y}}\frac{1-\beta_{P}}{1+\beta_{Y}},\quad v^{C}=v^{Y}\frac{t_{C}}{t_{Y}}\frac{1-\beta_{C}}{1+\beta_{Y}} \tag{14}$$

The marginal abatement cost derived in Liu et al. (2023a) only retains the left half of the formula (14) while ignoring the right half containing the slack variable[4]. The reason is that they wrote the dual optimization expression of the non-radial directional distance function incorrectly. Different from their approach, we directly construct the Lagrangian function to solve the profit maximization problem and rigorously derive the marginal abatement cost expressions of air pollution and carbon emissions, including their respective slack variables. One non-negligible concern is that if the marginal abatement costs of air pollutants and carbon emissions are independent of their respective slack variables, then there will be no difference in the shadow

[4] Specifically, the marginal abatement cost expressions for air pollution and carbon emissions in Liu et al. (2023a) are $v^{P}=v^{Y}\frac{t_{P}}{t_{Y}},v^{C}=v^{Y}\frac{t_{C}}{t_{Y}}$.

prices estimated using the non-radial directional distance function and the radial directional distance function.

When solving the marginal abatement cost, we usually assume that the shadow price of the expected output is equal to its market price, that is, v^Y is 1. Furthermore, in order to reflect the cost-saving effect of joint emission abatement compared with single emission abatement, we refer to Liu et al. (2023a) to define the synergistic effect as the ratio of the change in marginal abatement costs under single emission abatement and joint emission abatement. Before measuring the synergy effect, we first non-dimensionalize v^P and v^C as follows:

$$PRE = \frac{v^P_{\text{Single}} - v^P_{\text{Joint}}}{v^P_{\text{Single}}} \times 100, CRE = \frac{v^C_{\text{Single}} - v^C_{\text{Joint}}}{v^C_{\text{Single}}} \times 100 \tag{15}$$

Where, v^P_{Single} represents the marginal abatement cost of $PM_{2.5}$ under the single abatement scenario, v^P_{Joint} represents the marginal abatement cost of $PM_{2.5}$ under the joint abatement scenario. PRE represents the reduction ratio of the marginal abatement cost of $PM_{2.5}$ in joint abatement scenario compared with single abatement scenario. Similarly, v^C_{Single} represents the marginal abatement cost of CO_2 under the single abatement scenario, v^C_{Joint} represents the marginal abatement cost of CO_2 under the joint abatement scenario. CRE represents the reduction ratio of the marginal abatement cost of CO_2 in joint abatement scenario compared with single abatement scenario. From the cost-effective perspective, we can further define the cost-effective collaborative emission abatement ($CCEA$) as:

$$CCEA = \frac{1}{2}(PRE + CRE) \tag{16}$$

In the actual calculation, we use the number of employees at the end of the year in the city to measure the labor factor. For the measurement of city's capital stock, we refer to Huang et al.

(2025a) and use the perpetual inventory method to calculate, where the capital depreciation rate is set as 9.6% following Zhang et al. (2004). For the desired output, we use the gross domestic product of prefecture-level cities to measure. Following Chen et al. (2020a, 2022), for the measurement of energy consumption and carbon emissions in prefecture-level cities, we combine two sets of satellite imagery data (DMSP/OLS and NPP/VIIRS) to invert and unify the scale by using the particle swarm optimization-back propagation algorithm. For the measurement of city's air pollution, we apply ArcGIS software to parse the $PM_{2.5}$ grid data of China provided by Washington University in St. Louis[5]. **Table 2** illustrates the input-output indicator system of CCEA.

Table 2. CCEA's input-output indicator system.

Tier 1 indicators	Tier 2 indicators	Measurements
Input	Labor	Number of employees at the end of the year
	Capital	Perpetual inventory method
	Energy	Referring to Chen et al. (2020a, 2022)
Desired output	GDP	Real GDP
Non-desired output	CO_2 emissions	Referring to Chen et al. (2020a, 2022)
	$PM_{2.5}$	Parsing the $PM_{2.5}$ grid data of China provided by Washington University in St. Louis

4.2.2 Independent variable: NEMCC

In January 2014, the Chinese government firstly announced a list of new energy model cities. This paper uses this as a benchmark to design a quasi-natural experiment on NEMCC, and applies the DID method to assess its effect on CCEA. We create the policy dummy variable $treat$, assigned a value of 1 when the sample city is a model city, and 0 otherwise. Additionally, we create the time dummy variable $time$, assigned a value of 1 when the sample year is later

[5] The original satellite-derived $PM_{2.5}$ grid data is available at: https://sites.wustl.edu/acag/datasets/surface-pm2-5/#TOOLS.

than 2014, and 0 otherwise. Based on this, the study constructs the DID term $NEMCC = treat \times time$.

4.2.3 Mechanism variables

To test Hypothesis 2, we use the natural logarithms of energy consumption and GDP as our mechanism variables, denoted as LN_EC and LN_GDP, respectively. This paper uses energy consumption per unit of GDP to calculate energy efficiency (EE).

To test Hypothesis 3, green technology innovation can be measured by the number of green patents. Specifically, we calculate the natural logarithms of green patent applications and green invention patent applications, denoted as LN_GPA and LN_GPAI, respectively.

To test Hypothesis 4, we calculate the natural logarithm of the investment in emission reduction and pollution control (LN_ECPC), per capita investment (PER_ECPC), and investment per unit of GDP (IN_ECPC). Carbon emission intensity (CEI) is calculated by dividing carbon emissions by GDP per unit.

4.2.4 Mediating variable: digital economy

Given the widespread use of the entropy method employed by Tao et al. (2022) to estimate the level of DE progression in Chinese cities, we adopt this method to calculate the DI. For enhanced robustness, this study calculates the natural logarithms of the number of digital patents filed and licensed, denoted as DPA and DPL, respectively.

4.2.5 Control variables

Referring to existing studies (Dong et al., 2022; Hu, 2023; Shahbaz et al., 2022), this paper controls the following variables that possibly affect CCEA of the city: economic development (ED), population density (PD), upgrading of industrial structure (UI), expenditure on science and education (ES), market-oriented development (MD), financial development (FD). **Table 3** details the instructions for all control variables.

4.3 Data sources

This study examines 283 Chinese prefecture-level cities and above between 2009 and 2021. Research data mainly comes from the *China Urban Statistical Yearbook*, the CEIdata, and the statistical yearbooks and bulletins of cities and provinces. We obtain patent data from the State Intellectual Property Office. The sample period is set to 2009 due to the financial crisis of 2008. The regression process excludes cities with significant missing indicators. There are 62 pilot cities and 221 non-pilot cities in the final sample. Ultimately, we obtain 3679 observations.

Tables 3 and **4** show the measurements and descriptive statistical characteristics of each indicator, respectively.

Table 3. Variable definitions, acronyms, and measurements.

