When and Under What Conditions Does an Emission Trading Scheme Become Cost Effective?

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Abstract: This paper studies when and under what conditions the actions undertaken by the power plants involved in China's emission trading scheme (ETS) pilot became cost effective. Based on unique plant-level panel data and the difference-in-differences strategy, we identify that an insignificant initial reduction in cost efficiency occurred at the announcement stage for power plants in the pilot provinces; however, the cost efficiency of the pilot plants increased significantly following formal policy implementation. Additionally, the by-stage treatment effects differed across the pilot provinces due to localized market and non-market variations. Localized conditions of higher marketization, stricter policy enforcement, and lower carbon dependence enhanced this positive effect. The synthetic control results confirmed this variation in the policy effects. The carbon trading pilots resulted in improved efficiency in power plants in Shanghai, Guangdong, and Tianjin during the period 2013–2017, with an associated total cost saving of approximately 29.75 million RMB. To enhance the efficacy of the ETS policy, our findings suggest that the design of the policy should consider localized external factors.

Keywords: Carbon trading; ETS; Cost efficiency; Thermal power plant; China

JEL Codes: D24, H23, Q48, Q52, Q58

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1. INTRODUCTION

Due to the challenges of global warming, many countries have proposed carbon neutral plans to achieve net zero carbon dioxide emissions by the middle of this century. Finding the path for achieving the carbon neutral commitment with the lowest costs has thus become a significant challenge around the world. As a market-driven instrument of environmental regulation with high flexibility, an emission trading scheme (ETS) is believed to relieve energy and environmental stress in a more cost-effective way than other measures (Gallagher et al., 2019). It also has substantial mitigation potential with little negative impact on industrial competitiveness (Joltreau and Sommerfeld, 2019). Understanding the tradeoffs of economic agents between profitability objective and environmental compliance costs after ETS intervention is essential for effective governance. Although several attempts have been made to measure the impacts of an ETS on corporate performance (Xiao et al., 2021; Zhu et al., 2019), much less attention has focused on the cost dynamics attributed to ETS-induced efficiency changes.

This paper addresses this by examining China's ETS pilot policy to quantitatively estimate the impact of the ETS requirements on the cost of utilities. As the main contributor to greenhouse reduction, the power generation industry in China has been required to make significant changes to meet the need for climate mitigation (Duan et al., 2021). China has launched the carbon trading market in 2021 and initially covers the power industry, accounting for nearly 40% of China's carbon emissions. China's carbon trading reforms started in 2011, where the power generation industry in the provinces/megacities of Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen is covered. Power generation enterprises are expected to take the lead in carbon reduction efforts. However, thermal power enterprises in China have been facing unprecedented pressure from both the supply and demand sides (Liu et al., 2021). Strict emission reduction targets and control measures could therefore further aggravate the financial distress being experienced by thermal power enterprises. Therefore, the financial problems of thermal power enterprises are of considerable concern, and understanding the cost implications of the ETS pilot projects is relevant for addressing the financial stress of power plants and helping them to maintain a sustainable electricity supply while optimizing the economic costs of the carbon policy in general.

Our research question is twofold: when does the ETS affect the production cost and the associated cost efficiency of the thermal power plants, and are these effects different across the pilot provinces if the localized conditions vary? Our identification strategy relies on the difference-in-differences (DID) inference where the power plants in the pilot provinces comprise the treated group and the plants in the non-pilot provinces comprise the control group. As the ETS pilot policy took two years to implement after its announcement, we could distinguish the policy shock in two stages: the announcement and formal implementation. To examine the cost dynamics attributed to the two-stage policy shocks, both total production cost and cost efficiency are used as proxies to reflect the cost dynamics, which allows us to explore whether power plants have made genuine efforts rather than just tentatively cut down inputs or production to reduce emissions, because an improvement in cost efficiency leads to sustained cost savings.

The results of the DID estimation illustrate that during the announcement stage, the plants in the pilot provinces experienced an insignificant increase in total costs relative to the plants in the non-pilot provinces. When the pilot policy entered into force after 2013, we found a significant reduction in production costs for the treated group, which implies that the ETS announcement encouraged them to undertake actions to prepare for the change that will be necessary with the incoming carbon emission reduction requirements. Therefore, when the implementation stage starts officially, the plants are well prepared to cut emissions more cost-efficiently. We observed similar results if total costs were replaced by cost efficiency, as there was an insignificant downward adjustment of cost efficiency for the pilot power plants in the announcement stage but a significant increase in cost efficiency when the policy was formally implemented.

Several challenges were identified that may affect the validity of our results. First, the estimated policy effects may not result from the difference between the treated and control groups. We address this by constructing an event-study model to test the parallel trend assumption. Our results confirmed the existence of a parallel trend before the shocks. Second, potential endogeneity may arise if the ETS pilot provinces were not randomly selected. To address this issue, we employ the propensity score matching (PSM) before the DID estimation by constructing a counterfactual control group composed of non-pilots that had the same probability of being selected as pilots (Peikes et al., 2008). Our results survived in the matched DID estimation. Third, there are confounding policies, such as the SO_2 pilot policy and provincial CO_2 emission reduction targets in both the 12th Five-Year Plan (FYP) and the 13th Five-Year Plan. Our results remained after introducing a new policy dummy to capture the confounding effects. Fourth, cost efficiency is estimated through stochastic frontier specification, where the efficiency is truncated between 0 and 1. We thus apply the Tobit model to address the data truncation. All of these checks confirmed the robustness of our results.

