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Pricing for a low-carbon energy future: How China's Carbon Emissions Trading System drives eco-efficient power generation in China's coal-fired power industry.

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Keywords:	environmental economics, environmental policy innovation, environmental performance, business and society, business ethics
Abstract:	<p>Enhancing eco-efficient power generation is critical for sustainable energy transitions, especially in carbon-intensive coal-fired power sectors. This study leverages China's Carbon Emissions Trading Scheme (CETS) pilot program as a natural experiment to evaluate its impact on total factor power generation efficiency (TFPGE) in coal-fired power plants. Using an industry-level dataset covering 30 Chinese provinces from 2008 to 2019, we measure TFPGE via a super-efficiency slacks-based measure (SBM) data envelopment analysis (DEA) model, incorporating undesirable outputs like CO₂ emissions. Traditional difference-in-differences and multi-period difference-in-differences (DID) approaches are employed to assess the CETS's effect on TFPGE in pilot versus non-pilot provinces. Findings reveal: (1) a national TFPGE average of 0.9838, with regional variations (East: 1.0003, West: 0.9835, Central: 0.9676); (2) CETS significantly increases TFPGE by 2.9% in pilot regions, robust across tests; (3) the policy's impact is driven by enhanced resource commitment and clean combustion technologies, with stronger effects in western provinces (2.9% TFPGE increase) than central regions (1.7%), amplified by low thermal power dependency; (4) these results support Porter's hypothesis, showing carbon pricing fosters environmental commitment, innovation and efficiency. By highlighting regional heterogeneity, environmental commitment and technological mechanisms, this study addresses gaps in prior literature and offers policy insights for tailoring CETS to regional energy profiles and promoting clean technologies, advancing sustainable energy development in China and globally.</p>

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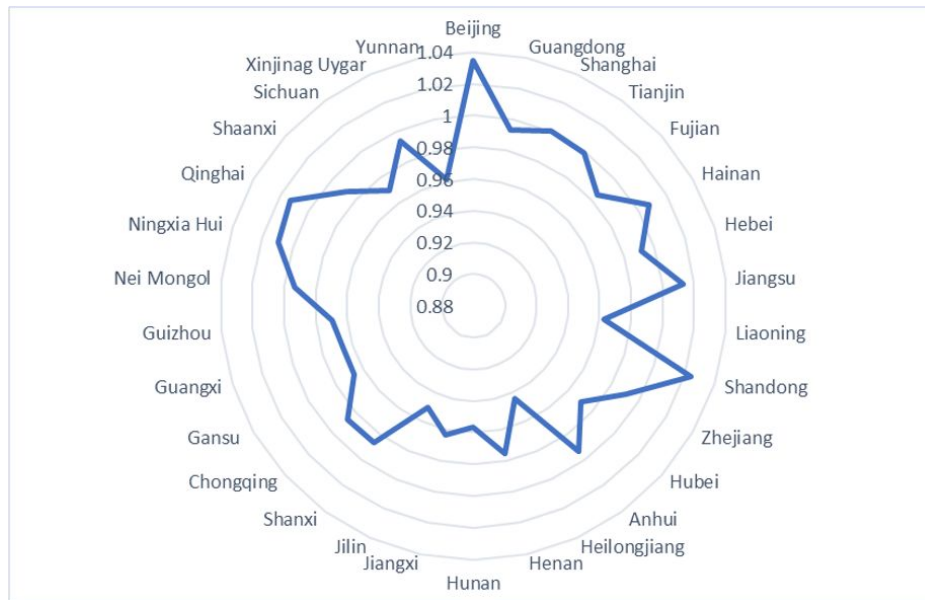


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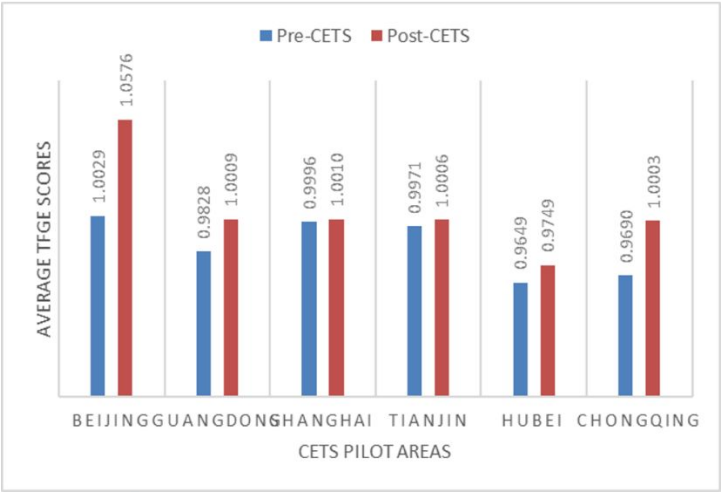


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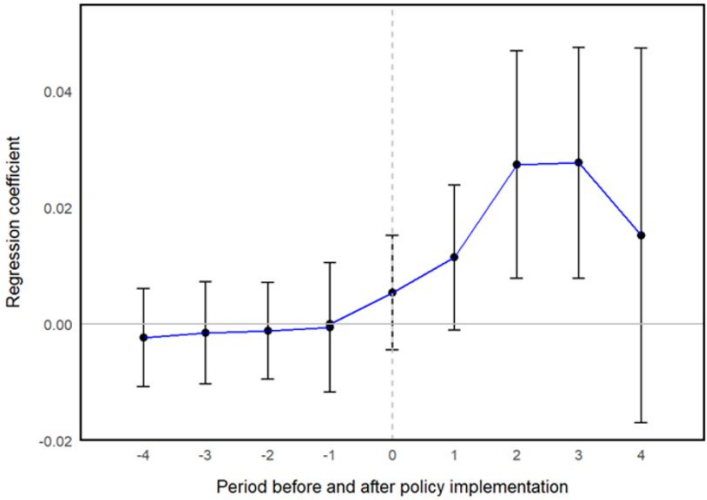


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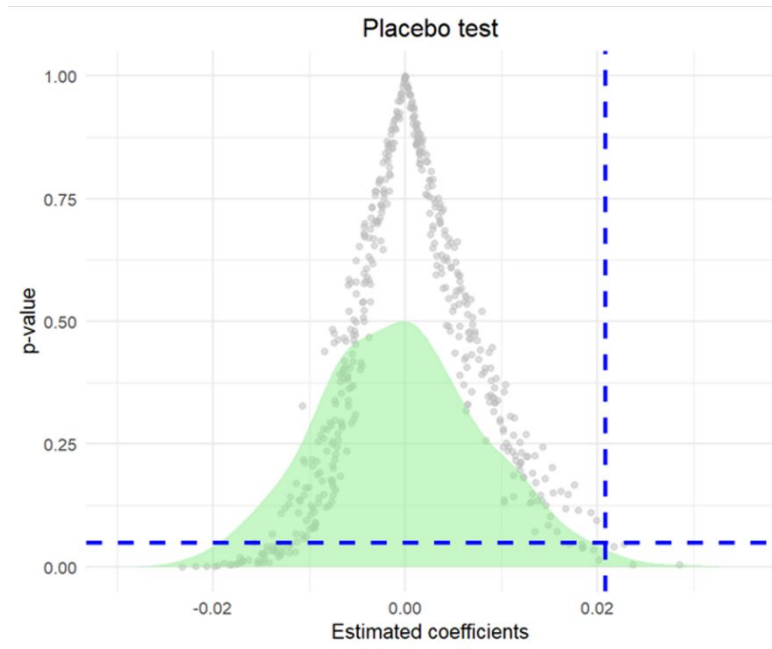


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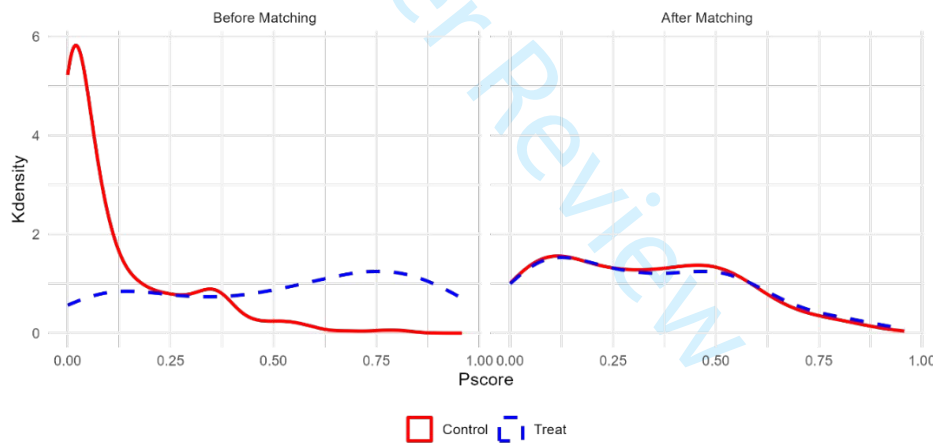


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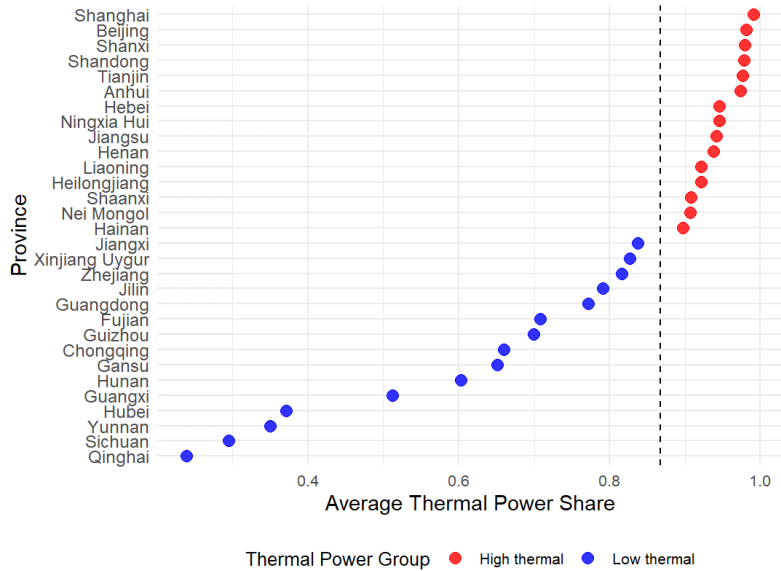


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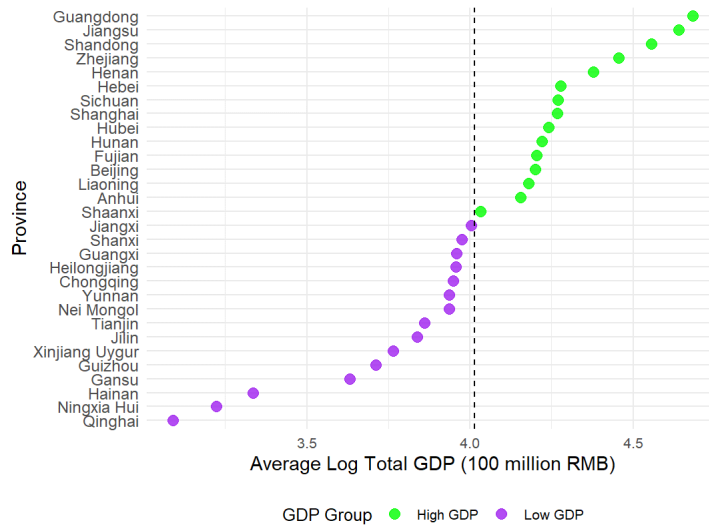


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Pricing for a low-carbon energy future: How China's Carbon Emissions Trading System drives eco-efficient power generation in China's coal-fired power industry.

ABSTRACT

Enhancing eco-efficient power generation is critical for sustainable energy transitions, especially in carbon-intensive coal-fired power sectors. This study leverages China's Carbon Emissions Trading Scheme (CETS) pilot program as a natural experiment to evaluate its impact on total factor power generation efficiency (TFPGE) in coal-fired power plants. Using an industry-level dataset covering 30 Chinese provinces from 2008 to 2019, we measure TFPGE via a super-efficiency slacks-based measure (SBM) data envelopment analysis (DEA) model, incorporating undesirable outputs like CO₂ emissions. Traditional difference-in-differences and multi-period difference-in-differences (DID) approaches are employed to assess the CETS's effect on TFPGE in pilot versus non-pilot provinces. Findings reveal: (1) a national TFPGE average of 0.9838, with regional variations (East: 1.0003, West: 0.9835, Central: 0.9676); (2) CETS significantly increases TFPGE by 2.9% in pilot regions, robust across tests; (3) the policy's impact is driven by enhanced resource commitment and clean combustion technologies, with stronger effects in western provinces (2.9% TFPGE increase) than central regions (1.7%), amplified by low thermal power dependency; (4) these results support Porter's hypothesis, showing carbon pricing fosters environmental commitment, innovation and efficiency. By highlighting regional heterogeneity, environmental commitment and technological mechanisms, this study addresses gaps in prior literature and offers policy insights for tailoring CETS to regional energy profiles and promoting clean technologies, advancing sustainable energy development in China and globally.