Variable definitions	Abbreviations	Measurements
Cost-effective collaborative emission abatement	CCEA	According to 4.2.1.
Pollution reduction effect	PRE	According to 4.2.1.
Carbon reduction effect	CRE	According to 4.2.1.
Economic development	ED	Natural logarithm of GDP per capita
Population density	PD	Population/urban area
Upgrading of industrial structure	UI	(value added of the tertiary industry/GDP) ×3 + (value added of the secondary industry/GDP) ×2 + (Value added of the primary industry/GDP) ×1
Expenditure on science and education	ES	Natural logarithm of the amount of financial expenditure on science and education.
Market-oriented development	MD	Number of private and self-employed urban workers/Number of employed urban workers
Financial development	FD	Financial institution's end-of-year deposits and loans/GDP
Energy consumption	LN_EC	Natural logarithm of energy consumption
Production capacity	LN_GDP	Natural logarithm of GDP
Energy efficiency	EE	Energy consumption per unit of GDP

Green patent applications	LN_GPA	Natural logarithm of the number of green patent applications
Patent applications for green inventions	LN_GPAI	Natural logarithm of the number of patent applications for green inventions
Expenditures on energy conservation and pollution control	LN_ECPC	Natural logarithm of the expenditure of energy conservation and pollution control
Per capita expenditure on energy conservation and pollution control	PER_ECPC	Natural logarithm of per capita expenditure of energy conservation and pollution control
Intensity of expenditure on energy conservation and pollution control	IN_ECPC	Expenditure of energy conservation and pollution control per unit of GDP
Carbon emission intensity	CEI	Carbon emission per unit of GDP
Digitization index	DI	According to Tao et al. (2022)
Digital patent applications	DPA	Natural logarithm of digital patent applications
Digital patent licenses	DPL	Natural logarithm of digital patent licenses

Table 4. Descriptive statistics.

Variables	N	Mean	SD	Min	Max
CCEA	3679	29.5013	13.9510	-64.5080	82.9303
PRE	3679	37.0129	20.4930	-18.6613	92.0977
CRE	3679	21.9897	14.3414	-110.3546	76.6143
ED	3679	10.6591	0.6272	4.5951	13.0557
PD	3679	5.7329	0.9396	0.6831	7.8816
UI	3679	2.2915	0.1450	1.8312	2.8357
ES	3679	13.1347	0.8735	9.5735	16.5864
MD	3679	1.3339	1.6545	0.0127	76.7012
FD	3679	2.4435	1.1965	0.5879	21.3018
LN_EC	3329	11.4634	0.7889	8.8401	13.6010
LN_GDP	3329	16.4691	0.9413	13.6869	19.8137
EE	3329	0.7680	0.4379	0.0610	4.0971
LN_GPA	3254	4.6232	1.7167	0.0000	9.8761
LN_GPAI	3254	3.6513	1.7586	0.0000	9.2767
LN_ECPC	3163	11.1855	1.0390	0.0703	15.3382
PER_ECPC	3163	5.2705	0.8441	0.0004	8.7310
IN_ECPC	3163	0.5959	0.6885	0.0000	21.0311
CEI	3449	0.5081	0.3954	0.0440	2.8232
DI	3102	0.1548	0.0688	0.0153	0.5515
DPA	3677	5.5691	1.9491	0.0000	11.6707
DPL	3677	5.1323	1.9264	0.0000	11.4470

5. Empirical analysis

5.1 Characterizing the evolution of trends in CCEA in China

According to the methodology in Section 4.2.1, we calculate the cost-effective collaborative emission abatement in China from 2009 to 2021 (see **Figure 5 (a)**). As shown, the CCEA remained relatively flat from 2009 to 2014, with the pollution reduction effect even decreasing slightly during this period. From **Figures 5 (b)** and **(c)**, carbon emissions exhibit an upward trend from 2009 to 2014, while $PM_{2.5}$ remains at a high level. By 2014, China had not achieved synergistic reductions in emissions of pollutants and GHGs despite promoting green growth and implementing environmental policies such as the sewage levy and green credit policies. CCEA increased gradually from 2014 to 2021, with both pollution and carbon reduction effects increasing significantly, demonstrating a synergistic effect. The evidence suggests that joint abatement involves significantly lower economic costs than individual abatement. $PM_{2.5}$ improved significantly after 2014, and carbon emissions "fell back" in 2014-2016. The data indicate that NEMCC implementation in 2014 helped enhance CCEA. Nevertheless, carbon emissions showed a clear upward trend from 2016 to 2021. This indicates that there has yet to be a full decoupling between carbon emissions and China's economic growth, and that high rates of economic development are still dependent on fossil energy consumption. In fact, the growth of carbon emissions does not contradict the growth of CCEA and carbon reduction effects. By definition, CCEA measures the proportion of costs saved by synergistic emission reductions compared to individual reductions, rather than the absolute amount of CO_2 or $PM_{2.5}$ reduction. Notably, GDP has shown a steady growth trend over the long term from 2009 to 2021. The results mean that the environmental regulations in China are gradually causing the country to move from extensive to intensive growth. NEMCC has both economic and environmental benefits and presents promising prospects for the future.

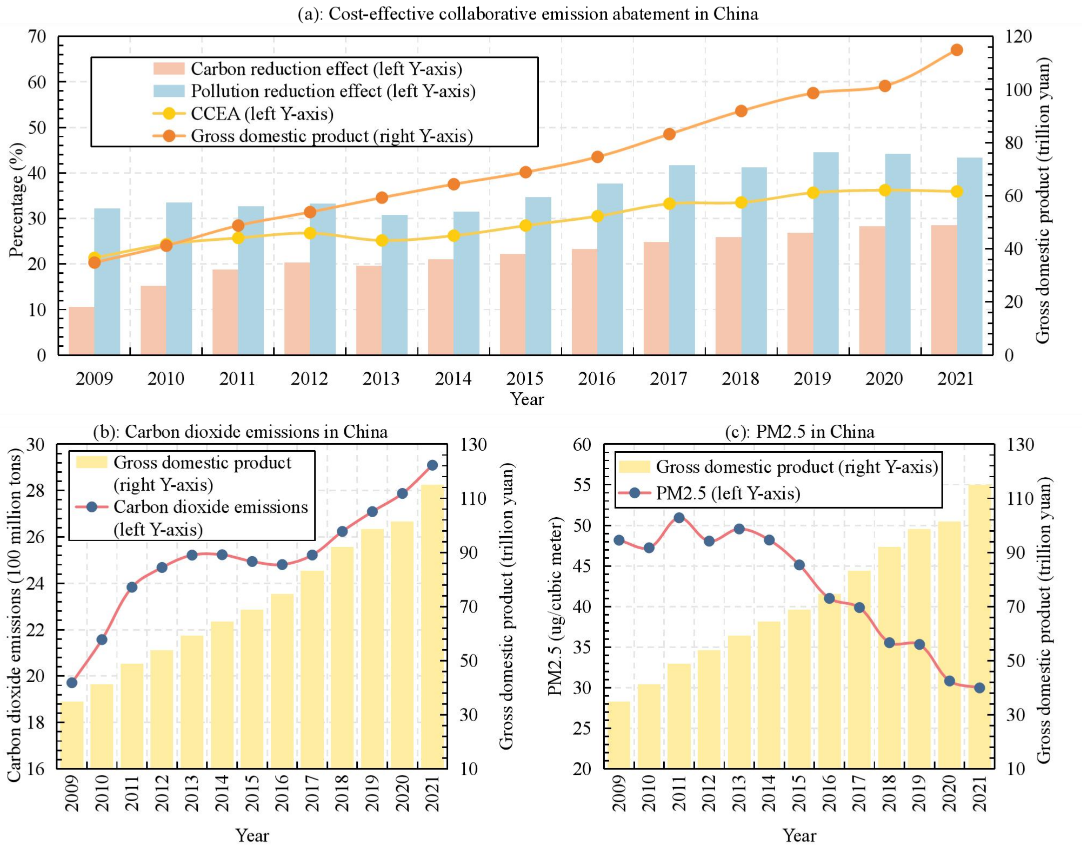

Fig. 5 Carbon emissions, $PM_{2.5}$ and CCEA in China, 2009-2021.