We then uncover the condition through which power plants in one pilot province differ from those in other pilot provinces. Our results illustrate that the treatment effects of the ETS differed across pilot provinces. Drawing on external forces from localized characteristics, both market and non-market factors, we find that the degree of marketization, environmental enforcement, and carbon dependence are three potential mechanisms that induce the heterogeneity. High-level marketization leads to more active and sensitive adaption to grasping business opportunities via fierce market competition, strict environmental policy enforcement increases potential regulatory pressure and makes firms take affirmative measures to avoid compliance cost, which means that regions with stronger market competition and policy enforcement allow firms to deal more proactively with shocks from the ETS. However, regions with a higher carbon dependence have difficulties transitioning to a low-carbon energy system due to technology lock-in and resistance, which hamper improvements in efficiency. Therefore, the effectiveness of the ETS depends not only on the actions of the plants covered by the scheme, but also on the external forces being exerted where the plant is located. An appropriate design of the ETS policy should consider these external factors to smooth the barriers that may mute the efficacy of the policy.

Finally, we quantify the cost savings attributed to the ETS. As the underlying effects of the ETS depend on the localized conditions, we estimate the effects by regions. Therefore, we employ the synthetic control method proposed by Abadie and Gardeazabal (2003) for regional analysis. We find that the cost efficiency in Shanghai, Guangdong, and Tianjin experienced a slight drop in 2011 when the pilot policy was announced, and then rose gradually relative to the synthetic control plants when the formal implementation began in 2013 or 2014, which is in line with our DID results. By comparing the regional difference, it can be seen that the ETS significantly improved the cost efficiency for plants in Shanghai, Guangdong, and Tianjin. Also, the estimated average annual cost efficiency improvement during the period 2013–2017 was 9.34 percentage points in Guangdong, 9.31 in Shanghai, and 5.76 in Tianjin. The cost saving attributed to ETS-induced efficiencies can be calculated by multiplying the efficiency improvement with the total costs of the plants. The results show that there was a total cost saving of 29.75 million RMB for plants in Shanghai, Guangdong, and Tianjin over the 2013–2017 period, accounting for 29.94 % of the total cost in 2017. However, the effects are invisible for thermal power plants in Chongqing and Hubei. The validity of the synthetic control results passed the placebo test as suggested by Galiani and Quistorff (2017).

This study makes three main contributions to the existing literature. First, we add to the discussion of policy instruments, in particular the debates on the price versus quantity instrument, for promoting carbon mitigation and a low-carbon economy. Our results shed light on the cost-effective advantage of a carbon ETS by proving the significant role of carbon trading in enhancing the cost efficiency of thermal power plants. This also provides a promising solution for the survival of thermal power plants, which is a pressing problem under the dual goals of power stability and carbon reduction. Second, our study enhances our understanding of the policy process on regulating carbon mitigation in the policy-making stage framework. We demonstrate firms' manifestations towards different policy stages by providing a comparison between the announcement and formal implementation stages. It implies that power plants respond to the announcement of the regulation and try to avoid further regulatory compliance costs after the formal implementation. Finally, we also add to the literature on the effectiveness of the ETS in different localized circumstances by highlighting the conditions that could effectively expand the benefits of the ETS for the cost performance of thermal power enterprises. Our findings therefore provide the theoretical inspiration for accelerating the carbon reduction process. Recommendations for policy are also presented to assist governments to design an ETS policy scheme that promotes carbon market reforms.

The remainder of the study is organized as follows. Section 2 summarizes the related literature. Section 3 presents the theoretical framework, methodology, data sources, and explanation of the variables. Section 4 illustrates the main results with robustness checks and discusses the conditions under which the effects of the ETS become significant. Section 5 presents a regional analysis by synthetic control and quantifies the cost savings associated with efficiency improvements, and Section 6 provides the discussion and conclusion.

2. LITERATURE REVIEW

Based on Porter hypothesis, effective design and implementation of environmental regulation could stimulate firms' innovation and enhance their competitive advantage (Porter, 1991). Weitzman (1974) proposed the important efficiency distinction between equivalent price and quantity controls in the regulated market. Economists have long debated this question, and previous research has also extended the discussion over the use of these two tools in climate change mitigation (Pizer, 2002). The price-based instrument is favored because of the cheaper costs and higher incentives to abate (Tyler and Cloete, 2015), while the preferences for the quantity-based policy are due to the fewer cost uncertainties, higher efficiency, and the advantage in inducing socially optimal technology choice (Krysiak, 2008; Narita and Requate, 2021). Among different regulation tools for carbon mitigation, hybrid ETS policies have gained more support as they yield sizeable cost reductions (Abrell and Rausch, 2017). As a market-based management mechanism, ETS creates strong motivation for firms to internalize the pollution costs through active reforms in a more cost-effective way (Gallagher et al., 2019).

ETS policy has been applied in different national contexts and created unique opportunities, such as ETS in the EU, Switzerland, the U.S., Canada, New Zealand, Korea and China (Narassimhan et al., 2018). Efforts have been devoted to explore the optimal mechanisms for effective carbon market, such as setting of appropriate carbon prices, and allocation methods of allowances and introducing new instruments (Hintermayer, 2020; Newbery et al., 2019; Peng et al., 2021). Although with different cap stringency and allocation practices across nations, existing studies have demonstrated the promising co-benefits due to the implementation of ETS (Bayer and Aklin, 2020; Calel and Dechezleprêtre, 2016; Teixidó et al., 2019).

China has recently become the trading market with the largest carbon emissions coverage in the world. Prior research has illustrated the importance of understanding the specific mechanism of China's ETS, which helps to identify and settle the obstacles to achieving carbon neutral commitment (Chen et al., 2021; Liu and Zhang, 2021). Since its official launch of ETS pilot policy, discussion on China's ETS impact and effectiveness has boomed over recent years. A large and growing body of research has highlighted the positive environmental effects of China's ETS, especially on carbon reduction (Gao et al., 2020; Xuan et al., 2020). Previous evidences show that the ETS-induced carbon mitigation could be achieved via improvement in energy and technical efficiency, lower energy consumption, fuel switch, or industrial structure adjustment (Y. Hu et al., 2020; Zhu et al., 2022). In line with from Porter hypothesis, a growing body of research also stresses the long-run positive effect of the ETS on promoting low-carbon innovation (J. Hu et al., 2020; Zhu et al, 2019), and green total factor productivity (Li et al., 2022). Renewable energy could also be the beneficiary of the ETS, for example, Liu and Zhang (2021) found that ETS has promoted the local development of non-fossil energy, such as the share of hydropower, nuclear, wind power and photovoltaic power. Considering regional development, research has tried to provide evidences on ETS's regional economic and social dividend, such as recovering GDP losses (Wu and Gong, 2021), improving employment (Yu and Li, 2021), and inducing poverty alleviation (Zhang and Zhang, 2020).