Keywords: Total factor Power generation efficiency; Carbon emission trading system, Coal-fired power; Environmental resource commitment; Clean combustion technology innovation; Energy structure upgrading

1. INTRODUCTION

The power sector, vital for economic and social stability, is a major driver of global carbon emissions through fossil fuel-based generation, contributing to climate change, pollution, and ecosystem degradation (Nakaishi et al., 2021; W. Wei et al., 2023). Global temperatures are projected to exceed the Paris Agreement’s 1.5°C target, with the International Energy Agency’s 2024 Electricity Outlook reporting a 1% rise in power sector CO2 emissions in 2024, following a 1.4% increase in 2023, driven by a 1.3% growth in fossil fuel generation amid a 4.3% surge in electricity demand, totalling 13,800 million tons of CO2. ¹ Coal-fired power, which accounted for 44% of global CO2 emissions from electricity and heat generation in 2022, ² also contributes significantly to air pollutants, producing 75% of SO2, 70% of NOx, and 90% of PM2.5 emissions in 2016 (Nakaishi et al., 2023). With emissions projected to grow by 62% from 2011 to 2050, led by China and India (Kabeyi & Olanrewaju, 2022), transitioning to cleaner energy is critical to meet

¹ See <https://www.iea.org/reports/electricity-2025>

² See <https://www.iea.org/data-and-statistics/data-tools/greenhouse-gas-emissions-from-energy-data-explorer>

the Paris Agreement's 1.5°C target. Improving Total Factor Power Generation Efficiency (TFPGE), which measures how efficiently power plants use resources while minimizing environmental impact, is a key strategy to reduce emissions while meeting rising energy demand. However, high costs and uncertain returns often hinder innovation (Sun et al., 2023a). Market-based policies, such as carbon emissions trading, can incentivize efficiency gains through innovation, as suggested by the Porter Hypothesis (Strielkowski et al., 2021; Y. Wei et al., 2024), yet their impact in coal-intensive sectors remains underexplored, particularly across diverse regional contexts.

China, the world's largest energy consumer and carbon emitter, faces severe environmental challenges driven by its coal-dominated power sector (L. Xie et al., 2022; G.-X. Zhang et al., 2023). According to the International Energy Agency, in 2022, China's CO₂ emissions from fuel combustion reached 10,613 Mt, with coal accounting for 79% of this total³. Coal-fired power, supplying 67.1% of electricity in 2017 compared to a global average of 38.1%, is marked by low efficiency and high emissions, contributing to pollution and resource depletion (Fang et al., 2022; Thakare & Daspute, 2024; X. Wang & Li, 2021; Q. Wu et al., 2023). While transitioning to renewables is essential to address global warming and energy challenges (Y. Liu & Feng, 2023), current renewable capacity remains insufficient to meet demand (Feng et al., 2022). Consequently, improving TFPGE is critical for reducing emissions, ensuring energy security, and achieving China's carbon peak and neutrality goals (Tang et al., 2023; Y. Wei et al., 2022). Given

³ See <https://www.iea.org/countries/china/emissions#what-are-the-main-sources-of-co2-emissions-in-china>

diverse regional energy profiles, tailored policies like the Carbon Emissions Trading System (CETS) are essential to enhance TFPGE and support China’s carbon peak (2030) and neutrality (2060) goals

Transitioning to clean energy is essential for China to meet its carbon peak by 2030 and neutrality by 2060, aligning with the Paris Agreement’s target of reducing per capita CO₂ emissions by 60–65% from 2005 levels by 2030, as outlined in the 13th Five-Year Plan (F. Dong et al., 2024). China is advancing green energy markets through robust policies (W. Wei et al., 2023), with the Carbon Emissions Trading System (CETS), launched in 2013, emerging as a cost-effective tool to enhance energy efficiency and innovation by making polluters pay for emissions (M. Liu et al., 2022; Pu & Ouyang, 2023; Q. Wu et al., 2023; N. Zhang & Wang, 2024). Implemented in seven high-emission regions, including power and steel sectors, CETS’s varied regional carbon prices and rules create a natural policy experiment. While studies have examined CETS’s effects on environmental governance (Luo et al., 2023), innovation (M. Liu et al., 2022; Pu & Ouyang, 2023; S. Ren et al., 2022), economic growth (S. Wu, 2023), and structural shifts (Ma et al., 2023; J. Wu et al., 2023), its impact on TFPGE in the coal-fired power sector remains underexplored. This gap is critical, as the coal sector’s high emissions intensity makes it a key target for decarbonization, yet the efficiency benefits of carbon pricing are unclear. This study addresses this gap by investigating how CETS influences TFPGE, exploring regional variations and innovation mechanisms.

Examining the link between China’s CETS pilot program and TFPGE in the coal-fired power industry is critical for understanding how carbon pricing can support China’s energy transition. TFPGE, a measure of how efficiently power plants use resources while minimizing environmental impact, is enhanced by well-designed policies that drive technological innovation

and energy upgrades. This study tests Porter's weak hypothesis in a coal-dependent context, where the weak form predicts CETS fosters green innovation (e.g., clean combustion technologies) and thus improvements in total factor productivity (Yu et al., 2024). While carbon pricing is recognized for reducing emissions (Tello, 2025), its efficiency impacts are debated, with some studies citing innovation-driven gains (R. Chen et al., 2024; Q. Wu & Wang, 2022; Yu et al., 2024), and others noting trade-offs like resource diversion (Sun et al., 2023a) or innovation suppression (Xin-gang et al., 2025a). Moreover, prior research often overlooks CETS's regional variations and mechanisms like environmental resource commitment and clean combustion technologies. Our study addresses these gaps by analysing CETS's impact on TFPGE, its mediating mechanisms, and its regional heterogeneity, offering insights for tailoring carbon pricing to diverse regional contexts. Specifically, our study aims to answer the following questions:

- (1) How does the CETS pilot policy impact TFPGE in China's coal-fired power industry, and to what extent do regional variations influence this relationship?
- (2) What role do resource commitment and clean combustion technology innovations play in mediating the relationship between the CETS pilot policy and TFPGE in China's coal-fired power industry?
- (3) Does Porter's weak hypothesis hold in the context of the CETS pilot policy's impact on TFPGE in China's coal-fired power industry, particularly in regions with varying energy structures?

To address these questions, this study employs a quasi-natural experiment, leveraging the official rollout of the CETS pilot policy as an exogenous event, and applies difference-in-differences (DID) and multi-period difference-in-differences approaches to evaluate its impact on TFPGE. The analysis draws on an industry-level dataset from the coal-fired power sector across

30 provinces and cities in mainland China (excluding Tibet Autonomous Region) from 2008 to 2019, a period that captures the pre- and post-CETS pilot implementation phases. Using a super-efficiency slacks-based measure (SBM) model integrated with data envelopment analysis (DEA), we calculate TFPGE to assess efficiency while accounting for environmental constraints. The findings reveal several key insights:

First, the national average TFPGE is 0.9838, with regional variations: the East leads at 1.0003, followed by the West at 0.9835, while the Central region lags at 0.9676, due to its heavy coal reliance and slower technology adoption. **Second**, using a Super-efficiency SBM-DEA model, a traditional differences-in-differences (DID), and a multi-period DID accounting for staggered CETS rollouts, we find that the CETS pilot policy modestly improves TFPGE by 2.90% in pilot regions, a result robust to multiple robustness checks, including a parallel trend test, placebo tests, propensity score matching DID (PSM-DID) model, dynamic time window test, quantile regression, and exclusion of specific samples, highlighting the policy’s role in decarbonizing a critical sector. **Third**, the policy’s effect is mediated by enhanced environmental resource commitment (e.g., investments in efficiency infrastructure) and advanced combustion technologies (e.g., ultra-supercritical systems), which improve efficiency and reduce emissions, offering partial support for Porter’s hypothesis, particularly its innovation-driven weak form. **Fourth**, heterogeneity analysis shows CETS is more effective in the West (2.9% TFPGE increase) and East (2.5%) than the Central region (1.7%), reflecting differences in coal dependency and policy enforcement, with stronger gains in low thermal power share regions (2.6%) versus high thermal power share areas (1.46%). These results underscore the role of regional energy profiles in shaping policy outcomes, suggesting region-specific carbon pricing and technology incentives to enhance TFPGE and support sustainable energy transitions.

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3 This study offers three key contributions to environmental planning and management,
4 focusing on carbon pricing and energy efficiency in China's coal-fired power sector.
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8 **First**, it advances the understanding of Total Factor Power Generation Efficiency (TFPGE)
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10 by showing that the CETS pilot policy modestly improves TFPGE by 2.90% in pilot regions, with
11 regional variations: 2.9% in the West, 2.5% in the East, and 1.7% in the Central region, reflecting
12 differences in coal reliance and policy enforcement. While prior studies have explored CETS's
13 role in environmental governance (Cao et al., 2021; X. Li et al., 2024; Q. Wu et al., 2023), they
14 often overlook its impact on efficiency metrics like TFPGE in the coal-fired power sector—a
15 critical area given its dominance in China's energy mix and emissions profile. By focusing on
16 regional heterogeneity, this study offers a fresh perspective on how carbon pricing can be
17 leveraged to improve efficiency, addressing a gap in the literature and providing a foundation for
18 more targeted environmental policies.
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31 **Second**, it enriches the theoretical discourse on environmental regulations by offering
32 partial support for Porter's hypothesis in China's coal-fired power sector. Our findings, supported
33 by instrumental variable analysis, show that CETS drives TFPGE through enhanced environmental
34 resource commitment (e.g., investments in efficiency infrastructure) and advanced combustion
35 technologies (e.g., ultra-supercritical systems), yielding ecological and economic benefits. This
36 contrasts with studies suggesting regulatory trade-offs (Sun et al., 2023b; Xin-gang et al., 2025a)
37 and aligns with innovation-driven gains (R. Chen et al., 2024; Q. Wu & Wang, 2022). By
38 examining industrial structure variations (e.g., 2.6% TFPGE increase in regions with less coal
39 reliance vs. 1.46% in high coal-reliance regions), we contribute to the debate on carbon pricing's
40 "win-win" potential, though profitability impacts remain beyond this study's scope.
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Third, the study provides actionable policy insights by identifying mechanisms and contextual factors that enhance CETS’s effectiveness. It demonstrates that environmental resource commitment and clean combustion technology are key mediators of the CETS-TFPGE relationship, suggesting a clear pathway for policy interventions to enhance resource commitment towards environmental initiatives and promote technologies like ultra-supercritical systems. Additionally, the study’s focus on regional and structural heterogeneity—stronger TFPGE gains in regions with less coal dependency—offers a framework for tailoring CETS implementation, such as raising carbon price floors in high coal-reliance regions like the Central region to boost TFPGE. These strategies support sustainable energy transitions in China and other coal-dependent economies, addressing disparities in efficiency gains.

The remainder of this paper is organized as follows: Section “**Literature review**” presents a literature review. Section “**Data and Methodology**” introduces the research methods and data sources. Section “**Analysis and Results**” presents our main results. Section “**Discussion**” presents our discussion. Section “**Conclusion and Policy Implications**” and Section “**Limitations and Future Directions**” provide conclusions, policy implications, limitations, and future directions of this study.

2. LITERATURE REVIEW

2.1 Total Factor Power Generation Efficiency

Eco-efficient power generation is vital for energy conservation, emission reduction, and sustainability (X. Wang et al., 2022). Ignoring greenhouse gas constraints misaligns with China’s “carbon peak” goals in thermal power (Jiang et al., 2024). Researchers now include undesirable outputs like CO2 in efficiency assessments to balance economic and environmental goals (Fang et

al., 2022; Jiang et al., 2024; Thakare & Daspute, 2024). Data Envelopment Analysis (DEA), a nonparametric method, is widely used to measure power generation efficiency (M. Meng & Pang, 2023; Yadava et al., 2025).

Early studies measured generation efficiency via standard coal consumption per kWh, reflecting technological and managerial levels but ignoring non-energy inputs like labor and capital (M. Meng & Pang, 2023). Total Factor Power Generation Efficiency (TFPGE) emerged to comprehensively assess efficiency, incorporating multiple inputs and outputs. Studies like (J. Wang & Wang, 2023) used super-efficiency SBM-DEA to evaluate electricity market reforms' impact on energy efficiency across 30 provinces (2010–2019), while (Nakaishi et al., 2021) assessed 104 coal plants' environmental efficiency in 2010. (Tang et al., 2023) analyzed ultra-low emission standards' effects on thermal power productivity (2010–2018). These highlight socioeconomic and environmental influences on operations, though fixed inputs like capital limit short-term policy impacts (Feng et al., 2022; M. Meng et al., 2023; Q. Wu et al., 2023).

Studies identify key drivers of Total Factor Power Generation Efficiency (TFPGE), including technological progress, trade openness, urbanization, industrial structure, government investment, and low-carbon policies (Eguchi et al., 2021; Jiang et al., 2024; Nakaishi et al., 2022; Tang et al., 2023; J. Wang & Wang, 2023; W. Wei et al., 2023). Technological innovation is the primary driver (Y. Pan et al., 2024). (Eguchi et al., 2021) emphasized technology and coal quality for efficiency in China's coal plants (2009–2011), while (H. Zhang & Wu, 2022) highlighted green technology and renewables. (Y. Pan et al., 2024) found technological and scale efficiency boosted production efficiency in 15 eastern power firms (2016–2020). (F. Dong et al., 2024) confirmed technological progress drives environmental efficiency across 30 provinces. (Jiang et al., 2024) noted efficiency gains in eastern and central regions, with technical efficiency rising in the west

(2013–2017). Regional economic growth and resource disparities enhance thermal power efficiency (Feng et al., 2022; Jindal et al., 2024; F. Ren et al., 2025). Installed capacity growth impacts environmental performance (B.-C. Xie et al., 2021), while management efficiency is vital, and weak organizational structures hinder progress (Nakaishi et al., 2021; Yadava et al., 2025).