5.2 Baseline regression

By using formula (1), we estimate the baseline effect of NEMCC on CCEA (see **Table 5** for results). Neither control variables nor fixed effects are included in Column 1. In Column 2, the city and time fixed effects are controlled. On this basis, Column 3 includes control variables. At the 5% level, all regression coefficients for NEMCC have significant positive values, indicating that NEMCC enhances CCEA. Additionally, we examine the influence of NEMCC on PRE and CRE. At least at the 10% level, the NEMCC regression coefficients are positive, meaning that NEMCC not only promotes the management of $PM_{2.5}$ and CO_2 in the pilot city, but also fosters CCEA. On the one hand, NEMCC contributes to the reduction of fossil fuel dependence in urban economic development (North, 1990). On the other hand, NEMCC plays a significant role in the industrialization of new energy technologies and in the development of new energy industry clusters (Yang et al., 2021). In addition, environmental pollutants and GHGs are homologous in their management (Rafaj et al., 2013), which facilitates the promotion of CCEA by the NEMCC. Therefore, Hypothesis 1 is confirmed.

Table 5. Baseline regression results.

Variables	(1)	(2)	(3)	(4)	(5)
	CCEA	CCEA	CCEA	PRE	CRE
NEMCC	3.9918***	3.6995**	3.7955***	4.2889*	3.3022**
	(1.0809)	(1.4509)	(1.4420)	(2.1829)	(1.3657)
ED			-0.1734	-0.0579	-0.2889
			(1.6651)	(2.9214)	(2.2797)
PD			1.6151	2.8407	0.3895
			(1.6426)	(2.4221)	(1.3362)
UI			19.3202**	36.9952***	1.6452
			(7.8925)	(12.9671)	(7.3065)
ES			0.9546	-1.1054	3.0147
			(2.0028)	(2.9085)	(2.0250)
MD			0.2139	0.2254	0.2024
			(0.2649)	(0.4435)	(0.1258)
FD			-0.2929	0.2974	-0.8833**
			(0.5038)	(0.9731)	(0.4083)
Constant	28.9631***	29.0025***	-34.8022	-50.5157	-19.0888
	(0.5890)	(0.1956)	(35.1570)	(53.7683)	(33.8235)
City FE	NO	YES	YES	YES	YES
Year FE	NO	YES	YES	YES	YES
Nobs	3679	3679	3679	3679	3679
R^2	0.0096	0.5366	0.5401	0.4784	0.5773

Note: * P<0.10， ** P<0.05， *** P<0.01. Values in parentheses are standard errors. We use clustered standard errors for regression estimation at the city-level.

5.3 Robustness tests

5.3.1 Parallel trend test

Before the development of the NEMCC, CCEA could have already shown an upward trend, resulting in a biased estimate (Huang et al., 2023). Referring to Beck et al. (2010), our study assesses the parallel trend of CCEA before and after the execution of NEMCC. The following formula is constructed:

$$CCEA_{it} = \delta_0 + \sum_{k=-5}^{k=7} \delta_k D_{i,t_0+k} + \sum \delta W_{it} + \eta_i + \theta_t + \varepsilon_{it} \tag{17}$$

Where D_{i,t_0+k} represents a group of dummy variables. $t_0 + k$ represents the k_{th} year after the NEMCC execution year t_0, when $D_{i,t_0+k} = 1$, otherwise $D_{i,t_0+k} = 0$. This paper estimates parallel trends during the first 5 years and the final 7 years of NEMCC implementation. We exclude the -1 period to circumvent the interference of multicollinearity.

In **Figure 6**, the parallel trend test results for Column 3 of **Table 5** are shown. The estimates of δ_k prior to the implementation of NEMCC fluctuate around 0 and are statistically significant at 95% confidence. As NEMCC is implemented, the estimates of δ_k gradually move away from 0, and after Post3, the 95% confidence intervals no longer intersect the 0 baseline, confirming that the study is consistent with the DID hypothesis.

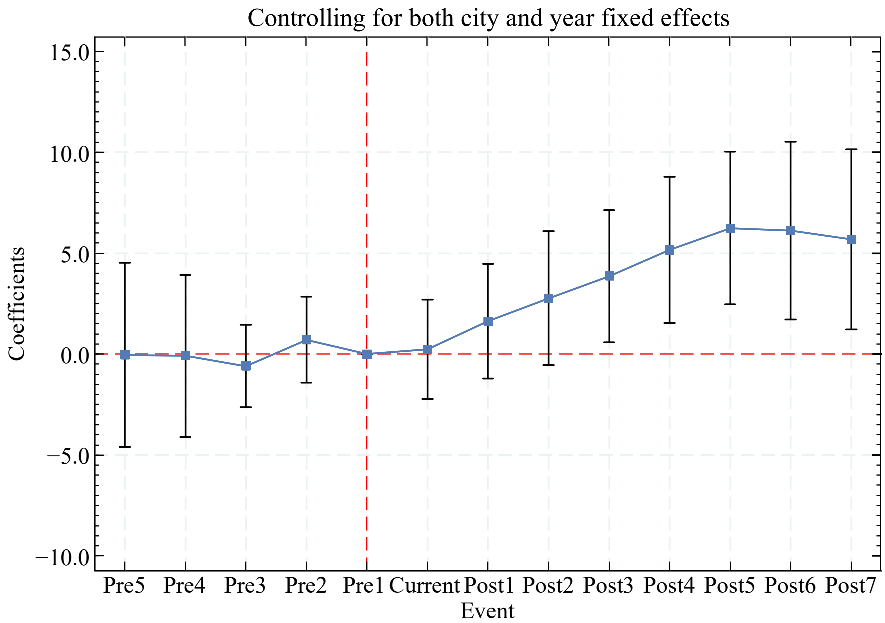

Fig. 6 Parallel trend test.

5.3.2 Placebo test

We follow the standard practice of placebo testing provided by Abadie et al. (2010) in order to avoid spurious effects due to unexpected factors. The pseudo-treatment group consists of 62 cities, and we repeat the random sampling 1000 times to estimate formula (1). **Figure 7** shows the kernel density estimation of pseudo-NEMCC coefficients. The pseudo-NEMCC regression coefficients are roughly normally distributed, with the majority of estimated points distributed to the left of the estimated baseline. Thus, the baseline regression findings are robust and are not arbitrary.