Despite these identified benefits, recent evidence has also indicated a negative impact of ETS policy in the short term. ETS could decrease productivity and employment in related industrial sub-sectors, and thus fail to avoid a negative shock on competitiveness (Zhang and Duan, 2020). Moreover, the administration and compliance costs incurred due to the complex implementation process of ETS could become a significant burden for the relevant sectors and firms (Wang et al., 2018). This cost burden could be extremely higher for the power sector, which may further shift more mitigation burden to the industry sector due to the tighter ETS target (Pietzcker et al., 2021). Thermal power plants in China are responsible for electricity system safety maintenance and system peak adjustment, while they are currently going through a difficult transition phase (Liu et al., 2021). Considering the dual role in reducing emissions and maintaining power stability, the financial performance of power plants under the ETS implementation is worthy of attention.

Although previous research has highlighted firm's efforts in pursuit of higher efficiency, much less attention has been paid to whether the economic loss caused by carbon reduction could be covered by efficiency improvement. Moreover, variations in cost performance due to ETS-induced efficiency change remains unknown, especially for entities in highly-regulated sectors such as power generation industry. Therefore, this study has tried to answer these questions based on power plants' operating data, which allows us to track how the system strives to balance environmental and economic demands arising from the implementation of carbon pricing policies.

3. RESEARCH DESIGN

3.1 Theoretical framework

Cost analysis

We formalize a theoretical model for analyzing the cost performance of power plants. We start with the function of cost performance below:

$$C = f(V, Z; \beta) \tag{1}$$

Internal factors of a power plant are the key to determining its cost performance. Therefore, V

refers to a vector of plant-level explanatory variables that could influence the plants' cost performance. Specifically, V considers factors such as output measured by total electricity power generation output (*output*), the price of inputs such as capital (p_e) and labor (p_l), the endowment structure (*klr*), and undesirable output of pollution (*erso2*). Moreover, regional environment could act as an important factor for the operation and management of business entities, further affecting their cost performance (Alsaleh and Abdul-Rahim, 2018). We thus additionally considering a vector of provincial factors related to economy, policy, technology and environment conditions as explanatory variables represented by Z. These provincial-level variables include GDP per capita (*pergdp*), industry structure (*indratio*), foreign direct investment (*fdi_r*), investment in pollution control (*indinvest*), marketization degree (*market*), environmental enforcement (*penalty*), policy uncertainty (*epustd*), technological innovation capacity (*totalpat*) and carbon dependence (*carbongdp*).

Policy analysis

An effective strategy to estimate the ETS impact could be to compare the differences in cost performance of pilot plants and non-pilot plants before and after ETS policy came into effect. Following Ashenfelter and Card (1985), in a simplified model with two regions (pilot, non-pilot) in two time periods (pre, post), the difference can be estimated as,

$$\hat{\beta}^{DD} = \left(\bar{C}_{pilot}^{post} - \bar{C}_{pilot}^{pre}\right) - \left(\bar{C}_{non-pilot}^{post} - \bar{C}_{non-pilot}^{pre}\right) \tag{2}$$

where$\left(\bar{C}_{pilot}^{post} - \bar{C}_{pilot}^{pre}\right)$ evaluate the changes in cost performance before and after ETS policy took effect in pilot plants, and $(\bar{C}_{non-pilot}^{post} - \bar{C}_{non-pilot}^{pre})$ refers to the changes in cost performance of non-pilot plants. The estimator $\hat{\beta}^{DD}$ represents the difference between these two changes and can be considered as the treatment effect after excluding interference of externalities.

3.2 Empirical method

Difference-in-Differences model

We choose DID model as our identification strategy to compare the cost performance of power plants with and without implementation of the ETS pilot policy. DID model helps reduce other exogenous interference by calculating the estimator $\hat{\beta}^{DD}$ as discussed above (Blackburn et al., 2020). The quasi-experiment in China's ETS pilot policy creates two groups of power plants in the treated and untreated provinces respectively, which is advantageous for conducting DID analysis. Previous research has also shown the validity of DID method in analyzing China's ETS policy (Chen et al., 2021).

The treatment group comprises thermal power plants located in the pilot provinces, and the control group comprises plants in the non-pilot provinces. China's ETS pilot policy was implemented in two phases: the pilot provinces were announced in 2011, and formal implementation occurred after 2013, allowing us to distinguish between the announcement effect and trading effect (Cui et al., 2021). It is assumed that regulated plants began preparing their carbon emission controls after the ETS announcement, while essential information such as carbon market quotas and carbon price could only be ensured after the official launch of the trading market. Policy recipients may behave differently at different policy stages (Ladino et al., 2021), and identifying these differences could enhance our understanding of the policy process on regulating carbon mitigation in the policy-making stage framework. In this study, we thus consider the impact of both the ETS announcement and its implementation on the pilot power plants. We use the DID methodology to estimate whether there is a significant difference in cost performance between ETS and non-ETS power plants by adopting the following equation.

$$Y_{it} = \beta_0 + \beta_1 ETS_{announce} + \beta_2 ETS_{implement} + \lambda X_{it} + \eta_i + \gamma_t + \varepsilon_{it} \tag{3}$$

where i and t refer to power plant and year, respectively. Y_{it} is the dependent variables of total cost and cost efficiency, and $ETS_{announce}$ and $ETS_{implement}$ are the interactive terms of treated pilot provinces and policy intervention year. $ETS_{announce}$ takes the value of one for all plants sitting in the pilot provinces after 2011, the year of the ETS announcement, and $ETS_{implement}$ equals one for pilot provinces after the formal implementation year of 2013 for Guangdong, Shanghai, and Tianjin provinces and 2014 for Chongqing and Hubei provinces. Therefore, β_1 and β_2 measure the ETS announcement effect and implementation effect, respectively. X_{it} is a set of covariates that will influence total cost and cost efficiency, including both plant-level and provincial-level characteristics, λ denotes the estimated coefficients for covariates. η_i and γ_t denote plant fixed effect and year fixed effect, respectively, controlling for the firm-level and year-level unobservable factors that could affect cost performance of power plants, and ε_{it} is the error term.