Environmental regulations, such as electricity market reforms, ultra-low emission standards, environmental taxes, and carbon pricing, aim to reduce environmental degradation and promote sustainability (Jin et al., 2024). Their impact on power sector efficiency varies. (J. Wang & Wang, 2023) found that market reforms improved energy efficiency across 30 Chinese provinces (2010–2019). (Nakaishi et al., 2023) reported enhanced environmental efficiency in 316 coal plants in 2010. However, ultra-low emission standards can reduce productivity due to high compliance costs (Tang et al., 2023). Despite these insights, limited research explores China’s CETS impact on TFPGE in the coal-fired power sector, despite its significant emissions. Regional variations in economic development, energy structures, and mechanisms like environmental resource commitment and clean combustion technology remain underexplored. This study investigates CETS’s influence on TFPGE, focusing on regional heterogeneity, environmental commitment, and technological innovation, providing insights into carbon pricing’s effect on efficiency.

2.2 Policy background and theoretical hypothesis

2.2.1 China’s CETS pilot policy

China’s CETS, designed to achieve climate change mitigation goals, emerged as a cost-effective alternative to traditional regulatory approaches during the Twelfth Five-Year Plan (2011–2016) (Bian et al., 2024). Officially launched on October 29, 2011, by the National Development and

Reform Commission, the CETS pilot policy began its first phase in 2013 across seven regions—Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen—primarily targeting high-emission sectors like power generation (Y. Wei et al., 2022). These regions implemented distinct carbon trading systems, creating a quasi-experimental setting ideal for policy evaluation (N. Zhang & Wang, 2024). By January 2021, the Ministry of Ecology and Environment initiated the national ETS trial phase, focusing on fossil fuel power generation and covering over 2,000 emitters and 4 billion tons of CO₂, making it the world's largest ETS. The system enforces government oversight through emissions tracking and verification, promoting accountability and incentivizing decarbonization in the power sector (Ma et al., 2023; N. Zhang & Wang, 2024). As a market-driven policy, the ETS is crucial for decarbonizing China's power sector and achieving national climate goals (Cao et al., 2021; Y. Wei et al., 2022), making its impact a vital research focus.

2.2.1.1 Research on the policy effects of China's CETS pilot policy

China's CETS pilot policy, reflecting global carbon market characteristics, spans diverse industries, significant greenhouse gas emissions, and varying regional carbon intensities, playing a pivotal role in achieving the country's carbon neutrality goals (Cong et al., 2024; Q. Wu & Wang, 2022). Existing research confirms the CETS's effectiveness in promoting decarbonization and efficiency gains. For instance, (G. Li et al., 2023) found that while the CETS advances decarbonization in the power sector, a rebound effect (0.186–0.866) partially offsets these gains, with lower carbon prices exacerbating this effect, highlighting the need for optimized pricing strategies. Similarly, (H. Zhang & Wu, 2022) demonstrated that the CETS significantly enhances energy conservation and emission reductions in pilot regions, while (N. Zhang & Wang, 2024)

reported a 0.043 increase in energy efficiency for ETS-participating plants compared to non-ETS ones. Furthermore, (B.-C. Xie et al., 2021) showed that CETS pilots improved the dynamic environmental efficiency of power generation firms in competitive markets. Despite these insights, the literature on environmental regulations and total factor productivity reveals mixed findings, particularly for market-based tools like the CETS, with limited focus on its impact on TFPGE in the coal-fired power sector—a critical gap given the sector’s dominance in China’s emissions profile. This study addresses this gap by examining the CETS’s influence on TFPGE, incorporating regional heterogeneity, environmental resource commitment, and clean combustion technology innovation as mediating mechanisms, and the moderating role of energy. This novel conceptual framework offers significant theoretical contributions to environmental and energy economics while providing practical insights for designing effective carbon pricing strategies to enhance efficiency in carbon-intensive industries.

2.2.2 Research hypothesis

CETS policy has proved to be a cost-effective and significant market-based environmental regulation in China. The CETS policy drives carbon reduction by encouraging enterprises to invest in cleaner production, fostering sustainable economic growth (Bai & Ru, 2024; X. Pan et al., 2022). It mitigates conflicts between economic development and environmental pollution (Bian et al., 2024) by incentivizing coal-fired power firms to adjust processes, reducing carbon permit costs, and enhancing efficiency. Thus, we hypothesize the following.

Hypothesis 1: CETS improves the TFPGE of coal-fired power plants in the pilot areas.

This study explores CETS policy mechanisms, examining the mediating effects of environmental resource commitment at the regional level, clean combustion technology innovation, and the moderating effect of industrial structure upgrading.

2.2.2.1 The mediating effect of environmental resource commitment at the local government level

A strong resource base is essential for achieving environmental policy goals, signalling commitment to sustainability (Cho et al., 2023). The resource-based view posits that strategic resource allocation creates lasting benefits, boosting performance (Bendig et al., 2023). Resource advantage theory emphasizes that leveraging resources drives innovation (Varadarajan, 2023). In modern firms, environmental commitments are core strategies, with resource allocation supporting sustainable practices (Y. Li, 2014). Firms with robust ESG strategies innovate to enhance efficiency and cut emissions, as shown in a study of 5,102 Chinese firms from 2006 to 2021 (Kenneth David et al., 2024).

Improving efficiency in the coal-fired power sector is costly and risky, requiring government support (Kabeyi & Olanrewaju, 2022). This study examines how local government Environmental Resource Commitment (ERC), measured as provincial environmental policy efforts and green technology investments, mediates the effect of the CETS on TFPGE. Per Porter's hypothesis, CETS encourages provinces to increase ERC through green energy practices, enhancing efficiency and reducing emissions. Provinces with high ERC often have robust monitoring and enforcement systems, ensuring more efficient power plant operations and better TFPGE outcomes due to prior investments in infrastructure and policies (D. Wang et al., 2024). Research shows that CETS enhances R&D intensity and fixed-asset investment efficiency in

regulated firms, curbing wasteful spending (H. Dong et al., 2022), while local government penalties further drive green technology innovation (Ou et al., 2024). Strong ERC enables effective management of the carbon market, including setting quotas and providing guidance, encouraging compliance among regulated power plants, and motivating non-targeted power plants to engage in carbon trading. This, in turn, sustains investments in emission-reducing technologies, boosting TFPGE in the regional coal-fired power sector. We propose that ERC significantly mediates the CETS policy’s impact on improving TFPGE. Given this, this paper proposes:

Hypothesis 2: CETS enhances TFPGE through the mediating effect of increased local government ERC.

2.2.2.2 The mediation effect of Clean Combustion Technology Innovation

Green development, driven by innovation, transforms industries by boosting efficiency and sustainability (Ou et al., 2024). In the energy sector, innovations lower renewable energy costs and enhance efficiency, supporting cleaner production (Sohag et al., 2024). For Chinese coal power firms, green technology innovation is vital to meet carbon reduction targets and advance China’s 2030/2060 goals, while strengthening competitiveness (Ou et al., 2024; Thakare & Daspute, 2024; Q. Wu et al., 2023). CETS channels capital to sustainable sectors through clear price signals, promoting clean energy technologies (D. Wang et al., 2024). Porter’s hypothesis, aligned with the resource-based view theory, posits that well-designed regulations like CETS drive innovation, enhancing efficiency and reducing emissions (Yu et al., 2024).

Despite neoclassical arguments that CETS raises production costs and limits innovation (W. Zhang et al., 2022), long-term carbon market incentives increase research investment, fostering green technology innovation and efficiency (Fan et al., 2023; Sun et al., 2023a; D. Wang

et al., 2024). CETS encourages firms to invest in low-carbon energy technology innovation, improving plant operations and reducing emissions (D. Wang et al., 2024). Firms can offset compliance costs through cleaner production technologies, leveraging an innovation compensation effect (J. Zhu et al., 2019). Studies confirm CETS's positive impact on innovation: (Cong et al., 2024) found that the carbon market significantly boosts green technology innovation in high-energy industries across 209 Chinese cities (2006–2017), particularly in the power sector, while (D. Wang et al., 2024) highlight its role in increasing R&D intensity. Additionally, (X. Meng & Yu, 2023). Focusing on clean combustion technology innovation (CCTI), such as combined heat and power systems and oxy-fuel combustion, this study examines CCTI's mediating role in CETS's effectiveness in improving TFPGE in coal-fired power plants, proposing that these technologies enhance combustion efficiency, reduce emissions, and directly elevate TFPGE. Thus, we propose:

Hypothesis 3: CETS enhances TFPGE through the mediating effect of increased CCTI.

2.2.2.3 The moderating effect of Energy Structure Upgrading

China's secondary industry, a major driver of energy consumption and carbon emissions, poses challenges to energy efficiency goals (K. Du et al., 2021). Shifting to cleaner energy structures is critical for enhancing TFPGE. Environmental regulations, like the CETS, guide industries toward low-carbon alternatives by promoting clean energy and reducing coal dependency (F. Chen et al., 2024). CETS's carbon reduction targets encourage coal-fired power plants to adopt practices like renewable energy integration or advanced clean energy methods, cutting emissions and fossil fuel use (Bai & Ru, 2024). Per Porter's hypothesis, such regulations amplify efficiency gains in regions with advanced industrial structures, as they leverage existing low-carbon infrastructure to respond

to carbon pricing (H. Zhang & Wu, 2022). Thus, we propose:

Hypothesis 4: The effect of CETS on TFPGE is stronger in regions with greater energy structure upgrading, measured as increased renewable energy share and reduced coal reliance.

3. METHODS

3.1 Variable Construction and Data Sources

3.1.1 Variable Construction

3.1.1.1 Dependent Variable

Our dependent variable, TFPGE, measures the resource-efficient production of electricity in China’s coal-fired power sector while accounting for environmental impacts, such as CO2 emissions. TFPGE is commonly assessed using DEA models due to their ability to handle multiple inputs and outputs without assuming a specific production function (M. Meng & Pang, 2023).

3.1.1.1.1 Data envelopment analysis (DEA) model development

In production theory, efficiency evaluation uses parametric (e.g., Stochastic Frontier Analysis) and non-parametric methods like Data Envelopment Analysis (DEA) (G. Li et al., 2022). DEA, a non-parametric approach, assesses decision-making units (DMUs) by constructing a production frontier, ideal for complex input-output relationships in the coal sector (Banker et al., 1984; Charnes et al., 1978). Unlike SFA, DEA requires no functional form assumptions, handles multiple inputs (e.g., capital, labor) and outputs (e.g., electricity, CO2), and is unit-invariant (Fang et al.,

2022; Q. Xie et al., 2021; Y. Zhu et al., 2022). The BCC model, an advancement over the CCR model, accounts for variable returns to scale, separating pure technical and scale efficiency (Banker et al., 1984; Yadava et al., 2025). DEA has been widely applied in power sector studies. (Y. Pan et al., 2024) evaluated 15 eastern Chinese power firms (2016–2020) using a model with undesirable outputs and the Malmquist-Luenberger index. (B.-C. Xie et al., 2021) combined DEA game cross-efficiency with the Malmquist index for 18 firms (2007–2016). (Feng et al., 2022) used the Super-DDF model for thermal power efficiency across 30 provinces (2013–2017). (Eguchi et al., 2021) and (F. Dong et al., 2024) applied meta-frontier DEA to analyze coal power inefficiencies and environmental efficiency, respectively.

Traditional DEA models (e.g., CCR, BCC) often overestimate efficiency by ignoring input/output slacks and struggle to differentiate efficient decision-making units (DMUs) (Nakaishi et al., 2021; Tone, 2001). They also assume deterministic data, overlooking real-world variability (Jin et al., 2024). To address these issues, (Tone, 2001) developed the Slack-Based Measure (SBM) DEA model, a non-radial approach that accounts for slacks, providing a more accurate efficiency measure. The SBM model was adapted to handle undesirable outputs like CO₂, making it suitable for evaluating Total Factor Power Generation Efficiency (TFPGE) under China's Carbon Emissions Trading Scheme (CETS) (J. Du et al., 2010; Tone, 2002). However, it still faces challenges in distinguishing efficient DMUs, leading to the super-efficiency SBM-DEA model, which removes efficient DMUs from the frontier, allowing scores above 1 for finer comparisons among high-performing coal plants (Fang et al., 2022; Tone, 2002). Studies applying SBM-DEA include (J. Wang & Wang, 2023), who analyzed electricity market reforms across 30 Chinese provinces (2010–2019), (Nakaishi et al., 2021), who assessed 104 coal plants, and (Shu et al., 2024), who evaluated global energy efficiency across 168 economies (2000–2017).