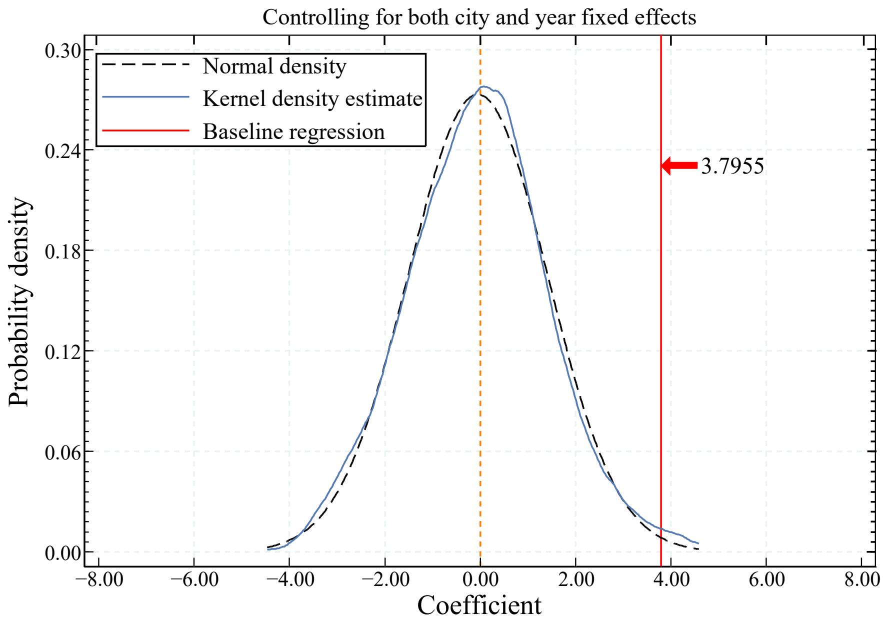

Fig. 7 Placebo test.

5.3.3 Clustering methods for replacing standard errors

Since some variables may be correlated at higher dimensions, formula (1) is re-estimated by adjusting the clustering level of standard errors from the city to the province. In **Figure 8**, Test 1 presents the estimated NEMCC regression coefficient. The estimated coefficient mean is 3.7955, with a 95% confidence interval of (1.3583, 6.2328), which does not overlap the 0 baseline. Accordingly, the benchmark regression results are robust.

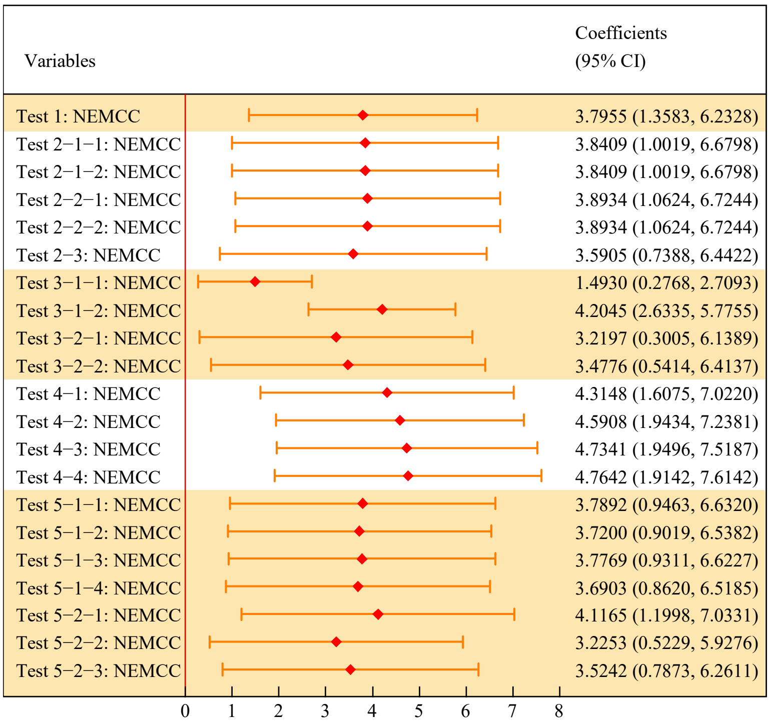

Fig. 8 Robustness tests.

5.3.4 Considering the non-randomness of sample selection

(1) *PSM-DID*[6]. Using the control variables from the baseline regression as covariates, we match control group areas with experimental group areas. In **Figure 8**, we present the results of Tests 2-1 and 2-2 of the PSM-DID model using both radius matching and kernel matching. Test 2-1-1 and Test 2-2-1 are configured with "_weight ! = ." and Test 2-1-2 and Test 2-2-2 are configured with "_support ==1" in the Stata command. NEMCC's estimated coefficients are all significantly positive at 95% confidence levels. Hence, the results are robust and are not influenced by non-random sample selection.

(2) *EBM-DID*[7]. Referring to Hainmueller (2012), this study uses entropy balanced matching (EBM) to adjust the mean and variance of the characteristic covariates for each sample individual.

[6] See Appendix A for specific steps and processes for PSM-DID.
[7] See Appendix B for specific steps and processes for EBM-DID.

On the basis of the adjusted data, we perform a weighted regression of formula (1). As shown in **Figure 8**, Test 2-3 shows that the confidence intervals of the NEMCC regression coefficients are greater than 0 at a 95% level of confidence, suggesting that the benchmark regression findings are robust.

(3) *Heckman two-stage model*. Referring to Zhang and Kong (2022), air circulation coefficient (ACC) is selected as the instrumental variable for NEMCC. On the one hand, there is a strong correlation between ACC and the quality of the air. Therefore, ACC significantly influences the government's environmental regulation and new energy development decisions, which meet the correlation requirement. On the other hand, ACC depends only on the natural geographic environment, with strong randomness and unpredictability, and has no direct correlation with the development of urban pollution reduction and carbon reduction, which meets the exogenous requirement. First, we constructed the Probit model, using instrumental variables and the control variables of formula (1) as independent variables, and NEMCC as dependent variable. In this way, we arrive at the inverse Mills ratio (IMR). Second, we added the IMR to control variables in formula (1) for regression estimation. According to **Table 6**, Column 2, the estimated coefficients for IMR are statistically significant, meaning that our study is subject to some degree of sample selection bias. It is statistically significant that NEMCC has a positive effect after controlling for IMR, excluding the influence of non-random sampling.

Table 6. Heckman two-stage model test.

Variables	(1)	(2)
	NEMCC	CCEA
ACC	0.0504***	
	(0.0174)	
NEMCC		45.3797***
		(15.1491)
IMR		-23.3380***

		(8.3910)
Constant	-6.5967***	42.0523
	(0.6113)	(41.0772)
Controls	YES	YES
City FE	NO	YES
Year FE	NO	YES
Nobs	3113	3113
R^2	0.0503	0.5737

Note: Same as **Table 5**.

5.3.5 Changing the estimation method

(1) *Double machine learning (DML)*. It is possible to solve the "curse of dimensionality" and multicollinearity problems with DML effectively (Chernozhukov et al., 2018). This paper divides the sample data into a test set and a training set on a 1:4 scale. Based on this, we estimate formula (1) using two machine learning algorithms: gradient ascent and lasso regression. Test 3-1-1 and Test 3-1-2 represent the NEMCC regression coefficients estimated by the two approaches. Both scenarios have 95% confidence intervals lie to the right of the 0 baseline for the NEMCC regression coefficients, which proves the baseline regression conclusions.