Event study

The validity of DID estimates is based on the parallel trend assumption that any external shocks other than the policy treatment would affect the pilot and non-pilot groups in a similar manner (Xiao et al., 2021). Therefore, the main concern in DID analysis is that the observed distinction between the power plants in the pilot and control provinces may not be the result of the policy treatment. A common diagnostic approach is to look at whether the outcomes in the treatment and control groups differ significantly before the policy change (Freyaldenhoven et al., 2019; Fuest et al., 2018). Event study allows to test this parallel trend assumption by providing comparison of yearly outcome trends in two groups (He et al., 2020). Therefore, we adopt an event study approach to detect trends before the ETS policy came into effect, and to present the yearly dynamic effect after the ETS announcement and implementation.

We use the following form of event studies:

$$Y_{it} = \sum_{j=-5}^{4} \beta_j D_t^j Treatment_i + \lambda X_{it} + \eta_i + \gamma_t + \varepsilon_{it}, \tag{4}$$

where plant and year are indexed by i and t, notation for years is $t = 1, 2, \ldots, T_0, \ldots T$, Y_{it} is the cost outcome, including total cost and cost efficiency, $Treatment_i$ indicates whether a power plant sits in the pilot province, and D_t^j is a set of time dummies equal to 1 if $t = j$ and 0 otherwise. The coefficient estimation of β_j thus could be conducted separately for each year except the base year of T_0, which is set to 2010, one year before the ETS pilot announcement. X_{it} concludes both plant-level and provincial-level control variables, identical with the previous DID model, η_i is a set of plant fixed effects, γ_t is a set of year fixed effects, and ε_{it} is the error term.

3.3 Data source

Thermal power plant data from 2006 to 2017 were collected from *Compilation of Statistical Data of China's Power Industry* and *Survey of China Electricity Council*. For provincial-level data, economic policy uncertainty (EPU) index data were obtained from Yu et al. (2021). To measure the degree of provincial marketization, the provincial market index from the China Market Index Database was employed. To calculate carbon intensity, carbon emission data were collected from the China Emission Accounts and Datasets (www.ceads.net). The number of environmental administrative penalty cases were found in the *China Statistical Yearbook on Environment*. Other provincial level data were calculated from data in the *China Statistical Yearbook*.

As we focus on the ETS effect on thermal power plants in the pilot provinces, Beijing and Shenzhen are excluded because there are no thermal power plant data for these two cities. Therefore, in this study, we only consider the cost performance of power plants in five pilot provinces: Shanghai, Guangdong, Tianjin, Chongqing, and Hubei. Our final dataset included 92 thermal power plants in China for the period 2006–2017[1], of which 18 power plants were in the treated group of ETS pilot provinces. Our dataset contains the observation period of at least three years both before and after policy treatment and allows us to carry out the research. Descriptive statistics are shown in Table 1**[[table 1 about here]]**.

3.4 Variable

Two dependent variables

This study mainly utilizes two dependent variables to measure policy effects on cost outcome, total cost, and cost efficiency. We collect plant-level data to examine the internal cost shift before and after the policy change. *Total cost* is used to study the direct effect of the policy on power plants' cost changes. However, in response to the increasing carbon emission costs resulting from the ETS, plants may conduct proactive measures such as technology improvement, equipment upgrading, and process optimization, which result not only in a reduction in total costs but also changes in the theoretical cost frontier. To explore this potential effect, *cost efficiency* is estimated to see whether the ETS leads to internal upgrading and improvements in efficiency in thermal power plants.

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[1] Unbalanced panel data due to missing data in 2016-2017 for few power plants.

Measurement of cost efficiency of thermal power plants

We calculate cost efficiency for each power plant from 2006 to 2017 to explore whether plants' cost efficiency has been improved through internal upgrading. Cost efficiency is calculated by conducting a stochastic frontier analysis, which has been widely used in efficiency research (Zhang, 2017; Zhang and Adom, 2018). Following the basic formulation proposed by Aigner et al. (1977), we construct the optimal cost frontier, which is specified as the function of input prices, output, and a set of explanatory factors (Filippini and Greene, 2016). Moreover, Mundlak's (1978) specification is adopted with the explanatory variables to control potential, unobserved, individual-specific heterogeneity (Filippini and Zhang, 2016). After log-transformation of cost function, maximum likelihood estimation can be used to determine the parameter values in the cost function, sample data can be used to determine the theoretical minimum cost for each power plant, and the ratio of theoretical minimum cost to actual total cost can be used to determine cost efficiency. The detailed steps in the stochastic frontier analysis are provided in Appendix S3.

Independent variable

$ETS_{announce}$ and $ETS_{implement}$ are two dummy variables for measuring plants covered by the CO_2 emissions trading policy after treatment. Specifically, they are constructed by interacting a pilot dummy variable that represents whether the power plant is in the ETS pilot provinces with dummy variables of policy announcement year (2011) and implementation year (2013 for Guangdong, Shanghai, and Tianjin and 2014 for Chongqing and Hubei), respectively.

Control variables

Plant-level covariates

Electricity output. Electricity power generation is the direct output of power plants and reflects the plant's installed capacity and production efficiency (Tzimas and Georgakaki). Higher power output usually requires for more labor and capital inputs, accompanied by higher production, operation and maintenance costs.