Recognizing the key role of environmental pollution in evaluating power generation efficiency, we adopt the static super-efficiency SBM-DEA model, which accounts for undesirable outputs, to measure TFPGE of China’s regional coal-fired power sector from 2008 to 2019, aligning with prior coal sector studies. This approach supports our study’s objectives by measuring TFPGE’s response to CETS-driven innovations (e.g., ultra-supercritical combustion systems via CCTI) and environmental resource commitment (e.g., ERC), while capturing regional variations in energy structure upgrading. For policymakers, super-efficiency SBM-DEA reveals how coal plants can produce power efficiently while reducing emissions, informing CETS optimization. To assess TFPGE, the DEA model can be described as follows. Each province and city is treated as $DMU_j (j = 1, 2, \dots, n)$ with m input elements $x_{ij} (i = 1, 2, \dots, m)$, s_1 desirable output element $y_{rj} (r = 1, 2, \dots, s_1)$ and s_2 undesirable output element $z_g (g = 1, 2, \dots, s_2)$. This study adopts a technology production set with variable returns to scale and an input-output orientation. Therefore, the production possibility set for all DMUs considering undesirable outputs, can be represented as:

$$P = \{(x,y,z)|x \geq X\lambda, y \leq Y\lambda, z \geq Z\lambda, \lambda \geq 0\} \tag{1}$$

where λ represents a constant vector. In the super-efficiency DEA model, the production set must exclude a particular DMU $(x_0y_0z_0)$ to create an updated production set, defined as follows:

$$P' \setminus (x_0y_0z_0) = \{(\bar{x}, \bar{y}, \bar{z})|\bar{x} \geq X\lambda, \bar{y} \leq Y\lambda, \bar{z} \geq Z\lambda, \lambda \geq 0\} \tag{2}$$

The above production set shows that, under identical conditions, the inputs of any DMU are at least as large as the collective inputs of all the other DMUs, the desirable outputs do not

exceed the collective desirable outputs of all other DMUs, and the undesirable outputs are at least as large as the collective undesirable outputs of all other DMUs. Additionally, the computation of TFPGE can be expressed through the following mathematical programming model, specifically a super-efficiency SBM-DEA model:

$$\min TFPGE = \frac{1 - \frac{1}{m} \sum_{i=1}^m s_i^- / x_{ik}}{1 - \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} s_r^+ / y_{rk} + \sum_{g=1}^{s_2} s_g^{z-} / z_{gk} \right)}$$

Subject to

$$\sum_{j=1, \neq k}^n x_{ij} \lambda_j - s_i^- \leq x_{ik} \quad i = 1, 2, \dots, m$$

$$\sum_{j=1, \neq k}^n y_{rj} \lambda_j + s_r^+ \geq y_{rk} \quad r = 1, 2, \dots, s_1$$

$$\sum_{j=1, \neq k}^n z_{gj} \lambda_j - s_g^{z-} \leq z_{gk} \quad g = 1, 2, \dots, s_2$$

$$\sum_{j=1, \neq k}^n \lambda_j = 1$$

$$1 - \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} s_r^+ / y_{rk} + \sum_{g=1}^{s_2} s_g^{z-} / z_{gk} \right) > 0$$

$$\lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0, s_g^{z-} \geq 0$$

$$j = 1, 2, \dots, n (j \neq k)$$

(3)

where TFPGE represents the value of TFPGE. A TFPGE score exceeding 1 signifies that the DMU is efficient; λ denotes the linear combination ratio; and s_i^- , s_r^+ , s_g^{z-} indicate the potential improvements in input elements, desirable outputs, and undesirable outputs, respectively. The current model is nonlinear and is thus transformed into a linear programming model to facilitate

easier computation. The total factor power generation efficiency values, TFPGE, are obtained by solving the model above with R software.

Following (Bi et al., 2014; Emrouznejad & Yang, 2016; M. Meng et al., 2023; M. Meng & Pang, 2023), we treat the coal-fired power sectors in 30 Chinese provinces as DMUs for TFPGE analysis from 2008 to 2019. Three inputs are evaluated: (1) *Capital* (K), calculated as provincial coal-fired power installed capacity multiplied by utilization rate; (2) *Energy consumption* (F), measured as tons of coal used for electricity generation; and (3) *Labor* (L), represented by the year-end employee count in the power sector. Two outputs are evaluated: (1) *Electricity generated* (E), measured in kilowatt-hours (kWh) as the desirable output, based on the provincial coal-fired power industry’s electricity consumption relative to total generation; and (2) *CO2 emissions*, calculated from coal combustion for electricity production, as the undesirable output.

3.1.1.2 Independent Variable

Our research examines how the CETS pilot policy in China impacts TFPGE in coal-fired power. The policy allows pilot regions—Beijing, Tianjin, Shanghai, Chongqing, Hubei, and Guangdong—to set emission limits based on local conditions, with distinct carbon markets and pricing systems. We analyze this by creating "city and province" dummy variables to distinguish treatment from control groups, and "time" dummy variables to compare pre- and post-CETS periods. The interaction of these two variables serves as the core explanatory variable.

3.1.1.3 Channel variables

3.1.1.3.1 Mediator Variables

To examine the mechanisms underlying the impact of CETS on TFPGE, we hypothesize that environmental resource commitment (ERC) and clean combustion technology innovation (CCTI) serve as two pathways.

Environmental resource commitment level at the regional level (ERC). Referring to the study of (Cho et al., 2023), the environmental resource commitment at the local level is measured using the ratio of fiscal expenditure on environmental protection.

Clean combustion technology innovation (CCTI). Following (He et al., 2023; Ou et al., 2024), this study measures green technological innovation in the coal-fired power industry using efficient and clean combustion technology patent applications. Patents reflect innovation quality and impact (Zhao, 2023), identified via the International Patent Classification Green Inventory (WIPO, 2010) (Hossain et al., 2024). Since patent approvals can lag, they may not capture current innovation (Q. Wu et al., 2023; Xiaobao et al., 2024). We use the CPC Y02E20 classification, part of the Y02 scheme by EPO and USPTO (2013), to count provincial patents on low-emission combustion technologies, crucial for power generation (Acemoglu et al., 2023). Y02E20, under Y02E, targets emission reductions in energy, alongside categories like renewables (Y02E10).

3.1.1.3.2 Moderator effect

To examine the moderation effect in the relationship between CETS and TFPGE, we hypothesize that Energy Structure Upgrading (Str) moderates the relationship between CETS and TFPGE, enhancing CETS's effectiveness in improving PGE. Following (X. Meng & Yu, 2023), we measure Str in the energy sector as the ratio of renewable energy generation to total energy

generation. A higher ratio reflects a shift from fossil fuel dominance to renewables, reducing fossil fuel intensity and promoting sustainable economic development.

3.1.1.3.3 Control Variables

To address endogeneity, we account for several covariates typically included in earlier research (Feng et al., 2022; M. Meng et al., 2023; M. Meng & Pang, 2023; Nakaishi et al., 2022; X. Wei & Zhao, 2024; B.-C. Xie et al., 2021). Specifically, our control variables include: (1) *Population density* (POPN), measured by the ratio of the total population at the end of the year to the land area of the administrative district. (2) *Human capital* (Human.capital), calculated by the ratio of education expenditure to the population. (3) *Economic growth* (GDPP), measured by provincial per capita GDP. (4) *Foreign direct investment* (FDI), as measured by the ratio of actual used foreign capital to GDP. (5) *Industrialization* (IS), measured by dividing the added value of the secondary industry by the GDP. A higher ratio reflects greater dependence on the secondary industry for economic development, which typically results in higher energy consumption and increased carbon emissions (X. Wei & Zhao, 2024). (6) *Electricity consumption* (EC), measured as the annual provincial electricity consumption in kilowatt-hours (KWH). The control variables are treated in logarithms in the regression analysis. Table 1 shows the descriptive statistics for all variables. The average value of TFPGE is 0.9854 (Std. Dev. = 0.0331), ranging from 0.9137 to 1.0945, indicating moderate eco-efficiency.

Table 1. Descriptive statistics of variables

Variables	Observation	Mean	St. Deviation	Min	Max
Total factor power generation efficiency	360	0.9854	0.0331	0.9137	1.0945

Treat	360	0.2	0.4003	0	1
Treat x Post	360	0.1167	0.3213	0	1
Environmental resource commitment	360	1.9893	0.3297	0.8331	2.8736
Clean combustion technology innovation	360	1.6155	0.6073	-0.0338	2.8698
Population density	360	3.558	0.318	2.744	4.097
Human capital	360	3.178	0.233	2.657	3.715
Per capita GDP	360	4.602	0.281	3.987	5.209
Foreign direct investment	360	5.318	0.672	3.912	6.73
Industrial Structure Upgrading	360	0.2515	0.2193	0.0015	0.9189
Industrialization	360	0.9686	0.0108	0.9366	0.9827

3.1.2 Data sources

Given the temporal constraints of CETS implementation and data availability, our study focuses on samples taken from 30 Chinese mainland provinces between 2008 and 2019 (excluding the Tibet Autonomous Region). After filtering out samples with incomplete key variables, our original dataset comprises 360 province-level observations across 30 provinces and cities from 2008 to 2019. The data used in this study were obtained from publicly accessible, proprietary, and published sources. Labor and employment statistics were sourced from the China Population and Employment Statistical Yearbook and the China Statistical Yearbook, published by the National Bureau of Statistics of China (<https://data.stats.gov.cn>). Energy statistics, including fossil energy consumption, were derived from the China Energy Statistical Yearbook, and electricity statistics, including installed capacity and power generation, from the China Electric Power Statistical

Yearbook, both published by the National Bureau of Statistics and the China Electricity Council, respectively. Environmental statistics, including CO2 emissions, were obtained from the China Statistical Yearbook, the China Provincial Environment Yearbook, and the China Emissions Accounts and Datasets (CEADs) (<https://www.ceads.net>). Clean combustion technologies Patent and intellectual property data were retrieved from the China National Intellectual Property Administration (<https://english.cnipa.gov.cn>), the State Intellectual Property Office of China (SIPO), the World Intellectual Property Organization's Patentscope (<https://www.wipo.int/patentscope/en/>), and the INCOPAT patent database (<https://www.incopat.com>); access to INCOPAT may require a subscription. Green technology data were accessed via the WIPO GREEN platform (<https://www.wipo.int/wipo-green/en/>). Additional data on science and technology were sourced from the China Science and Technology Statistical Yearbook. Data time is from 2008 to 2019 and is subject to the terms of use specified by each provider.

3.1.3 Model Construction

3.1.3.1 Difference-in-differences model design

The difference-in-differences (DID) model is a popular approach for assessing policy impacts or natural experiments, estimating causal effects by comparing outcome differences between treatment and control groups. This study employs the DID method to evaluate the impact of China's CETS pilot policy on PGE in the coal-fired power industry across 30 provinces from 2008 to 2019. The policy began in 2013, setting 2013–2019 as the implementation period and 2008–2012 as the pre-policy period. The experimental group includes Beijing, Tianjin, Chongqing,

Shanghai, Hubei, and Guangdong (including Shenzhen), with the remaining provinces as the control group. Thus, the following model is constructed:

$$TFPGE_{it} = \alpha_0 + \alpha_1 treat_{it} \times post_{it} + \delta control_{it} + \gamma_i + \theta_t + \varepsilon_{it} \quad (4)$$

Where i and t represent province and year, respectively. TFPGE stands for total factor power generation efficiency. $treat$ denotes the province grouping variable, 1 for pilot provinces of CETS and 0 for non-pilot provinces. $post$ is the time grouping variable, 1 for 2013–2018, and for 2008–2012 is 0. Controls are the set of control variables. γ is the province-fixed effect that does not vary with time. θ is the time-fixed effect. ε_{it} is the random error term. The impact of the CETS on TFPGE is estimated mainly by observing the coefficient of $treat \times post$.

3.1.3.2 Multi-Period DID model

The multi-period difference-in-differences (DID) method effectively captures variations between treatment and control groups before and after policy implementation, mitigating the impact of confounding factors, addressing endogeneity, and accommodating staggered policy rollouts across regions. This study leverages the carbon emission trading pilot as a quasi-natural experiment, employing a multi-period DID model to assess the impact of the CETS pilot program on TFPGE in China's coal-fired power industry, following the methodology of (Xin-gang et al., 2025b)). The benchmark regression model is constructed accordingly.

$$TFPGE_{it} = \alpha_0 + \alpha_1 treat_{it} \times post_{it} + \delta control_{it} + \gamma_i + \theta_t + \varepsilon_{it} \quad (5)$$

Where i and t represent province and year, respectively. TFPGE stands for total factor power generation efficiency. $treat$ denotes the province grouping variable, 1 for pilot provinces

of CETS and 0 for non-pilot provinces. $post$ is the time grouping variable, and in this paper, 2013 and 2014 are taken as policy implementation threshold, respectively, and $post_{it} = 1$ indicates that period after policy implementation, and $post_{it} = 0$ represents the period before the policy implementation. Controls are the set of control variables. γ is the province-fixed effect that does not vary with time. θ is the time-fixed effect. ε_{it} is the random error term. The impact of the CETS on TFPGE is estimated mainly by observing the coefficient of $treat \times post$.