(2) *Synthetic DID (SDID)*. SDID reduces reliance on the parallel trend assumption and is applicable to any number of treated individuals (Clarke et al., 2024), combining the advantages of synthetic control methods and DID methods. In Stata, SDID estimation is currently implemented by Arkhangelsky et al. (2021) and Kranz (2022), respectively, by setting the SDID command parameters to "optimized" and "projected". These two methods estimate the regression coefficients of NEMCC as shown in Test 3-2-1 and Test 3-2-2. According to the results, all NEMCC regression coefficients are positively significant, suggesting that NEMCC is effective in reducing coordinated emissions.

5.3.6 Elimination of lag effect interference

The NEMCC may have different effects over time. Therefore, lagged effects are taken into account when estimating the regression. The outcomes are Test 4-1, Test 4-2, Test 4-3, and Test 4-4, which examine the effect of NEMCC lagged by 1 to 4 periods on CCEA separately. All regression coefficients proved to be significantly positive, confirming the robustness. Remarkably, the regression coefficient of NEMCC gradually increases from 4.3148 to 4.7642 as the number of lagged periods increases. This suggests that there is an incremental marginal effect of policy on the impact of NEMCC on the CCEA in the short run.

5.3.7 Considering the other interferences

(1) *Excluding contemporaneous policy shocks*. Regulations affecting the environment during the same period may also have an impact on regional synergistic emission reductions. To exclude the above confounding factors, we add the policy dummy and time dummy interaction terms for LCP, CET, and ATA, respectively, to formula (1). Further, we simultaneously include the interaction terms for the three competitive policies. For each of these practices, the NEMCC regression coefficient corresponds to Test 5-1-1, Test 5-1-2, Test 5-1-3, and Test 5-1-4. Based on the coefficients above, the benchmark regression proves to be robust at the 95% level.

(2) *Excluding contemporaneous external event shocks*. The NEMCC may be affected by a number of episodic events. As a consequence, we consider the potential impact on the benchmark regression results of the 2015 stock market disaster and the 2020-2022 COVID-19 epidemic. First, we exclude the 2015 sample; second, we retain only the 2009-2019 sample; and finally, we retain the 2009-2014 and 2016-2019 samples. The NEMCC regression coefficients for the three

practices are Test 5-2-1, Test 5-2-2, and Test 5-2-3. All three NEMCC regression coefficients are positive, and their 95% confidence intervals do not overlap with 0. This suggests that NEMCC significantly improves the CCEA.

5.4 Mechanism tests

The outcomes of the mechanistic analysis of NEMCC affecting the cost-effective synergistic emissions reduction are presented in **Table 7**.

Columns 1 to 3 reflect the mechanisms at the source prevention stage. At the 5% level, NEMCC significantly reduces LN_EC, indicating a reduction in urban energy demand as a result of its implementation. NEMCC promotes new energy consumption while reducing fossil fuel use. Since pollutants and GHGs are mainly dependent on fossil energy consumption, reducing fossil energy consumption contributes to CCEA. Firms in the pilot area are encouraged to pursue multiple pathways towards energy transition to stay competitive in the marketplace (Cheng et al., 2023). Due to the high fossil energy consumption in China, NEMCC demonstrates energy reduction effects in the pilot cities. To comply with the NEMCC's energy consumption requirements, some firms prefer to reduce fossil energy use rather than introduce new energy innovations when the costs are greater than the benefits (Huang et al., 2025b). This likewise contributes to the overall savings in energy consumption. NEMCC does not exhibit a significant effect on LN_GDP, suggesting that it does not exhibit any effect on production reduction. The NEMCC imposes a certain green transition cost on the pilot region, which may result in a reduction in production or even a shutdown (Huang et al., 2025b). Nevertheless, the results indicate that the pilot areas were effective in balancing green transformation with maintaining production scale, and were able to gradually transition energy use patterns. Furthermore, the NEMCC estimated coefficient on EE is negative, which is consistent with theoretical expectations, but does not meet the statistical significance threshold. However, NEMCC has not demonstrated a significant improvement in regional energy efficiency, which indicates that further progress is possible. In conclusion, the above results partially support Hypothesis 2, suggesting that NEMCC improves CCEA by promoting energy reduction.

Columns 4 and 5 reflect how NEMCC influences green technology innovation at the process control stage. As indicated by the regression coefficients of NEMCC on both LN_GPA and LN_GPAI, NEMCC is capable of promoting cities to implement green technology innovation, which can effectively increase CCEA. Green technology innovation has been shown to help in carbon emissions and pollution management (Zhang et al., 2023b; Habiba et al., 2022), thereby favorably affecting CCEA. The "compliance cost effect" and the "innovation compensation effect" explain the exact opposite of the influence of environmental regulations on CCEA (Porter and Linde, 1995; Zhang et al., 2024; Ouyang et al., 2020). However, this study found that the "innovation compensation effect" of the NEMCC is greater than the "compliance cost effect" of the NEMCC, providing empirical support for Porter's hypothesis. To achieve environmental protection and sustainability, NEMCC has developed a mature policy design framework to support green technological innovation. NEMCC has developed a mature policy framework to support green technological innovation, which contributes to economic growth and environmental protection. This analysis confirms Hypothesis 3.

Columns 6 to 9 demonstrate the relevant mechanism at the end-of-pipe stage, covering both the investment in abatement and carbon emission intensity. At least at the 10% level, there is statistical significance in the regression coefficients of NEMCC on LN_ECPC, PER_ECPC, and IN_ECPC. As an environmental regulatory policy, NEMCC critically assesses the environmental performance of cities. By investing in emission reduction and pollution control programs, local governments are able to eliminate environmental risks caused by irrational emissions of pollutants and GHGs (Deschenes et al., 2017). Remarkably, the regression coefficient of NEMCC on CEI is negative, in line with theoretical intuition, but insignificant at 10%. Indeed, this is in agreement with the results in Column 3 regarding NEMCC's effect on EE. Although NEMCC has introduced a number of measures to improve EE and CEI, the policy effect can still be improved. To promote CCEA, NEMCC should focus on improving EE and CEI in the future. Accordingly, Hypothesis 4 may partially be supported, suggesting that NEMCC improves CCEA by promoting increased investments in emission reduction and pollution control.

Table 7. Mechanism analysis results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Source prevention and control			Process control		End-of-pipe treatment			
	LN_EC	LN_GDP	EE	LN_GPA	LN_GPAI	LN_ECPC	PER_ECPC	IN_ECPC	CEI
NEMCC	-0.0937**	0.0203	-0.0134	0.1675***	0.2619***	0.1616***	0.1385**	0.1906*	-0.0060
	(0.0467)	(0.0123)	(0.0573)	(0.0641)	(0.0664)	(0.0616)	(0.0581)	(0.1091)	(0.0201)
Constant	3.0225***	6.3571***	-0.8765	-5.3206***	-9.2541***	-0.7665	-5.2090***	-0.8933	2.6101***
	(0.8139)	(0.418)	(1.3566)	(1.5744)	(1.6445)	(1.5848)	(1.6338)	(1.2734)	(0.6394)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Nobs	3328	3328	3328	3252	3252	3161	3161	3161	3447
R^2	0.9613	0.9954	0.8154	0.9558	0.9369	0.8485	0.7895	0.5022	0.9519

Note: Same as **Table 5**.