Input price. The main inputs are energy and labor, which directly affect cost (Filippini and Greene, 2016). We include the prices of labor and energy per unit as the input prices for electricity production. Specifically, *lnpe* is total energy cost divided by the amount of energy consumption, and *lnpl* is total labor cost divided by the amount of labor. Moreover, both labor cost and energy cost are adjusted by the provincial electricity price to avoid the influence of inflation on cost.

Endowment structure. The capital labor ratio is used to measure endowment structure, which refers to the ratio of the quantities of the two main inputs, capital input and labor input, for power plants (Chen et al., 2021). In this study, capital refers to the installed power capacity and labor is measured by total employees, representing the basic internal resource allocation in electricity production.

SO_2 emission. SO_2 is one of the main pollutants emitted by thermal power plants, and is also regarded as an important measure for the level of air pollution. SO_2 emission per unit of power generation could reflect a plant's environmental management and cleanliness performance in electricity production (McLinden et al., 2016).

Province-level covariates

GDP per capita (*lpergdp*). GDP per capita reflects the regional economy development level. Considering higher demand for electricity in economically developed areas, GDP per capita could potentially influence the operations and financial performance of power plants. It is calculated by annual provincial GDP divided by total population and constructed in a logarithmic form (Xiao et al., 2021).

Industry structure (*indratio*). Industry structure is assessed by calculating the ratio of added value of the secondary industry to GDP. The proportion of secondary industry indicates the development of industry and the regional industrial economic structure (Huang and Du, 2020). It could influence the regional power supply and demand situation and may further affect operation efficiency of power plants.

Foreign economy (*fdi_r*). The ratio of foreign direct investment to annual GDP is used to measure economic openness (Yang et al., 2021). Since the development of infrastructure such as electricity is an important factor attracting foreign investment, the ratio of foreign direct investment could be considered as a potential factor affecting the development of power plants. In order to avoid the influence of exchange rate fluctuations, we also adjust foreign direct investment by the annual exchange rate.

Environmental investment (*lindinvest*). Environmental investment reflects provincial environmental protection and pollution control efforts, and is expected to help reduce environmental pollutants from the power sector. It is assessed by the treatment of industrial pollution in log form (Xuan et al., 2020).

Policy uncertainty (*epustd*). We use the economic policy uncertainty index to evaluate the policy environment. The uncertainty of policy may affect the policy risks as perceived by power plants and thus influence their operational and management activities (Yu et al., 2021).

Innovation capacity (*ltotalpat*). Regional innovation capacity reflects the development and intensity of regional innovation systems, further influencing technical performance of regional subjects. Regional innovation capacity is measured by the number of total patent applications in the logarithm (Liu and Zhang, 2021).

Marketization (*market*). Marketization reflects the dynamics of the market and advancement of the market economy, which could affect business entities' capacity of market responsiveness and resource allocation. Following Wang et al. (2019), we use the comprehensive market index, which considers the relationship between government and market, development of the non-state economy, product market, factor market, market intermediary organization, and legal system environment.

Environmental enforcement (*lpenalty*). A higher intensity of environmental law enforcement could also lead to enterprises experiencing higher environmental pressures (Blundell, 2020). Environmental enforcement is measured by the number of provincial environmental administrative penalty cases in the logarithm.

Carbon dependence (*carbongdp*). Carbon dependence describes the level of carbon pollutants emitted during economic development and could also reflect the difficulty and potential burden of reducing carbon dioxide emissions. Carbon dependence is measured by total provincial CO_2 emission inventory divided by annual GDP (Zhang and Duan, 2020).

4. MAIN RESULTS

4.1 Baseline results

In order to identify the effect of the ETS announcement and implementation, we test three aspects: (a) only $ETS_{announce}$, (b) only $ETS_{implement}$, (c) both $ETS_{announce}$ and $ETS_{implement}$. We first estimate the ETS effect on the total costs of thermal power plants. Columns (1) and (2) in Table 2**[[table 2 about here]]** show that the ETS effect on power plant costs is not significant when considering the policy announcement and implementation separately. Next, we consider both policy announcement and implementation in one equation (Table 2 column 3), and although the results are not significant, there is initially an increase in power plant costs after the year of announcement and then a decrease in costs after the formal implementation year. The results indicate that the ETS announcement may provide a warning for the pilot power plants that encourages them to begin to prepare for the changes that will be necessary with the incoming carbon emission reduction requirements, which means that when the implementation stage starts officially, the plants are well prepared to cut emissions with the most cost-efficient approach.

There are two possible reasons for the cost reduction. The first reason is that the pilot power plants directly compressed spending on capital and labor or cut down their electrical production to reduce carbon emissions (Zhang and Duan, 2020). This can be regarded as a short-term response, as it is not sustainable if the plant is to remain competitive. The second reason is that thermal power enterprises improved their cost efficiency by undertaking internal reform measures in their operations and management, such as improving resource utilization efficiency, conducting technological innovation, optimizing operation processes, and so on. The latter is what we expected from the ETS policy as enhancement in cost efficiency will lead to sustained cost savings in the long run. Therefore, we evaluate the ETS effect on the cost efficiency of pilot power plants to see whether it induces continuous improvement in cost performance.

The results in Table 2 column (6) shows that cost efficiency may initially be reduced (not statistically significant) and then be significantly improved due to the ETS implementation. Enhancement of cost efficiency implies that the cost reductions are not a temporary situation resulting from directly cutting down expenditure or output, but rather that the power plants in the pilot provinces have undertaken long-term reform measures, such as upgrading their facilities, technologies, or management when confronted by the environmental regulation stress. Our results are in line with Cui et al. (2021), who argue that firms' respond to the ETS by conserving energy, switching to low-carbon fuels, reducing labor and capital inputs, and improving firm productivity to reduce emissions while maintaining the same level of output. This also sends a good signal that the ETS policy has forced thermal power enterprises to carry out internal reforms to reduce compliance costs. Moreover, since the pilot power plants are assumed to undertake long-run internal reform measures to reduce carbon emission, the remaining reduction in total cost in addition to the cost efficiency may also be explained by other benefits from decarbonization efforts. For example, power plants could spend less expenditure on sewage charges or environmental taxes, or apply more subsidies for their clean transition, such as optimizing energy structure and enhancing resource recycling.