3.1.3.2 Model construction of the impact mechanism

3.1.3.2.1 Mediating effect model

To investigate the underlying mechanism, this study chooses environmental resource commitment at the local government level (ERC) and clean combustion technology Innovation (CCTI) as mediator variables. We first examine the impact of the CETS pilot policy on clean combustion technology innovation and environmental resource commitment using Eqs. (6) and (7), respectively. The specific steps are outlined below.

$$Log(ERC_{it}) = \beta_0 + \beta_1 treat_{it} \times post_{it} + \rho control_{it} + \gamma_i + \theta_t + \varepsilon_{it} \tag{6}$$

$$Log(CCTI_{it}) = \beta'_0 + \beta'_1 treat_{it} \times post_{it} + \rho control_{it} + \gamma_i + \theta_t + \varepsilon_{it} \tag{7}$$

We proceed to analyse the impact of environmental resource commitment at the local government level (ERC) and clean combustion technology Innovation (CCTI) on total factor generation efficiency using Eqs. (8) and (9), respectively.

$$TFPGE_{it} = \varphi_0 + \varphi_1 treat_{it} \times post_{it} + \varphi_2 Log(ERC_{it}) + \theta control_{it} + \gamma_i + \theta_t + \varepsilon_{it} \tag{8}$$

$$TFPGE_{it} = \varphi'_0 + \varphi'_1 treat_{it} \times post_{it} + \varphi'_2 Log(CCTI_{it}) + \theta control_{it} + \gamma_i + \theta_t + \varepsilon_{it} \quad (9)$$

Where coefficients β_1 and β'_1 Capture the impact of the CETS pilot policy on environmental resource commitment at the local government level and clean combustion technology Innovation, respectively. Meanwhile, coefficients $\beta_1 \times \varphi_2$ and $\beta'_1 \times \varphi'_2$ capture the indirect effect of the CETS pilot policy on green total factor energy productivity, while the coefficients φ_1 and φ'_1 Capture the direct effect of the CETS pilot policy on total factor power generation efficiency. The significance of these coefficients indicates a mediating effect.

3.1.3.2.2 Moderating effect model

This study mainly takes reference to the study of (X. Li et al., 2024). And embeds the energy structure upgrading (Str) variable affecting TFPGE into Eq. (1) to examine the significance level of the influence mechanism.

$$TFPGE_{it} = \theta_0 + \omega_1(treat_{it} \times post_{it} \times Str_{it}) + \omega_2(treat_{it} \times post_{it}) + \omega_3 Str_{it} + \tau control_{it} + \gamma_i + \theta_t + \varepsilon_{it} \quad (10)$$

In this equation, the significance of the $treat \times post \times Str$ coefficient is mainly examined, and the remaining variables are defined in accordance with Eq. (1)

4. RESULTS

Using Equation (3), TFPGE was calculated for each province from 2008 to 2019 and results are shown in s **Supplementary Table S2**. High performers like Beijing (mean PGE = 1.03483),

Shandong (1.02424), Qinghai (1.01346), Jiangsu (1.01283), Ningxia Hui (1.00928), Hainan (1.00805), and Shanghai (1.00037) benefit from advanced economic and technological capabilities. Provinces like Tianjin (0.9991), Xinjiang Uyghur (0.9934), Guangdong (0.99339), and Zhejiang (0.9912) show moderate efficiency, driven by high energy demands and industrial focus. Lower performers, including Henan (0.9754), Hubei (0.9706), Sichuan (0.9703), Liaoning (0.9627), Yunnan (0.9611), and Heilongjiang (0.9442), face inefficiencies, weak policy enforcement, and structural issues. **Figure. 1** visualizes these provincial TFPGE variations.



Figure. 1 Provincial average TFPGE scores.

From 2008 to 2019, the eastern region led in TFPGE, surpassing 1, especially from 2014 to 2019, followed by the western region, while the central region lagged below 1. The East’s efficiency stems from advanced technology, high-quality imported coal, skilled labor, and strict

regulations. The central region's lower TFPGE results from slower technology adoption, limited R&D, weaker policy enforcement due to industrial priorities, and reliance on inefficient subcritical plants. **Figure. 2** visualizes these regional TFPGE variations.

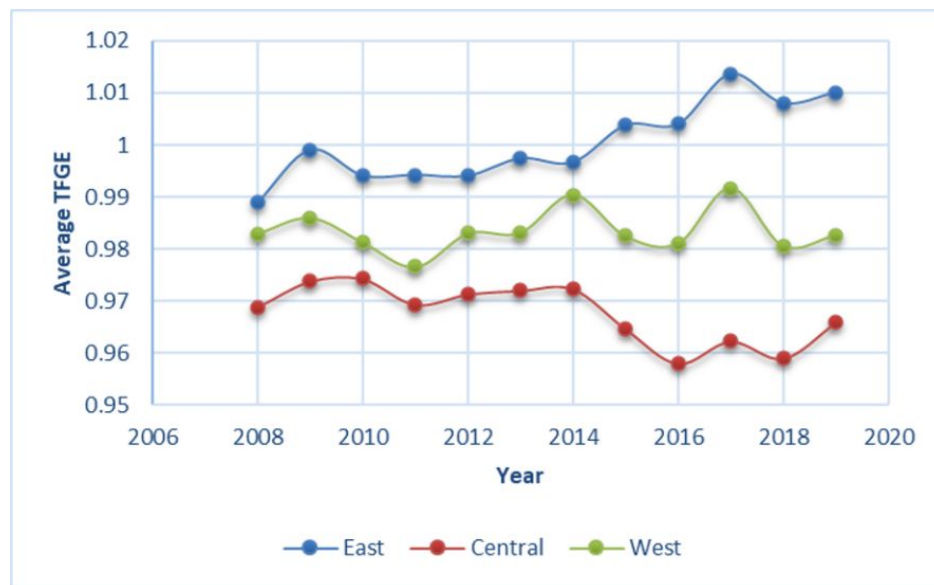


Figure. 2 Average TFPGE values of the three main regions over time.

4.2 Baseline results

Table 2 examines the impact of the CETS pilot program on TFPGE in China's coal-fired power industry using a benchmark models in Eqn 1 and 2 (traditional DID, and Multi-period DID, respectively). In column (1), the traditional DID model with province and year fixed effects and control variables shows a significant positive effect of the CETS pilot program (Treat x Post) on TFPGE in pilot provinces compared to non-pilot provinces post-policy implementation. In column (2), the Multi-Period DID model, which accounts for staggered policy timing, yields a slightly lower but still significant effect (coefficient = 0.0276, $p < 0.01$), suggesting a 0.0276- unit increase. These results confirm Hypothesis 1, indicating that the CETS pilot program modestly enhances

TFPGE by approximately 0.0276-0.0290 units in pilot regions, with the Multi-Period DID providing robust estimates for staggered policy implementation.

Table 2. Overall impact of CETS pilot policy on Total factor Power Generation Efficiency

Variables	Total factor power generation efficiency	
	Traditional DID	Multi-Period DID
	(1)	(2)
Treat × Post	0.0290*** (0.0072)	0.0276*** (0.0071)
Human.capital	0.0084 (0.0392)	0.0178 (0.0513)
GDPP	-0.0936 (0.0945)	0.1011*** (0.0182)
FDI	0.0098 (0.0138)	0.0153 (0.0744)
EC	0.0772* (0.0330)	0.0941* (0.0354)
POP _N	0.1050 (0.0944)	0.0982. (0.0533)
IS	0.3659 (0.6986)	0.2518 (0.8532)
Province FE	Yes	Yes
Year FE	Yes	Yes
N	360	360
R ²	0.7073	0.7041

Robust standard errors clustered by province parentheses, and values ***, **, *, ., indicate 0.1%, 1%, 5%, and 10% significant levels, respectively. FE and N are the abbreviations for Fixed effects and number of observations, respectively.

4.2 Parallel trend test

The Difference-in-Differences method used as a quasi-experimental approach relies on a key assumption: the parallel trends hypothesis. This means that before the policy change, the Power Generation Efficiency of both the treatment group and the control group should follow the same trend over time. This study uses data from four years before and after the policy implementation to test the parallel trends assumption for PGE. The findings are shown in **Figure 3**. Before the CETS pilot policy began, the estimated coefficients for the treatment and control groups varied slightly around 0 and stayed within the 95% confidence interval, showing no significant difference. This supports the parallel trends assumption.

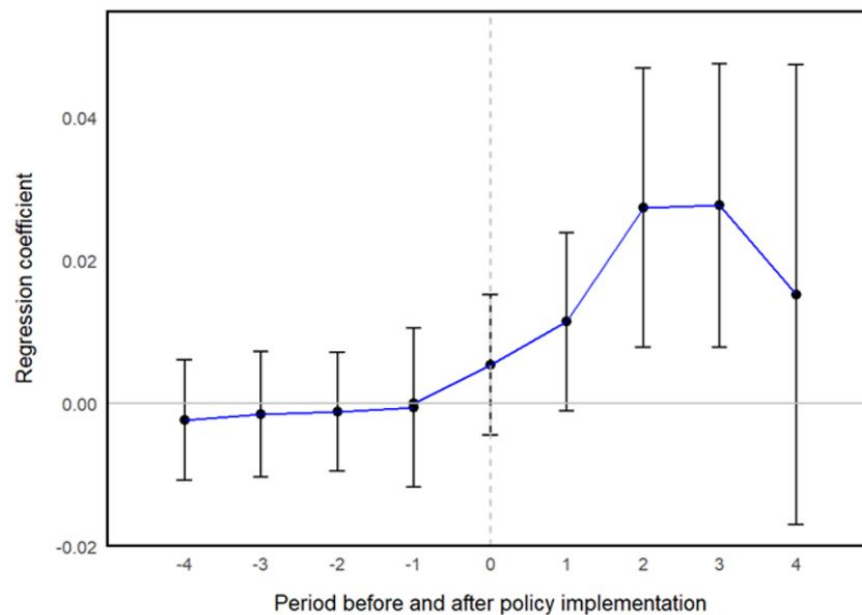


Figure 3. Results of the parallel trend test.

4.3 Placebo test

To ensure that the effect of the CETS pilot policy on TFPGE is not influenced by unknown or unobserved factors, we conducted a placebo test. In this test, we randomly selected 7 out of 30 provinces to form a pseudo-experimental group, treating the remaining provinces as the control group. Using TFPGE as the dependent variable, we performed 1000 random samplings and applied a DID regression for each iteration. **Figure 4** presents the kernel density estimation (KDE) plot of the estimated coefficients for PGE from these placebo tests. The results indicate that the distribution of the placebo coefficients, as well as their mean, significantly deviates from the actual estimated effect of the CETS policy on TFPGE. This deviation suggests that the observed impact of the CETS on TFPGE is robust and unlikely to be driven by other unobservable factors or omitted variables, thereby confirming the reliability of our findings.

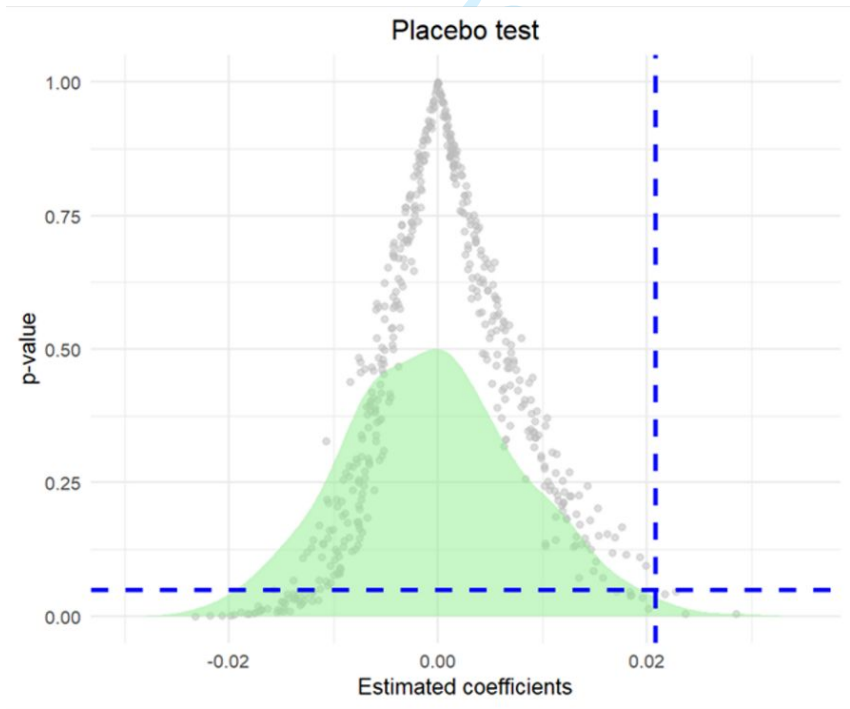


Figure 4. Results of the province placebo test.

4.4 Robustness test

4.4.1 Using the PSM-DID model

The DID method may have selection bias, limiting its quasi-natural experiment effectiveness. We validate the regression results using propensity score matching for accuracy. A logit model was applied to match the experimental and control groups using industrialization, population density, energy consumption, and economic development as variables. Caliper matching was used to minimize selection bias due to individual differences. Per (Rosenbaum & Rubin, 1985), a good matching effect is achieved if the absolute standard deviation of sample variables after matching is below 20%, ensuring valid and reliable estimates. The results in Supplementary Table S2 meet Rosenbaum and Rubin's criterion, with p-values above 10%, confirming the validity of the sample matching. **Figure 5** illustrates the matching outcome. After applying DID estimation to the matched samples (results in **Table 3** [column 1]), the CETS continues to significantly enhance TFPGE, supporting the study's conclusions.