5.5 Moderating effect tests

5.5.1 Discussion of the moderating role of the digital economy

According to Section 4.2.4, we measure the three proxy variables DI, DPA, and DPL of the digital economy (DE). Then, this study estimates formula (3) (see Columns 1~3 of **Table 8** for results). The regression coefficients of the three interaction terms, NEMCC×DI, NEMCC×DPA, and NEMCC×DPL, are significantly positive, confirming that the DE positively facilitates the impact of NEMCC on CCEA. The result indicates that NEMCC promotes CCEA to a greater extent as the city's DE grows.

First, the DE reduces the marginal cost of technology diffusion (Colombelli et al., 2024). This promotes the widespread dissemination of new energy and other clean technologies among various stakeholders through the knowledge spillover effect of the DE, therefore facilitating CCEA. Second, the DE provides a platform for digital collaboration between multiple stakeholders (Wang et al., 2020a; Carballo et al., 2022; Babich and Hilary, 2020). In the pilot cities, enterprises can leverage the digital platform to develop, trade, and disseminate green, low-carbon products, services, and technologies, thus enhancing the facilitating effect of NEMCC on CCEA. Third, the DE enhances information transparency (Matheus et al., 2021; Li et al., 2020; Du et al., 2023). This helps enhance the social regulation of NEMCC and improves green technology innovation by increasing external attention to firms, thus enhancing CCEA. Fourth, the DE provides essential technical support for the collection, monitoring, and statistical evaluation of environmental information for the implementation of NEMCC, thus expanding its facilitating effect on CCEA.

5.5.2 Heterogeneity analysis of moderating effects

(1) *Influence of intellectual property protection*. Due to the low cost of imitation, digital technologies may facilitate infringement behaviors such as copying, plagiarism, and illegal monopolization (Teece, 2018). Infringements will hinder the dissemination of low-carbon

production technologies and reduce incentives for enterprise innovation (Schmiele, 2013), thus diminishing the regulatory role of the DE. On the one hand, intellectual property protection reduces the additional costs resulting from digital technology infringement (Guerriero, 2023). On the other hand, intellectual property protection provides a favorable innovation environment for talents and digital technologies (Zeng et al., 2023). Hence, the DE can play a more significant moderating role in regions with better intellectual property protection. According to Wang et al. (2023), this study computes the level of intellectual property protection in cities. According to the median, this study delineates the cities into high and low groups. Columns 4 and 5 of **Table 8** display that, at the 10% level, NEMCC × DI estimated coefficients of the high group are statistically significant. We further test the differences between the NEMCC × DI coefficients in Columns 4 and 5 by implementing the Chow test. The results show that the F-statistic is 3.97, which is statistically significant at 1% significance level, indicating that the coefficients between groups differ significantly. The results suggest that the moderating role of the DE varies across regions that have varying levels of intellectual property protection. Existing literature has clarified that the progression of digital technology depends heavily on intellectual property protection (Foster, 2024; Chen and Wu, 2022). Our results are consistent with these studies. Therefore, if the intellectual property protection system is improved, the DE can more effectively facilitate the influence of NEMCC on CCEA.

(2) *Influence of innovation environment*. The innovation environment includes key elements such as policies, funds, talents, markets, research platforms, etc., and serves as the fundamental support for digital technology innovation (Iden and Bygstad, 2024). On the one hand, the right innovation environment is able to induce various innovative factors to the region, thereby

enhancing the R&D capabilities and promoting the progression of the DE (Jiang et al., 2023). On the other hand, if an appropriate innovation environment is created, resources can be effectively allocated (Xu et al., 2024), thus promoting the DE's progressing. Therefore, when the city has a strong innovation environment, DE is able to moderate more effectively. Since the region's innovation output is primarily in the form of patents, this paper computes the city's innovation level as the natural logarithm of the number of patent applications. We then compute the median level of innovation and categorize cities into high and low groups. In **Table 8**, Columns 4 and 5 show that the estimated coefficients of NEMCC×DI for the high group are significant at the 5% level, while those for the low group are significant at the 10% level. Meanwhile, the Chow test results show that the F-statistic is 4.22 (P<0.001), indicating that there is a significant difference in the coefficients of NEMCC×DI in Columns 6 and 7. The results indicate that the variation in the innovation environment has a significant impact on the moderating effect of the DE. The DE can play a stronger moderating role in regions with better innovation environments. Studies have demonstrated that a vibrant innovation environment plays an essential role in promoting the growth of the urban DE (Liu et al., 2024a; Hinings et al., 2018). These studies support our findings.

Table 8. Results of the moderating effect analysis.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Intellectual property protection		Innovation environment	
				High	Low	High	Low
DI	-2.5165			-27.1583	37.9332	3.4202	-32.4525
	(15.3152)			(21.2390)	(23.6880)	(15.6977)	(27.5451)
NEMCC	-2.5651	-9.1935**	-7.6484*	-2.0710	-3.8397	-1.8804	-5.7746
	(3.0067)	(4.5940)	(4.2205)	(4.1095)	(4.2801)	(2.5035)	(4.9732)
NEMCC×DI	33.6426**			32.7633*	37.7278	28.1358**	50.7894*
	(15.6153)			(19.2471)	(25.9147)	(13.8833)	(30.5237)
DPA		0.4872					
		(0.6898)					
NEMCC×DPA		1.9497***					
		(0.6575)					

DPL			0.1877				
			(0.6731)				
NEMCC×DPL			1.8531***				
			(0.6491)				
Constant	-13.0225	-23.5080	-24.5858	79.7248	-88.0850*	-25.5005	24.3094
	(38.3755)	(34.9469)	(34.8767)	(61.3862)	(51.2607)	(50.8613)	(50.5855)
Controls	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Nobs	3102	3677	3677	1551	1551	1551	1551
R^2	0.5737	0.5435	0.5432	0.5880	0.5812	0.5919	0.5744
Chow test				3.97[<0.001]		4.22[<0.001]	

Note: The explanatory variables are CCEA. The values in [ ] are the P-values corresponding to the F-statistic in the Chow test. The rest is the same as **Table 5**.

5.6 Heterogeneity analysis

5.6.1 Geographical distribution heterogeneity

Many factors, including natural location, climate environment, and political and economic activities, have contributed to significant differences between northern and southern China regarding green development and technological innovation, which have attracted wide research attention (Fengbo et al., 2024; Wang et al., 2023b; Wei et al., 2023; Huang et al., 2021b). Based on existing research (Almond et al., 2009; Chen et al., 2025), we divided the urban samples into southern cities and northern cities according to the Qinling-Huaihe line in China and re-estimated the impact of NEMCC on CCEA. **Table 9** presents regression results for northern and southern cities in Columns 1 and 2. NEMCC's positive regression coefficient on CCEA is significant in southern cities, whereas it is not significant in northern cities. This suggests that southern cities seem to benefit more from the NEMCC's efforts to promote CCEA development. There is less market intervention by local governments in southern cities and their economies are more vibrant, open, and innovative (Xie et al., 2022). Despite the concentration of top universities in northern cities, many high-quality graduates choose to work in southern cities (Liang et al., 2021). The innovation base and potential of southern Chinese cities are greater than those of northern

Chinese cities. Thus, when the NEMCC is implemented, southern cities will be able to respond more quickly and flexibly to policy changes. Southern cities can efficiently mobilize production factors to promote the new energy project development, resulting in cost-effective synergistic emission reduction.