4.2 Test for parallel trend assumption

The most important premise for the DID analysis is to satisfy the parallel trend assumption. In other words, to provide evidence that pilot and non-pilot areas had similar trends before the ETS policy. Therefore, we adopt the event study method to test the trend before and after the ETS policy. The policy effects on total cost and cost efficiency from 2006 to 2017 are shown in Figures 1(a) and 1(b) **[[fig 1 about here]]**. The default baseline year is 2010, one year before the ETS policy announcement.

As is shown in Figure 1, the coefficients in the pre-ETS period (before 2011) do not show obvious differences between the pilots and non-pilots, which meets the parallel trend assumption for the DID analysis. In the post-regulation period (after 2011), the effect of the ETS announcement is not significant for the first two years; however, a clear downward trend in the ETS effect on total cost appears after 2013, the year of the ETS implementation. This indicates that the ETS has reduced the costs of power plants since 2013. A consistently clear upward trend of policy effect on cost efficiency can be observed in the same period. Moreover, results from event study analysis also address the expectation effect before ETS implementation, as no non-clear differences are found between the pilots and non-pilots before 2011.

We also perform other methods to test the parallel trend. We first follow Liu and Zhang (2021) and conduct a set of pre-period placebo intervention tests by adding the interaction terms of $Treatment*Post_{2007}$, $Treatment*Post_{2008}$, $Treatment*Post_{2009}$ and $Treatment*Post_{2010}$. If there is no significant difference in cost outcome between pilot and non-pilot plants in the above parallel trend analysis, the estimated coefficients of the *treatment*post* are expected to be statistically insignificant. Otherwise, there may be some unobservable factors other than the ETS that induce the higher cost performance of the pilot plants. The results in Appendix Table 1 show that the coefficients of the interaction terms are insignificant for both total cost (columns 1-4) and cost efficiency (columns 6-9), which addresses this concern.

We also follow the method of J. Hu et al. (2020) to test the parallel trend by using pre-ETS period data. A time trend variable (*Trend*) is constructed to measure time linear trends between the pilot and non-pilot provinces, which are assigned values of 1, 2, 3, 4, 5 in 2006, 2007, 2008, 2009, 2010, respectively. As it is assumed there were no systematic differences in cost trends between the pilot and non-pilot areas before the ETS policy announcement, the coefficient of *treatment*×*trend* is supposed to be statistically insignificant. The results in Appendix Table 1 columns (5) and (10) support this assumption, which once again suggests that the parallel trend assumption of the DID approach is not violated.

4.3 What makes the policy effect different?

We then explore potential factors that could impact on the effectiveness of the ETS, as the actual effects on cost performance of the ETS may vary in practice. Since China ETS policy started in pilot provinces and has been recently expanded for nationwide implementation, it is important to explore different provincial policy elements and identify key mechanisms that could influence ETS policy effectiveness. It allows us to give more specific and practical policy implications for enhancing ETS effectiveness. We thus try to uncover the local conditions that could effectively expand ETS benefits from the perspective of policy implementation environment (marketization degree), policy enforcement intensity (environmental enforcement) and difficulty in achieving policy goals (carbon dependence). Based on the benchmark DID model, we further interact $ETS_{implement}$ with these three provincial characteristics that may act as the impact mechanisms in Table 3**[[table 3 about here]]**.

A. Impact of Marketization

Policy implementation environment is a crucial influencing factor in determining policy effectiveness (Haggerty et al., 2018). As a market-driven instrument, the ETS policy could be particularly influenced by the local market economy development (Ren et al., 2020). The external market environment exerts pressures on enterprises, which need to adjust their competition strategy formulation to adapt to survive and prosper (Collis, 1991, Scherer & Ross, 1990). Market competition factors of transaction volume, price, cost, and competitiveness directly affect trading activities and market efficiency (Healy et al., 2014). High-level marketization promotes capital flow, market element development, and resource allocation (Wu, 2002), and in a high-level marketization environment, the more efficient and competitive enterprises are more likely to obtain business opportunities and resources via market competition (Gao et al., 2010; Xie, 2017), which could lead to more active internal adjustments, more sensitive market adaption, and potentially higher production efficiency for enterprises (Cui et al., 2020). Therefore, in order to grasp the competition opportunities and winning advantages, power plants are more likely to engage actively in emissions trading with higher efficiency under the circumstances of rapid market development and fierce competition. When carbon emissions are brought into the market, enterprises respond more quickly in the face of market reform resulting from the ETS. Based on this view, advancement of the market economy is considered an important catalyst for ETS policy effectiveness.

The marketization index is adopted in this study to reflect market economy development according to Wang et al. (2019). In Table 3 columns (1) and (4), we aim to estimate whether heterogeneity in provincial market development could influence ETS effectiveness. The significantly positive coefficients of $ETS_{implement}*market$ in both the cost and cost efficiency equations show that the development of provincial marketization contributes to the cost savings and efficiency enhancement induced by the ETS pilot policy. The results are consistent with Chen et al. (2021) and J. Hu et al. (2020), who found that the marketization level enhances the positive effect of the carbon ETS on entities' efficiency or innovation performance.