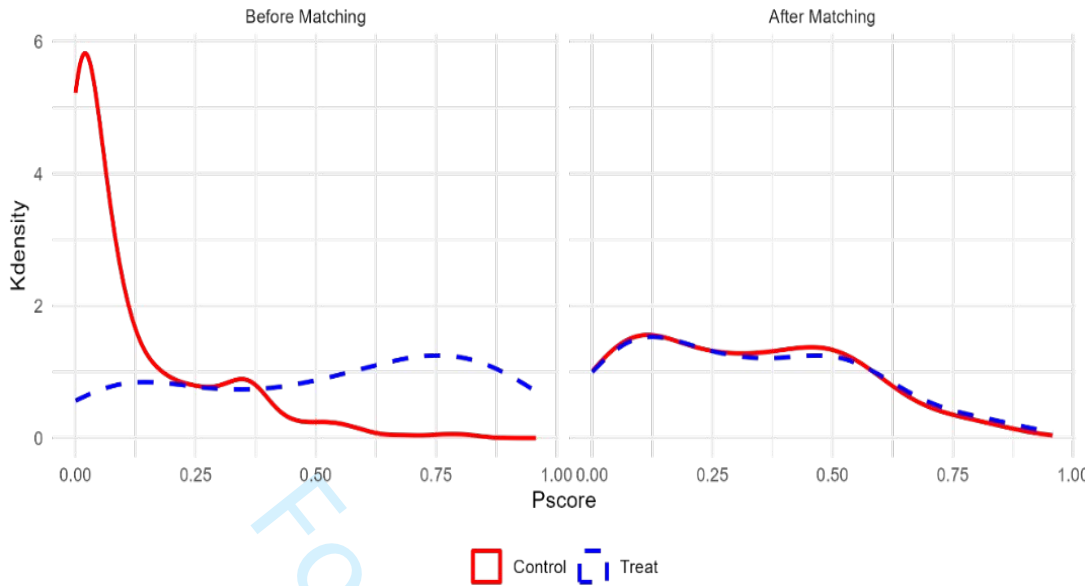


Figure 5. Kernel density functions before and after matching.

4.4.2 Based on the year of replacement policy implementation

To account for the staggered implementation of the CETS across pilot cities from 2013 to 2014 and its delayed impact, this study uses 2015 as the policy implementation base year for a DID analysis. As shown in Column 2 of Table 3, the results align closely with those using 2013 as the base year, reinforcing the robustness and reliability of the study’s findings on the CETS’ positive effect on TFPGE.

4.4.2 Eliminate some special samples

To enhance the accuracy of our regression analysis, we excluded specific samples with unique characteristics. We focused on two cases that could skew the results: (1) Beijing and Shanghai, major economic hubs, likely implemented stricter energy conservation and emission reduction

policies alongside the ETS during the 12th Five-Year Plan, potentially influencing the baseline regression; (2) Chongqing, the only centrally governed municipality in western China, has distinct economic development traits that may also impact the regression outcomes.

We performed two exclusion experiments to address the identified concerns. First, we excluded data from Beijing and Shanghai to remove potential policy overlap effects (results in [Table 3](#), column 3). Second, we excluded Chongqing's data to eliminate the influence of its unique Western economic development traits (results in [Table 3](#), column 4). After these exclusions, the Treat x Post coefficients remained significant, confirming the robustness and reliability of our baseline regression results.

Table 3. Results of the robustness test

Variables	Total Factor Power generation efficiency			
	(1)	(2)	(3)	(4)
Treat × Post	0.0274*** (0.0033)	0.0224* (0.0094)	0.0161* (0.0069)	0.0162. (0.0081)
Control	Yes	Yes	Yes	YES
Province FE	Yes	Yes	Yes	YES

Year FE	Yes	Yes	Yes	YES
N	84	360	336	348
R ²	0.8169	0.7141	0.6912	0.7110

Robust standard errors clustered by province parentheses, and values ***, **, *, ., indicate 0.1%, 1%, 5%, and 10% significant levels, respectively. FE and N are the abbreviations for Fixed effects and number of observations, respectively.

4.4.4 Dynamic time windows test

This study builds on the methodology of (X. Li et al., 2024) to examine how the impact of the CETS on PGE varies over different time periods by adjusting the time window around the policy’s introduction in 2013. We analyse time windows of 1, 2, 3, and 4 years before and after 2013 to assess the policy’s effect. The results, presented in Table 4, show that the CETS’ effect on TFPGE remains stable across these time windows, with the estimated coefficients and their statistical significance consistently increasing up to the 3-year window before slightly stabilizing. This pattern underscores the robustness and reliability of the findings, confirming the sustained positive impact of the CETS on TFPGE over time.

Table 4. Results of the dynamic time window test

Variables	Dynamic time window test			
	1 year	2 year	3 year	4 year
TFGE	0.0120** (2.47)	0.0203*** (3.10)	0.0233*** (3.09)	0.0218** (2.67)
N	60	120	180	240

Robust standard errors clustered by province parentheses, and values ***, **, *, ., indicate 0.1%, 1%, 5%, and 10% significant levels, respectively. N is the abbreviation for the number of observations.

4.4.5 Quantile regression

Quantile regression helps address issues like outliers, collinearity, and heteroscedasticity, which can destabilize regression coefficients and skew results. By examining the CETS policy's impact on PGE across different quantiles, we can mitigate these concerns. **Table 5** presents the results, showing that the main explanatory variable of TFPGE, the DID term (Treat x Post), has significant coefficients at the 30%, 60%, and 90% quantiles (0.150, $p = 0.017$; 0.196, $p = 0.045$; 0.097, $p = 0.061$, respectively). This indicates robustness of the baseline regression across varying efficiency levels.

Table 5. Quantile regression results

variables	TFGE		
	(1)	(2)	(3)
Quantile	0.3	0.6	0.9
Treat x Post	0.150** (0.063)	0.196** (0.097)	0.097* (0.052)
Control	YES	YES	YES

Province FE	YES	YES	YES
Year FE	YES	YES	YES
N	360	360	360
R-squared	0.485	0.504	0.208

Standard errors are in parentheses, ** and * indicate the significance at the 5% and 10% levels, respectively. FE and N are the abbreviations for Fixed effects and number of observations, respectively.

4.5 Mechanism effect analysis

The mechanism impact of the CETS pilot policy on TFPGE is examined using the mechanism model constructed above, with ERC and CCTI serving as mediating variables and Str serving as moderating variables. The test results are displayed in Table 6 Columns (1)-(2) and (3)-(4) of Table 7 test the mediating effects of ERC and CCTI between CETS pilot policy and TFPGE, respectively, and column (5) tests the moderating effect played by Str.

(1) Level of Environmental resource commitment at the local government level

In column (1), the Treat x Post coefficient on ERC is 0.0471 (5% significance), showing the CETS pilot policy increases ERC in pilot provinces. In column (2), with ERC as a mediator, its coefficient is 0.0599 (0.1% significance), and Treat x Period’s direct effect on TFPGE is 0.0290 (5% significance), indicating partial mediation. The CETS enhances ERC by improving regulations, supervision, resource allocation, and market environment, which in turn boosts TFPGE, verifying hypothesis 2. Higher ERC further strengthens CETS’s impact on TFPGE in the coal-fired power industry.

(2) Clean combustion technology innovation.

In column (3), the Treat x Post coefficient on CCTI is 0.0766 (5% significance), indicating the CETS pilot policy fosters clean combustion technology innovation in pilot provinces. In column (4), with CCTI as a mediator, its coefficient on TFPGE is 0.0428 (0.1% significance), and Treat x Post's direct effect is 0.0293 (1% significance), showing partial mediation. The policy drives technological innovation, enhancing TFPGE, confirming hypothesis 3.

(3) Energy structure upgrading (Str)

In Column (5), the Treat x Post x Str interaction term coefficient is 0.0259 (1% significance), with Treat x Post at 0.0536 (1% significance) and Str at 0.0569 (5% significant). This indicates Energy structure upgrading moderates the CETS policy's effect on TFPGE, confirming hypothesis 4. The policy's impact on TFPGE is stronger in provinces with a higher renewable energy share, highlighting the role of the energy mix.

Table 6. Results of the impact mechanism test

Variables	Mediating effect			Moderating effect	
	ERC	TFPGE	Log (CCTI)	TFPGE	TFPGE
	(1)	(2)	(3)	(4)	(5)

Treat × Post × Str					0.0259**
					(0.0749)
Treat × Post	0.0471*	0.0290*	0.0766*	0.0293***	0.0536**
	(0.0205)	**(0.0070)	(0.0355)	(0.0067)	(0.0194)
Structure (Str)					0.0569*
					(0.0277)
ERC					0.0599***
					(0.0129)
CCTI					0.0428***
					(0.00113)
Control	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	360	360	360	360	360
R ²	0.9338	0.91906	0.9146	0.9253	0.7194

Robust standard errors clustered by province parentheses, and values ***, **, *, ., indicate 0.1%, 1%, 5%, and 10% significant levels, respectively. FE and N are the abbreviations for Fixed effects and number of observations, respectively.

4. 6 Heterogeneity analysis

4.6.1 Subgroup heterogeneous analysis

To explore how the CETS pilot policy varies across regions, we assess its effectiveness by considering factors like economic development, resource availability, and population density. For

instance, the eastern region's favorable terrain and climate support a dense population and industrial growth. To investigate this heterogeneity, we divide 30 provinces into three groups based on China's administrative divisions: eastern, central, and western. The eastern region includes provinces and cities like Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The Central region includes provinces such as Shanxi, Jilin, Anhui, Jiangxi, Henan, Hubei, Hunan, and Heilongjiang. The western region includes provinces such as Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Inner Mongolia, Guangxi, and Xinjiang.

Table 7 shows that the CETS policy ($\text{Treat} \times \text{Post}$) significantly boosted TFPGE across regions, with the West showing the largest increase (0.029^{***} , $p < 0.001$), followed by the East (0.025^{***} , $p < 0.001$) and Central (0.017^{***} , $p < 0.001$). The West's gains stem from its low baseline TFPGE (0.594994) and coal abundance, aiding efficiency upgrades in areas like Inner Mongolia. The East benefits from advanced technology, FDI (0.072^{***}), and energy consumption (0.277^{***}), despite negative impacts from GDP per capita (-0.316^{***}) and population (-0.441^{**}). The Central region's smaller gains reflect structural constraints and weaker policy enforcement, highlighting regional variations in CETS effectiveness.

Table 7. Comparison of CETS effects on TFPGE in different geographical locations

Variables	East	Central	West
	(1)	(2)	(3)
$\text{Treat} \times \text{Post}$	0.025^{***}	0.017^{***}	0.029^{***}

	(0.009)	(0.006)	(0.011)
Human.capital	0.056	0.026	0.050
	(0.056)	(0.048)	(0.057)
GDPP	-0.316***	-0.019	0.002
	(0.099)	(0.069)	(0.082)
FDI	0.072***	0.003	-0.024*
	(0.023)	(0.018)	(-0.014)
EC	0.277***	0.032	0.009
	(0.084)	(0.048)	(0.040)
POPN	-0.441**	0.091	0.495**
	(0.182)	(0.123)	(0.229)
IS	1.396	-0.130	-1.043
	(1.386)	(0.505)	(1.124)
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	142	96	132
R ²	0.257	0.187	0.185

Robust standard errors clustered by province parentheses, and values ***, **, *, ., indicate 0.1%, 1%, 5%, and 10% significant levels, respectively. FE and N are the abbreviations for Fixed effects and number of observations, respectively.

4.6.2 Regional power structure and regional economic development heterogeneous analysis

We further examine the CETS policy’s impact across provinces, focusing on power structure (thermal power share in total generation) and economic development (total GDP at 2015 constant

prices). The thermal power share reflects the industry's role in electricity production, with a higher share indicating greater reliance on thermal power, affecting TFGE outcomes (M. Meng & Pang, 2023). A higher share indicates a greater reliance on thermal power, influencing the policy's effect on TFPGE. Total GDP measures economic development levels, highlighting regional disparities in energy structure (Bi et al., 2014; Cao et al., 2021; Jin et al., 2024). This analysis reveals how the energy mix and economic factors influence CETS policy effectiveness.

We categorized 30 Chinese provinces into subgroups based on pre-policy (2008–2013) averages of thermal power share and total GDP. Provinces with thermal power share above the median (86.75%) were classified as “High thermal” (e.g., Anhui, Beijing), and those below as “Low thermal” (e.g., Chongqing, Fujian). For economic development, provinces with log total GDP above the median (4.015, ~5.543 billion RMB) were “High GDP” (e.g., Beijing, Jiangsu), and those below were “Low GDP” (e.g., Gansu, Qinghai). This classification highlights variations in energy structure and economic development, aiding analysis of CETS policy effectiveness. **Figure. 6(a)** and **Figure. 6(b)** illustrate these disparities using data from the China Electric Power Statistical Yearbook and China Statistical Yearbook, respectively. We re-estimate Eqn. 4. The results are presented in **Table 8**.