5.6.2 Human capital heterogeneity

Based on the percentage of students enrolled in general education to the total population, we determine the city's human capital level (HCL). Further, we categorize samples above the median level of human capital as high and those below as low. As shown in Columns 3 and 4 of **Table 9**, the regression coefficient of NEMCC on CCEA for the high HCL group is 5.7869 and is significant; the regression coefficient of NEMCC in the low group is 0.9298 but is not statistically significant. Accordingly, NEMCC's impact on CCEA is greater in cities with higher HCL. Increasing the efficiency and effectiveness of green technological transformations relies heavily on human capital (Jie et al., 2024). On the one hand, highly educated talents, as carriers of technological knowledge, are more skilled in acquiring, transforming, and utilizing knowledge (Sun et al., 2020). A higher level of human capital denotes that the city is more capable of absorbing, applying, and transforming NEMCC-related cutting-edge technological knowledge. Consequently, cities with high levels of human capital can more easily transform new energy technologies into practice, which in turn improves CCEA. On the other hand, higher HCL implies greater exchange and collaboration of high-tech talent within and outside the region (Huang et al., 2021a). Further enhancing the spillover effects of green technology innovations, it promotes the use of renewable resources in production, improving the CCEA.

5.6.3 Environmental regulation heterogeneity

As a proxy for environmental regulation intensity (ERI), we use the comprehensive utilization rate of general industrial solid waste. According to the median environmental regulatory intensity, we divide the sample cities into high and low groups. Columns 5 and 6 of **Table 9** present the regression results for high and low regulatory intensity groups. NEMCC has a positive effect on CCEA in the high group at least at 5%, and the direction is positive. As for the low group, the regression coefficient does not pass the test for statistical significance. According to the above results, the greater the ERI, the greater the facilitation effect of NEMCC on CCEA. Possibly, firms in cities with more stringent environmental managements invest more in green projects to achieve environmental goals such as pollution control and carbon reduction (Peng and Tao, 2022). For companies unable to meet stringent environmental requirements via traditional energy utilization and production methods, advanced technologies will be employed in order to reduce energy consumption and environmental emission, including the introduction of new energy-driven production facilities. In contrast, enterprises facing lax environmental regulations are less affected by the NEMCC and have less incentive to innovate in clean energy and green technologies, resulting in a less pronounced promotion of CCEA (Wu et al., 2020).

Table 9. Heterogeneity analysis results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	North or south areas		Human capital		Environmental regulation	
	North	South	High	Low	High	Low
NEMCC	3.8342	3.8776**	5.7869***	0.9298	4.3762**	3.5570
	(2.9538)	(1.6134)	(1.8649)	(2.2913)	(1.8689)	(2.1522)
Constant	10.7194	-104.8022	-71.3687	7.416	-16.5221	-30.1022
	(54.7306)	(66.3403)	(52.9503)	(48.161)	(58.9044)	(44.0204)
Controls	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Nobs	1261	2418	1846	1833	1846	1833
R^2	0.6084	0.4879	0.5311	0.5588	0.5056	0.5702
Chow test	2.76[<0.001]		2.44[<0.001]		1.60[<0.050]	

Note: The explanatory variables are CCEA. The values in [ ] are the P-values corresponding to the F-statistic in the Chow test. The rest is the same as **Table 5**.

6. Conclusions and policy implications

This study proposes a new method for calculating CCEA from a cost-effectiveness perspective. On this basis, we construct a DID model in order to examine the influence and mechanism of NEMCC on CCEA using 283 prefectural-level and above cities in China from 2009 to 2021. Results of the study indicate that: (1) From 2009 to 2011, the overall CCEA of Chinese cities gradually improved, with significant increases in both pollution reduction and carbon reduction effects, demonstrating synergistic effects. (2) NEMCC significantly promotes CCEA, and this conclusion passes the robustness test. (3) NEMCC improves CCEA by reducing energy consumption, promoting green technology innovation, and increasing investment in emission reduction and pollution control. (4) NEMCC has a stronger effect on CCEA enhancement in southern cities, cities with high human capital levels, and cities with tighter environmental regulatory initiatives. (5) The CCEA-boosting effect of NEMCC is amplified as cities' digital economy progression increases. The digital economy exerts a stronger moderating effect in cities with higher intellectual property protection and cities with better innovation environments.

The findings of this paper are valuable for improving the framework and promoting policies of NEMCC to achieve cost-effective synergistic emission reduction through new energy consumption. Our findings lead us to make the following policy recommendations:

First, NEMCC's overall design should be strengthened, and its scope should be systematically expanded. The government should create a replicable, improvable city case template based on the experience of successful NEMCC implementation. An emphasis should be placed on improving the institutional framework for NEMCC with respect to environmental performance assessment, the construction of reward and punishment mechanisms, and the development of a regulatory framework. Thus, relevant enterprises will be incentivized to take part in new energy production and consumption activities, thereby ensuring that pollution control and carbon reduction co-benefits are enhanced.

Second, place greater emphasis on the impact of NEMCC on the entire environmental management cycle. Results indicate that the NEMCC promotes energy savings and green technology innovation, which in turn impacts the cost-effective collaborative emission abatement. Therefore, we should accelerate the development of the renewable energy industry chain, promote the integration of renewable energy with traditional industries, and leverage the “energy reduction” effect. Meanwhile, enhance the incentive mechanisms for new energy innovation, such as tax incentives, financial subsidies, etc., to release the “innovation compensation” dividend of NEMCC. In addition, NEMCC can increase investment in emission reduction and pollution control, thus promoting synergistic emission reduction. Therefore, the implementation of NEMCC should be accompanied by an appropriate increase in environmental protection subsidies for enterprises in pilot cities to reduce the financial burden associated with purchasing environmental protection equipment and improving environmental protection processes.

Third, policies are expected to be differentiated according to urban conditions, thereby maximizing their marginal effects. According to our findings, the influence of NEMCC on CCEA varies across cities’ characteristics. Therefore, when improving and promoting NEMCC, city location, resource endowment, institutional foundation, and other development characteristics must be fully considered. For example, northern cities must promote the extent of openness to the outside world, market inclusiveness, and talent support to attract innovative resources for new energy technologies. For cities without adequate human capital, it is imperative to emphasize housing support, salary incentives, settlement policies, development platforms, etc., to formulate competitive talent policies and create a conducive talent ecology for new energy development. For cities with high energy consumption and high emissions, governments are expected to increase the strength of environmental regulations appropriately. Based on this, they should gradually phase out inefficient production capacity primarily powered by fossil fuels, increase new energy consumption, and enhance CCEA.

Fourth, to deeply empower NEMCC development with the digital economy. According to our findings, the DE strongly facilitates the impact of NEMCC on CCEA. Therefore, local governments should strengthen the R&D and application of digital technologies, expand the application scenarios of digital technologies, and promote the deep integration of NEMCC implementation with the DE. Additionally, we find that intellectual property protection and the innovation environment are crucial to fully utilizing the moderating role of the DE. Therefore, local governments should strengthen intellectual property legislation to provide protection for enterprise innovation and maximize the spillover effects of new energy and green technologies. Local governments must create a favorable innovation environment by providing preferential rents, tax reductions, and talent subsidies to attract enterprises and talent. Optimize the allocation of innovation factors by strengthening the joint development of industry-university-research and ensure NEMCC's digital technology support.