B. Impact of environmental enforcement

Local environmental enforcement regime could reflect the orientation of environmental official, the institutional capacity of enforcement teams, and the external political support (Francesch-Huidobro et al., 2012). The intensity of environmental enforcement is assumed to be a key factor in the effective implementation of a carbon emission trading market. For policy recipients, as "rational" economic entities, the core organizational goal is profit maximization (Schoemaker, 1993). The level of environmental supervision and enforcement will impact on an enterprise's management decisions about how they will adapt to the policy requirements and enforcement (Heyes and Kapur, 2009; Pashigian, 1982). In areas with stricter environmental regulations, enterprises will be vigilant about policy requirements and rules and implement adaptive strategies to avoid penalties (Sun et al., 2019). Thus, the greater the intensity of environmental law enforcement, the higher the costs faced by enterprises for non-compliance, and the more likely enterprises will follow the ETS regulations to avoid violation penalties (Blundell, 2020). For policy enforcers, the operation of the ETS requires a high level of execution, such as collection and management of emission information, supervision of market transactions, punishment of non-compliance with trading rules, and management of levies on excessive pollution. A high intensity of policy enforcement provides necessary support and ensures orderly operated market transaction for the implementation of emission trading (J. Hu et al., 2020).

To test whether environmental law enforcement affects ETS policy effectiveness, we use the interaction between $ETS_{implement}$ and the number of environmental administrative penalty cases. The results from Table 3 columns (2) and (5) show that the ETS has a greater promoting effect on cost reduction and cost efficiency improvement in regions with higher policy enforcement intensity, which is consistent with J. Hu et al. (2020). It implies that plants have taken active measures to enhance cost efficiency and relieve the cost burdens of adapting to the policy regulation pressure. Therefore, policy enforcement is essential for ensuring ETS effectiveness, as it affects the behaviors and strategies of both ETS market managers and participants. Support from local governments, especially those responsible for environmental law enforcement, could be an important contributing factor in the effective implementation of China's ETS.

C. Impact of carbon dependence

Due to different local resource endowments and economic development process, the difficulty of achieving environmental policy objectives could vary substantially across regions. Regional dependence on high carbon-emitting industries is a major obstacle to achieving carbon reduction targets (Janipour et al., 2020). Arthur (1989) first put forward the theory of path dependence in the process of technological evolution, which explains that the advantage of scale return for early entrants makes it difficult for the latecomer technology to gain benefits. Regional economies could therefore become locked into development paths that lose dynamism (Martin and Sunley, 2006). Similarly, a carbon-based energy system that benefits from long-term incremental returns may also create a lock-in effect that hampers the transition to low-carbon alternatives (Erickson et al., 2015). Participants who are benefitting from the existing fossil fuel-intensive system will try to maintain it, which further reinforces the lock-in of existing technology systems and impedes low-carbon innovation (Liu et al., 2017). Therefore, the primary carbon emission intensity of different regions could affect ETS effectiveness on plant cost performance. Regions with higher carbon dependence may have higher resistance to low-carbon energy systems and technological innovation, resulting in reduced ETS effectiveness on the cost efficiency improvement of pilot plants.

We adopt the indicator of carbon emissions per GDP to measure carbon emission intensity. In line with our hypothesis, it is found that carbon emission intensity imposes a significant negative ETS impact that leads to higher costs and lower cost efficiency of power plants (Table 3, columns (3) and (6)). This finding supports the conjecture that provinces with a higher economic dependence on carbon-intensive industries experience more pressure when preparing for the ETS, as they have more difficulty reducing emissions due to the significantly higher costs of introducing and reforming low-carbon technologies and facilities. A relatively more tolerant attitude towards pollution due to high economic dependence on polluting entities could be another reason, as there may be less motivation for radical transformation. On the other hand, those with a lower emission intensity can respond more flexibly to the ETS reform and achieve more cost savings. A potential problem is that current difficulties with emissions reduction may depend more on emission status in the previous period. Therefore, in our unreported results, we also test whether a one-year lag of carbon intensity affects current cost performance. The results remain consistent and shows robustness of the negative ETS effect on both cost savings and cost efficiency.

Therefore, we conclude that there are four potential factors that will influence ETS effectiveness in improving power plants' cost performance. A higher degree of marketization, stricter environmental enforcement, and lower carbon dependence provide a favorable environment for thermal power plants to achieve more cost savings and higher cost efficiency when facing the emissions reduction pressure required by the ETS policy.

4.4 Robustness check

A. PSM-DID analysis

A significant challenge is that the ETS pilot provinces were not randomly selected, which can result in potential endogeneity issues and violate DID assumption. Although we have controlled provincial economic, policy, technology and environment factors in the model, the DID model and event study design that we adopted are still subject to potential estimation bias from selection. To relieve the non-random selection bias of the ETS treatment, the propensity score matching method and difference-in-difference model (PSM-DID) are integrated to examine the robustness of the baseline DID results. PSM is first performed to match the pilot and non-pilot groups. The basic idea is to create a counterfactual control group composed of non-pilots that had the same probability of being selected as pilots (Peikes et al., 2008). First, a logistic regression is applied to estimate propensity scores, and the radius matching procedure within calipers of 0.05 is conducted to obtain control groups. Second, the DID model is applied using the treatment group and new counterfactual control group after matching, which dropped those unmatched observations with the PSM procedure.

The PSM-DID results in Appendix Table 2 show that both the baseline and heterogeneous analyses are robust after dropping the unmatched samples. Therefore, the matching process between the treated and control groups does not significantly affect our main outcomes. Also, the balancing test of the PSM procedure is shown in Appendix Table 3, indicating no significant differences between covariates in the treated and untreated group after matching. All standardized biases are less than 18%, which suggests a high matching quality of data pairs.

B. Excluding potential effect of confounding factors

The DID approach also assumes no other confounding factors that might affect the outcome variable simultaneously with the policy treatment. Therefore, we control other factors with potential impact on plants' cost efficiency over the same period. First, as the SO_2 pilot scheme was implemented in 2007, which was within our research period, we construct a dummy variable *SO2ETS* to control for its confounding impact on power plants. *SO2ETS* is equal to 1 if the plant sits in a pilot province for the SO_2 ETS, which included Jiangsu, Zhejiang, Tianjin, Hubei, Hunan, Inner Mongolia, Shanxi, Chongqing, Shaanxi, Hebei, and Henan. Even with the lower significance of the carbon mitigation impact mechanism, the core results when considering the SO_2 ETS program are still robust (Appendix Table 4).