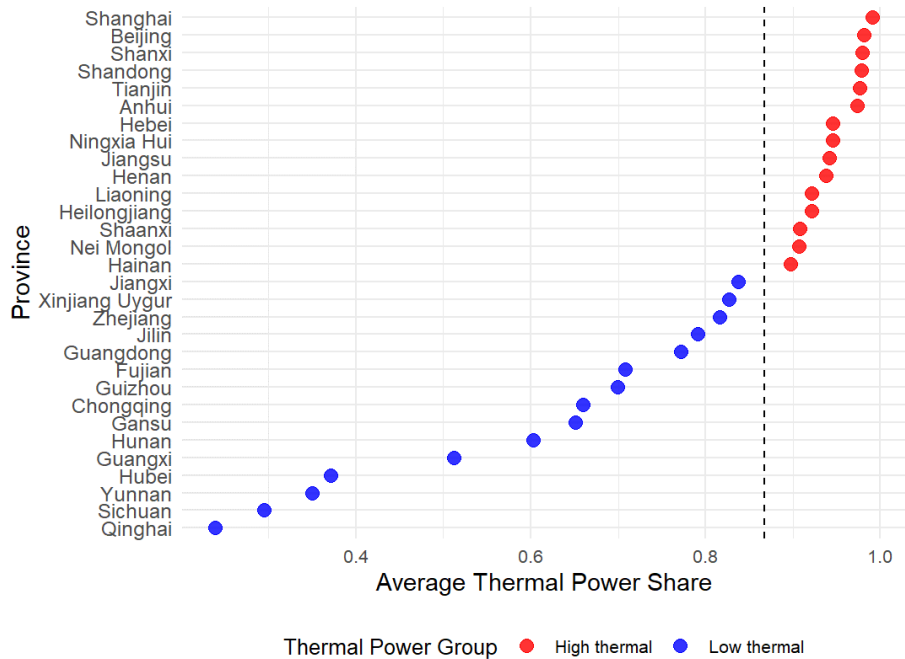


Figure. 6(a) Provincial categorization by thermal power share.

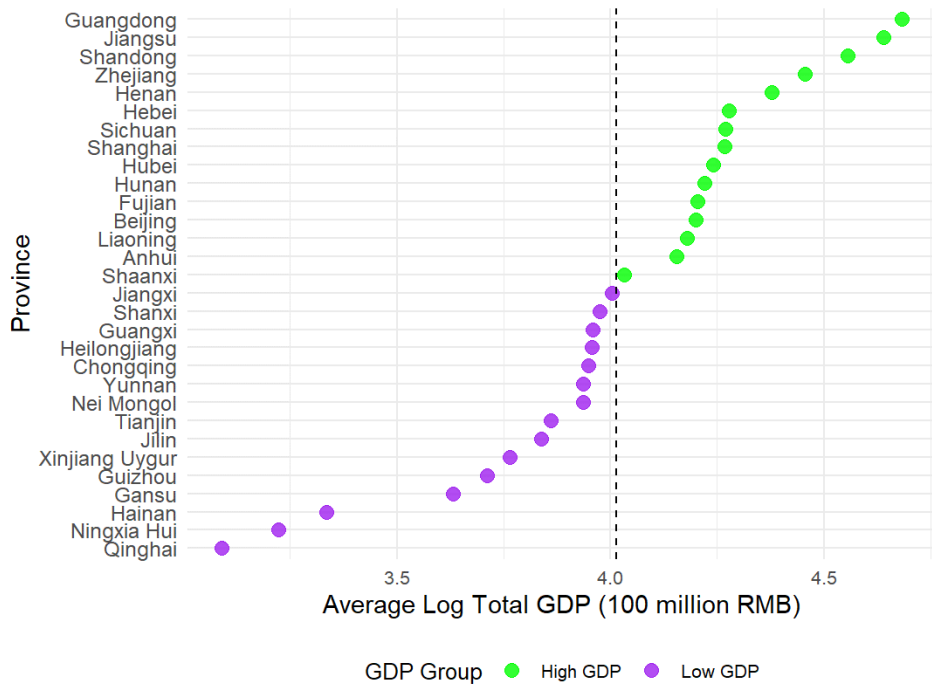


Figure. 6(b) Province categorization by Log Total GDP.

Table 8, columns (1) and (2), examines the CETS pilot policy's heterogeneous effects on TFPGE based on thermal power share, using province and year-fixed effects with controls. In high thermal power share provinces (column 1), the policy's effect (Treat x Post) is 0.0146 but not significant. In low thermal power share provinces (column 2), the effect is 0.0260 (0.1% significance), showing greater TFPGE improvement. High thermal share provinces face structural challenges, like higher emission reduction costs and limited alternatives, hindering TFPGE gains. Conversely, low thermal share provinces, with more diversified energy mixes and renewable integration, can adopt cleaner practices more easily, making CETS incentives (e.g., carbon credit trading) more effective in boosting TFPGE.

Table 8, columns (3) and (4), shows the CETS pilot policy's heterogeneous effects on PGE across economic development levels, using fixed effects and controls. High GDP provinces (column 3) show a non-significant effect (0.0168), while low GDP provinces (column 4) exhibit a significant effect (0.0168, 5% significance), indicating greater policy impact in less developed regions. Low GDP areas, with less advanced infrastructure, see larger efficiency gains through new clean technology investments and face less industrial resistance. Conversely, high GDP regions, with higher baseline efficiency and advanced technology, experience diminishing returns, reducing the CETS's marginal impact on TFPGE. The CETS policy's impact on TFPGE varies by region, showing greater effectiveness in provinces with lower thermal power reliance and lower GDP.

Table 8. Heterogeneous effects of the CETS pilot policy on TFPGE across provinces with varying thermal power share and levels of economic development

Variables	High thermal	Low thermal	High GDP	Low GDP
	(1)	(2)	(3)	(4)
Treat × Period	0.0146 (0.0137)	0.0260*** (0.0062)	0.0168 (0.0096)	0.0236* (0.0105)
Human.capital	0.0917 (0.0800)	-0.0599* (-0.0269)	0.1200. (0.0676)	-0.0552* (-0.0238)
GDPP	-0.1484 (0.1713)	0.0302 (0.0973)	-0.2123 (-0.1942)	-0.0135 (-0.0510)
FDI	0.0200 (0.0204)	-0.0169 (-0.196)	0.0455 (0.0494)	-0.0028 (-0.0078)
EC	0.0990 (0.1312)	0.0590 (0.0343)	0.2516 (0.1904)	0.0776*** (0.0178)
POPNI	0.1247 (0.1425)	0.1469. (0.0709)	-0.0834 (-0.2254)	0.1163 (0.0972)
IS	0.4049 (0.1312)	-0.8365 (-2.221)	-2.773 (-2.555)	0.3929 (0.4418)
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	180	180	180	180
R ²	0.7267	0.6391	0.6864	0.8237

Robust standard errors clustered by province parentheses, and values ***, **, *, ., indicate 0.1%, 1%, 5%, and 10% significant levels, respectively. FE and N are the abbreviations for Fixed effects and number of observations, respectively.

5. DISCUSSION

This study provides a nuanced examination of the CETS pilot policy's impact on Total Factor Power Generation Efficiency (TFPGE) in China's coal-fired power sector, revealing several key insights that advance both theoretical and practical understanding in environmental planning and management.

First, the CETS pilot policy significantly enhances TFPGE, yielding an average increase of 2.90% across China's provincial coal-fired power sector. This finding aligns with prior studies (Cao et al., 2021; Q. Wu et al., 2023), which suggest that carbon pricing mechanisms impose mandatory constraints that drive efficiency gains. However, our study extends this understanding by focusing on the coal-fired power sector—a critical yet understudied area given its dominant role in China's energy mix and emissions profile. The 2.90% TFPGE increase reflects how CETS promotes resource commitment towards environmentally-friendly production practices and thus incentivizing coal-fired power enterprises to invest in low-carbon technologies, such as advanced combustion systems, which improve production processes and reduce emissions. This result underscores the policy's potential as a tool for balancing energy security with environmental sustainability, particularly in a sector historically resistant to change due to its reliance on coal.

Second, the CETS's impact on TFPGE exhibits significant regional heterogeneity, with the western and eastern provinces experiencing greater efficiency gains (2.9% and 2.5%, respectively) compared to the central region (1.7%). This disparity highlights the role of regional economic and

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3 industrial contexts in shaping policy outcomes. In the eastern region, where coal supports rapid
4 economic growth, CETS likely amplifies efficiency gains by pushing firms to adopt cleaner
5 technologies to meet stringent emission targets. In the western region, despite lower energy
6 consumption, limited technological innovation creates a higher marginal benefit from CETS-
7 driven upgrades, as firms transition from outdated infrastructure. Conversely, the central region's
8 lower TFPGE gains (1.7%) may stem from structural challenges, such as reliance on less efficient
9 subcritical plants, slower adoption of advanced technologies, and weaker policy enforcement due
10 to competing industrial priorities. These findings build on prior research, e.g., (Yu et al., 2024), by
11 emphasizing the need to account for regional variations in CETS implementation—an aspect often
12 overlooked in studies that treat China's provinces as a homogeneous unit. This regional lens offers
13 a fresh perspective, addressing a gap in the literature and providing a foundation for more equitable
14 and effective environmental policies.

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17 Third, the CETS's effect on TFPGE varies with the thermal power share in the energy mix,
18 with provinces having a low thermal power share experiencing a 2.6% PGE increase compared to
19 1.46% in high thermal power share regions. This finding suggests that CETS is more effective in
20 regions with a diversified energy mix, where renewable energy integration facilitates the adoption
21 of cleaner practices. In contrast, high thermal power share regions face structural barriers, such as
22 higher emission reduction costs and limited access to alternative energy sources, which constrain
23 efficiency gains. This result extends the literature by linking energy mix diversity to carbon pricing
24 outcomes, offering a new angle on how industrial structure moderates the CETS-TFPGE
25 relationship. It also provides empirical support for tailoring CETS policies to regional energy
26 profiles, a consideration that adds depth to prior studies, e.g., (R. Chen et al., 2024), and informs
27 the design of localized environmental strategies.

Fourth, the CETS enhances TFPGE by promoting environmental resource commitment and fostering clean combustion technology innovation, key mechanisms driving efficiency gains in the coal-fired power sector. Our analysis reveals that the policy increases the firms' willingness to commitment necessary resources for sustainable power generation, encouraging them to adopt technologies like ultra-supercritical combustion systems, which reduce emissions while improving energy efficiency. This finding aligns with Porter's hypothesis, which posits that environmental regulations can enhance environmental commitment, spur innovation and efficiency, leading to a "win-win" outcome (Porter & Linde, 1995). Unlike studies such as (Tang et al., 2023) and (X. Meng & Yu, 2023), which argue that environmental regulations may stifle innovation due to compliance costs, our results demonstrate that CETS promotes environmental commitment and drives technological advancements in the coal-power sector, supporting the findings of (Ou et al., 2024) and (X. Li et al., 2024) on the environmental benefits of carbon trading. By modestly validating Porter's hypothesis in the specific context of China's coal-fired power sector, this study contributes to the theoretical debate on the environmental commitment and innovation effects of environmental policy. Moreover, the role of environmental resource commitment and clean combustion technology as mediators highlights a practical pathway through which CETS can achieve sustainability goals, offering a concrete mechanism that policymakers can target to amplify the policy's impact.

6. CONCLUSIONS AND POLICY IMPLICATIONS

6.1 CONCLUSIONS

This study examines the impact of China's Carbon Emissions Trading Scheme (CETS) pilot policy on Total Factor Power Generation Efficiency (TFPGE) in the coal-fired power sector across

30 Chinese provinces (2008–2019), employing a super-efficiency SBM DEA model and difference-in-differences methods. Five key findings emerge. First, TFPGE averages 0.9838, with the East (1.0003) leading, followed by the West (0.9835) and Central region (0.9676). Second, CETS increases TFPGE by 2.90% across China’s provincial coal-fired power sector. Third, environmental resource commitment and clean combustion technology innovations mediate the CETS-TFPGE relationship, as the policy fosters environmental investments and technological upgrades, enhancing efficiency and reducing emissions. Fourth, regional variations show greater TFPGE gains in western (2.9%) and eastern (2.5%) provinces than in the central region (1.7%), reflecting differences in economic development and energy structures. Fifth, aligning with Porter’s hypothesis, CETS drives innovation and efficiency, particularly in regions with diverse industrial structures. These results highlight CETS as an effective tool for improving TFPGE, with implications for regional energy transitions and environmental planning. By addressing regional heterogeneity and technological mechanisms, this study offers insights into carbon pricing’s role in sustainable energy development in a coal-reliant context.

6.2 POLICY IMPLICATIONS

Drawing on our empirical findings, we propose the following policy recommendations to enhance the CETS’s effectiveness in improving TFPGE and advancing sustainable development in China’s coal-fired power sector:

1. Leverage CETS to Drive Clean Combustion Technology Adoption

Our findings confirm that the CETS boosts TFPGE by promoting clean combustion technology innovations, a key mechanism for efficiency gains and emissions reductions. Local governments

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3 should use CETS as a lever to incentivize coal-fired power enterprises to invest in advanced
4 technologies, such as ultra-supercritical combustion systems or carbon capture and storage (CCS).
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6 To achieve this, policymakers can adjust carbon prices to make low-carbon technologies more
7 financially attractive, offering subsidies or tax incentives for firms that adopt these innovations.
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9 This aligns with Porter's hypothesis, which our study validates, showing that environmental
10 regulations can spur technological innovation while improving efficiency. Additionally,
11 governments should establish innovation hubs or public-private partnerships to accelerate the
12 development and deployment of clean combustion technologies, ensuring that coal-dependent
13 regions are not left behind in the energy transition.
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25 2. Tailor CETS Implementation to Regional Contexts

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29 The regional variations in the CETS's impact on TFPGE—stronger in the East (1.0003) and
30 West (0.9835) but weaker in the Central region (0.9676)—underscore the need for context-specific
31 environmental strategies. In the Central region, where coal dependency remains high and TFPGE
32 is lowest, the CETS has not sufficiently reduced fossil fuel reliance. Policymakers should introduce
33 targeted incentives, such as higher carbon prices or grants for phasing out inefficient plants, to
34 accelerate energy structure upgrades. For example, supporting the adoption of renewable energy
35 sources like wind or solar in the Central region could reduce coal dependency while boosting
36 TFPGE. In contrast, the East and West regions, which benefit more from CETS due to their
37 economic development and diversified power structures, can serve as models for best practices,
38 such as integrating CETS with renewable energy subsidies. By tailoring CETS policies to regional
39 industrial and economic contexts, governments can maximize the policy's effectiveness and ensure
40 equitable progress toward sustainability across provinces.
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3. Strengthen Inter-Regional Collaboration to Amplify CETS Benefits

The CETS’s positive impact on TFPGE can be amplified through inter-regional collaboration. Provinces with higher TFPGE, such as those in the East, can share best practices in clean technology adoption and policy implementation with lagging regions like the Central provinces. Governments should establish platforms for knowledge transfer, such as inter-provincial task forces or technology-sharing initiatives, to facilitate the diffusion of successful strategies. For instance, the East’s success in achieving a TFPGE of 1.0003 could be replicated in the Central region through workshops on integrating CETS with renewable energy investments. Additionally, fostering industry partnerships between coal-fired power enterprises across regions can promote the adoption of sustainable practices, ensuring that the CETS’s benefits extend beyond individual provinces to advance the entire energy sector toward sustainable development.