However, this study still has three limitations: first, we examined the impact of NEMCC on CCEA at the macro level of cities and could not explain the mechanism of action at the micro level of firms. Future studies could utilize the micro enterprise database for more in-depth analysis. Second, manufacturing, which contributes significantly to China's energy consumption, is more directly affected by NEMCC in terms of CCEA. There is a need for future studies to concentrate on the manufacturing industry for analysis and discussion, which will provide new perspectives for enhancing China's NEMCC framework and achieving cost-effective reductions in emissions. Third, the limitations of Chinese urban databases create obstacles for our research. For example, due to missing data, we are unable to further explore effectively the impact of NEMCC on urban fossil energy consumption and new energy consumption, and we don't consider other pollutants and GHGs (only $PM_{2.5}$ and CO_2) in the measure of CCEA. With the improvement of China's urban database, future studies can overcome the above problems.

Appendix A: The specific process of PSM-DID

We use the control variables from the baseline regression as covariates and applied a Logit model to calculate the propensity score for city i to be selected as a new energy demonstration city. Then, we use the following two methods for propensity score matching (PSM): (1) Radius matching. We searched for individuals matching within a radius of 0.01 for the samples from the treatment groups. (2) Kernel matching. This paper uses the default kernel function and bandwidth.

In this paper, we test the common support hypothesis through the propensity score common support domain bar chart (**Figure A.1**). Most of the observations are within the common range of values.

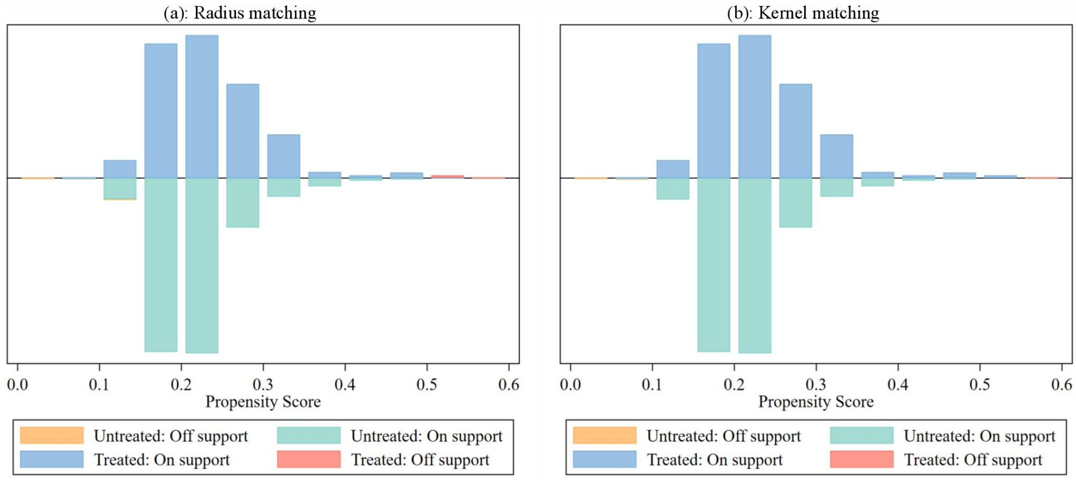

Fig. A.1 The common range of values for propensity scores.

Table A.1 demonstrates the final matching results for radius and kernel matching. According to the results, both methods lose 15 and 6 samples, respectively, and the vast majority of samples are retained, indicating that the matching is effective.

Table A.1. The results of PSM.

Group	Off support	On support	Total
Panel A: *Radius matching*			
Untreated	10	2863	2873
Treated	5	801	806
Total	15	3664	3679
Panel B: *Kernel matching*			
Untreated	5	2868	2873
Treated	1	805	806
Total	6	3673	3679

Table A.2 demonstrates the results of the balance test. Referring to Rosenbaum and Rubin (1985), it is recommended that the standard deviation after matching be less than 20% in order for the matching effect to be achieved. **Table A.2** demonstrates that the absolute values of the standard deviations of the matched variables after PSM are all within 10%. As a result of checking the T-test concomitant probability values, we discovered that the T-value is no longer significant after matching, indicating that the original hypothesis, i.e., the PSM, is valid. We re-estimate formula (1) using the matched samples, and the analysis is described in 5.3.4 (1).

Table A.2. Balance test results.

Variable	Sample	Mean		% Bias	%Reduction in bias	t-value
		Treated	Control			
Panel A: *Radius matching*						
ED	U	10.760	10.631	20.3	98.6	5.18***
	M	10.753	10.755	-0.3		-0.05
PD	U	5.821	5.708	12.2	97.9	3.02***
	M	5.815	5.818	-0.3		-0.05
UI	U	2.317	2.284	22.2	93.0	5.64***
	M	2.314	2.316	-1.6		-0.31
ES	U	13.320	13.083	26.4	96.7	6.84***
	M	13.300	13.292	0.9		0.17
MD	U	1.246	1.358	-7.9	93.1	-1.70*
	M	1.251	1.259	-0.5		-0.17
FD	U	2.632	2.391	19.3	89.5	5.07***
	M	2.603	2.629	-2.0		-0.37
Panel B: *Kernel matching*						
ED	U	10.760	10.631	20.3	80.3	5.18***
	M	10.758	10.733	4.0		0.80
PD	U	5.821	5.708	12.2	77.3	3.02***
	M	5.820	5.794	2.8		0.56
UI	U	2.317	2.284	22.2	78.0	5.64***
	M	2.316	2.309	4.9		0.96
ES	U	13.320	13.08	26.4	80.1	6.84***
	M	13.315	13.27	5.3		1.03
MD	U	1.246	1.358	-7.9	98.2	-1.70*
	M	1.248	1.246	0.1		0.05
FD	U	2.632	2.391	19.3	84.9	5.07***
	M	2.626	2.590	2.9		0.52

Note: U=Unmatched, M=Matched. * P<0.10， ** P<0.05， *** P<0.01.

Appendix B: The specific process of EBM-DID

This study uses the control variables from the baseline regression as covariates for EBM. **Table B.1** demonstrates the means and variances of covariates before and after matching. As can be seen, EBM eliminates the differences between untreated and treated control samples on each covariate. We re-estimate formula (1) using the matched samples, and the analysis is described in 5.3.4 (2).

Table B.1. Statistical characterization of covariates in EBM.

Variable	Mean			Variance			Standardized difference	
	Treated	Untreated		Treated	Untreated		U	M
		U	M		U	M		
ED	10.760	10.631	10.760	0.428	0.380	0.428	0.198	0.000
PD	5.821	5.708	5.821	0.798	0.904	0.798	0.126	0.000
UI	2.317	2.284	2.317	0.022	0.021	0.022	0.219	0.000
ES	13.320	13.083	13.320	0.896	0.714	0.896	0.250	0.000
MD	1.246	1.358	1.247	0.739	3.296	0.741	-0.130	0.000
FD	2.632	2.391	2.632	1.820	1.310	1.820	0.179	0.000

Note: U=Unmatched, M=Matched.

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