4. Enhance CETS Oversight with a Focus on Industrial Structure Dynamics

Our study finds that the CETS’s alignment with Porter’s hypothesis is moderated by regional industrial structures, with stronger effects in regions with diversified economies. To sustain and enhance these benefits, local governments must strengthen CETS oversight by developing robust monitoring and evaluation frameworks. Regular assessments should track not only TFPGE improvements but also how industrial structures evolve in response to the policy. For example, in coal-heavy regions like the Central provinces, policymakers should monitor whether CETS encourages diversification (e.g., growth in renewable energy sectors) and adjust the policy as needed to prevent over-reliance on coal. This could involve setting regional power generation efficiency targets or linking carbon quotas to industrial diversification goals. By focusing oversight

on industrial structure dynamics, governments can ensure that CETS drives long-term sustainability while addressing regional disparities.

7. LIMITATIONS AND FUTURE DIRECTIONS

While this study provides valuable insights into the effectiveness of China's CETS pilot policy on TFPGE in the coal-fired power sector, several limitations must be acknowledged to contextualize its findings and guide future research.

First, our analysis is constrained by its focus on the coal-fired power sector across 30 Chinese provinces from 2008 to 2019, which limits the generalizability of the findings to other industries, regions, or countries. The coal sector's unique characteristics—such as its high emissions intensity and heavy reliance on clean combustion technologies—may not reflect the dynamics of other sectors like manufacturing or transportation, where CETS might have different impacts on efficiency. Similarly, China's regional economic disparities and policy implementation variations may not mirror conditions in other countries with different energy mixes or regulatory frameworks. Future research should explore the CETS's effects across diverse industries and international contexts, such as comparing its impact in coal-dependent economies like India with more diversified energy systems like those in the European Union, to assess the policy's broader applicability.

Second, due to data constraints, this study examines the short-term impact of CETS on PGE using provincial-level data, leaving the long-term and firm-level effects underexplored. The 2008–2019 timeframe captures the initial rollout of the CETS pilot but does not account for its evolution, particularly following the launch of China's national carbon market in 2021. Moreover, provincial-level data obscures firm-level behavioral responses, such as how individual coal-fired power enterprises adjust their investment strategies or technology adoption under CETS. Future

studies should leverage firm-level datasets to investigate micro-level dynamics, such as how firm size, ownership structure, or financial capacity influence PGE responses to CETS. Additionally, extending the analysis beyond 2019 to include the national CETS phase could reveal long-term trends, such as whether the observed 2.90% TFPGE increase persists or amplifies as the policy matures.

Third, our TFPGE analysis adopts a static approach, which overlooks the dynamic effects of CETS on efficiency over time. The difference-in-differences (DID) and the multi-period DID models used in this study capture average treatment effects but do not account for temporal variations, such as how TFPGE evolves as firms adapt to CETS over multiple years or how policy adjustments (e.g., changes in carbon prices) influence efficiency trajectories. This static perspective limits our understanding of the policy’s sustained impact, particularly in regions with varying TFPGE gains (e.g., 2.9% in the West vs. 1.7% in the Central region). Future research should employ dynamic models, such as panel vector autoregression or dynamic DEA approaches, to capture both short-term and long-term effects of CETS on TFPGE, providing a more comprehensive view of its temporal dynamics and regional heterogeneity.

Finally, while our findings modestly support Porter’s hypothesis by demonstrating that CETS enhances resource commitment, drives clean combustion technology innovation, and efficiency gains, the optimal intensity of environmental regulation and its interaction with other market-based mechanisms remain unclear. The 2.90% TFPGE increase suggests that CETS is effective, but the policy’s impact varies with regional energy structures (e.g., 2.6% TFPGE increase in low thermal power share regions vs. 1.46% in high thermal power share regions), raising questions about whether current carbon pricing levels are optimal for all regions. Additionally, the interplay between CETS and complementary policies, such as carbon taxes or

renewable energy subsidies, could amplify its effectiveness, particularly in coal-heavy regions like the Central provinces. Future research should investigate the optimal design of CETS, such as determining the carbon price threshold that maximizes TFPGE without imposing excessive costs on firms. Moreover, studies should explore how CETS interacts with other market-based mechanisms to create a cohesive policy framework, potentially using simulation models or comparative case studies to identify synergies that enhance TFPGE across diverse regional contexts.

Despite these limitations, this study makes a significant contribution by providing a regionally nuanced analysis of CETS effects, identifying environmental resource commitment and clean combustion technology as a critical mediator, and validating Porter's hypothesis in the context of China's coal-fired power sector. These findings lay a robust foundation for future research to build upon, particularly in addressing the gaps identified above. By focusing on long-term impacts, firm-level dynamics, temporal effects, and policy interactions, future studies can further enhance our understanding of carbon pricing's role in driving sustainable energy transitions, offering new perspectives for environmental planning and management in coal-dependent economies.

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Supplementary Material

**Pricing for a low-carbon energy future: How
China’s Carbon Emissions Trading System
drives eco-efficient power generation in
China’s coal-fired power industry.**

List of the supporting information:

Supplementary Table S1. TFPGE values for China’s provincial coal-fired power industry.

Supplementary Table S2. Comparison of sample means before and after matching.

Supplementary Table S1. TFPGE values for China's provincial coal-fired power industry

Region	Province	Total Factor Power Generation Efficiency												Mean
		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	
East	Beijing	1.0029	1.0002	1.0001	1.0002	1.0112	1.0145	1.0165	1.0494	1.0552	1.0897	1.0836	1.0943	1.03483
	Guangdong	0.9714	0.9843	0.9852	0.9783	0.9950	1.0000	1.0001	1.0004	1.0001	1.0049	1.0004	1.0006	0.99340
	Shanghai	1.0028	1.0031	1.0011	1.0001	0.9907	1.0015	1.0024	1.0005	1.0005	1.0006	1.0006	1.0007	1.00037
	Tianjin	0.9957	0.9945	1.0047	1.0002	0.9904	1.0002	1.0004	1.0012	1.0004	1.0005	1.0006	1.0008	0.99913
	Fujian	0.9810	0.9851	0.9850	1.0006	1.0000	0.9910	0.9876	0.9736	1.0139	0.9719	0.9655	0.9636	0.98490
	Hainan	1.0089	1.0087	1.0038	1.0180	1.0113	1.0061	1.0064	1.0049	1.0026	1.0061	1.0071	1.0127	1.00805
	Hebei	0.9686	1.0189	0.9745	1.0025	0.9792	0.9852	0.9853	1.0006	0.9806	1.0003	1.0009	1.0005	0.99144
	Jiangsu	1.0089	1.0152	1.0199	1.0196	1.0116	1.0151	1.0174	1.0049	1.0087	1.0155	1.0098	1.0072	1.01283
	Liaoning	0.9688	0.9683	0.9656	0.9507	0.9637	0.9695	0.9702	0.9586	0.9595	0.9749	0.9512	0.9517	0.96271
	Shandong	0.9847	1.0191	1.0004	0.9787	0.9804	0.9872	0.9871	1.0496	1.0355	1.0899	1.0838	1.0945	1.02424
Central	Zhejiang	0.9837	0.9917	0.9938	0.9868	1.0001	1.0005	0.9889	0.9974	0.9866	0.9956	0.9847	0.9845	0.99119
	Hubei	0.9652	0.9682	0.9691	0.9631	0.9590	0.9662	0.9824	1.0005	0.9918	0.9486	0.9530	0.9821	0.97076
	Anhui	0.9850	0.9913	1.0001	0.9935	0.9913	0.9923	1.0000	1.0001	0.9860	1.0000	0.9881	0.9903	0.99318
	Heilongjiang	0.9442	0.9596	0.9577	0.9444	0.9572	0.9468	0.9493	0.9372	0.9267	0.9295	0.9398	0.9374	0.94416
	Henan	0.9718	0.9774	0.9739	0.9775	0.9741	0.9818	0.9794	0.9682	0.9687	0.9753	0.9686	0.9875	0.97536
	Hunan	0.9648	0.9680	0.9676	0.9747	0.9629	0.9611	0.9591	0.9422	0.9311	0.9396	0.9431	0.9638	0.95650
	Jiangxi	0.9679	0.9658	0.9687	0.9631	0.9726	0.9747	0.9650	0.9504	0.9517	0.9630	0.9643	0.9550	0.96353
	Jilin	0.9599	0.9656	0.9567	0.9502	0.9636	0.9585	0.9530	0.9393	0.9318	0.9567	0.9363	0.9346	0.95052
	Shanxi	0.9915	0.9944	1.0001	0.9878	0.9896	0.9947	0.9902	0.9794	0.9756	0.9851	0.9781	0.9756	0.98684
	Chongqing	0.9703	0.9838	0.9574	0.9593	0.9745	0.9759	1.0004	1.0131	1.0050	1.0003	1.0160	0.9912	0.98727
West	Gansu	1.0001	0.9760	0.9696	0.9710	1.0009	0.9741	0.9613	0.9516	0.9376	0.9483	0.9395	0.9703	0.96669
	Guangxi	0.9658	0.9726	0.9802	0.9847	0.9765	0.9753	0.9682	0.9462	0.9378	0.9798	0.9543	0.9541	0.96628
	Guizhou	0.9886	0.9937	0.9889	0.9652	0.9778	0.9646	0.9633	0.9537	0.9457	0.9581	0.9589	0.9748	0.96944
	Nei Mongol	1.0030	1.0013	0.9894	0.9862	0.9862	1.0003	1.0016	1.0001	0.9803	1.0000	0.9852	0.9853	0.99324
	Ningxia Hui	0.9951	0.9937	0.9890	1.0194	1.0114	1.0149	1.0135	1.0125	1.0114	1.0136	1.0164	1.0204	1.00928
	Qinghai	1.0087	1.0144	1.0197	1.0114	1.0111	1.0132	1.0172	1.0207	1.0085	1.0022	1.0144	1.0200	1.01346
	Shaanxi	0.9925	0.9803	1.0003	0.9905	0.9796	1.0017	1.0014	0.9698	1.0011	1.0001	0.9654	0.9680	0.98757
	Sichuan	0.9490	0.9561	0.9551	0.9401	0.9618	0.9526	1.0003	0.9261	1.0014	1.0010	1.0000	1.0002	0.97031
	Xinjiang Uygur	0.9757	1.0002	0.9774	0.9665	0.9737	0.9807	1.0114	1.0128	1.0032	1.0042	1.0044	1.0113	0.99344
	Yunnan	0.9634	0.9733	0.9667	0.9477	0.9590	0.9607	0.9554	1.0004	0.9598	1.0004	0.9324	0.9137	0.96108
East mean		0.9888	0.9990	0.9940	0.9942	0.9940	0.9973	0.9966	1.0037	1.0040	1.0136	1.0080	1.0101	1.000282
Central mean		0.9688	0.9738	0.9742	0.9693	0.9713	0.9720	0.9723	0.9647	0.9579	0.9622	0.9589	0.9658	0.967605
West mean		0.9829	0.9859	0.9812	0.9765	0.9830	0.9831	0.9904	0.9825	0.9811	0.9916	0.9806	0.9827	0.98346

Supplementary Table S2. Comparison of sample means before and after matching

Variable	Status Matched Unmatched	Mean_ Treated	Mean_ Control	%Bias	%Reduction	t_stat	p_value	Var_Ratio
EC	M	3.181	3.212	-9	-21.6	-0.41	0.681	1.26
EC	U	3.1254	3.148	-7.4	NA	-0.57	0.567	0.88
GDP	M	4.3239	4.3561	-9	84.8	-0.41	0.68	1.29
GDP	U	4.3327	4.1159	59.5	NA	4.95	0	0.56
IS	M	0.9707	0.9706	0.4	99.1	0.02	0.984	0.64
IS	U	0.9649	0.9695	-47.6	NA	-3.2	0.002	2.63
POPN	M	3.6294	3.6564	-9.4	36.9	-0.43	0.669	2.5
POPN	U	3.5206	3.5677	-14.9	NA	-1.15	0.253	0.89

Note: t_stat, and Var_ratio are abbreviations for t statistics and variance ratio