Second, China's State Council has set CO_2 emission reduction targets for each province in both the 12th FYP (2011-2015) and the 13th FYP (2016-2020) for controlling greenhouse gas emissions. Provincial emission control targets may further affect the performance of power plants in different provinces. Therefore, we additionally include the variable *Co2Target* in our model to control for the impact of this work plan, which is constructed based on the provincial target rate for reducing CO_2 emissions per unit of GDP[2]. Our main results when considering the provincial CO_2 emission reduction targets are consistent (Appendix Table 5).

C. Adopting different model specifications

In this paper, the explained variable *costeff* refers to cost efficiency, which is censored data ranging from 0 to 1. A potential concern lies in that an ordinary regression model may omit the problem of censored data; therefore, we use the Tobit model to test the robustness of the cost efficiency results in Appendix Table 6 columns (1)–(4). Moreover, since we have control of both the plant-level and provincial-level covariates, a possible problem is that *costeff* is estimated at plant level, and the plant-level characteristics may cause a multicollinearity problem in the DID analysis. Therefore, we drop the plant-level covariates and use provincial-level controls to estimate the treatment effect on cost efficiency. The results are shown Appendix Table 6 columns (5)–(8). The results in Appendix Table 6 support the robustness of our analysis.

5. FURTHER ANALYSES OF FIVE PILOT PROVINCES

5.1 Synthetic control method

In the above analysis, we discussed the treatment effect of the ETS on all pilot provinces. In this section, we aim to further specify the ETS effect on cost efficiency in different pilot provinces. We focus on the provincial effect of cost efficiency as it is more reflective of the internal upgrading activities undertaken by the enterprises. It is considered more important that thermal power enterprises achieve consistent cost savings.

To undertake this provincial analysis, we employ the synthetic control method proposed by Abadie and Gardeazabal (2003). This method has several advantages. First, the SCM method helps to address selection bias by constructing a counterfactual unit for each treated unit. Targeted evaluation on different treated units is thus allowed to evaluate heterogeneity in policy implementation. Second, the optimal weight used to construct the control counterpart is determined by the data and their matching results, which avoids the bias from subjective choice. Third, as we control for plant-level covariates when conducting the DID analysis, the SCM helps to address the potential multicollinearity problem in the traditional DID model. Therefore, we further utilize the SCM method to measure the treatment effect of the ETS on cost efficiency in different provinces.

[2] As there is no specific provincial-level target for CO2 emission reduction in the 11th Five-Year Plan (2006-2010), *Co2Target* before 2011 is set to be 0.

Following Abadie et al. (2010), we presume that there are *J+1* units, with the first unit being treated and the remaining units making up the control pool. $\hat{\alpha}_{1t}$ is the estimator of the intervention effect for treated unit at time t. y_{1t}^{I} is the observed outcome for the treated unit in period t. Supposing that T is the number of whole time periods and T_0 is the pretreatment period, for $t > T_0$, the treatment effect can be given as follows:

$$\hat{\alpha}_{1t} = y_{1t}^{I} - \hat{y}_{1t}^{N} \tag{5}$$

where y_{1t}^{N} is the supposed counterfactual outcome if the treated unit was not treated. This synthetic counterfactual of a treated unit is constructed by combining the other control units linearly in the SCM method. For $t > T_0$, y_{1t}^{N} can be estimated with:

$$\hat{y}_{1t}^{N} = \sum_{j=2}^{J+1} w_j^{*} y_{jt} \tag{6}$$

where W* is an optimal vector of weights to minimize the distance between the preintervention covariates for the treated unit and control units. If X_1 is a vector of pretreatment covariates for the treated unit and X_0 is a vector of the same covariates for the untreated units, the discrepancy between X_1 and X_0W can also be expressed as:

$$\parallel X_1 - X_0W \parallel_V = \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)} \tag{7}$$

where V can be considered to be some symmetric and positive semidefinite matrix to get the minimum root mean squared prediction error (RMSPE). In other words, it helps the synthetic control unit to approximate the outcome trajectory of the treated unit during the pretreatment stages, thus minimizing the preintervention discrepancy between the treated and control units.

5.2 Provincial treatment effect

Figure 2**[[fig 2 about here]]** provides the cost efficiency between the treated power plants and synthetic control plants in five pilot provinces, showing that the trend for the ETS treatment effect is similar in pilot provinces such as Guangdong, Shanghai and Tianjin. Initially it shows a slight drop in 2011 and then it gradually increases and surpasses the cost efficiency of synthetic control plants. The positive effect is enlarged after ETS implementation, especially over the period of 2013-2015, and contracted between 2016 and 2017. The different outcome between announcement and implementation stage is consistent with the previous baseline analyses, which showed that the average treatment effect is initially negative after the ETS announcement and then reverses to be significantly positive following the implementation of the ETS in 2013, though the former effect is not significant. Therefore, these analyses again illustrate that the announcement of the ETS leads to preparation for emissions reduction in the pilot power plants, which results in additional costs and temporary loss of cost efficiency. The reversal of the trend occurred after the pilot plants had adapted to the policy intervention by collecting enough information and upgrading their devices and technology, eventually benefitting from the implementation of the ETS policy. Moreover, the reduction of positive treatment effect in 2016 may due to China's announcement to establish a national carbon emissions trading market, which is accompanied by the refinement of relevant market rules and regulations. The new reaction and adjustment of the power plants may affect the continuous improvement of cost efficiency. The rebound of the positive treatment effect in 2017 may indicate that the ETS could provide an incentive for long-term cost efficiency growth.

Our results imply that the cost efficiency of pilot plants could be improved due to active internal reform measures, pilot plants without the ETS intervention are thus assumed to be have less incentive for upgrading technology and optimizing operation. The drop of the fitted synthetic control curve in Figure 2 provides some evidences that the cost efficiency of synthetic control units decreases compared with treated plants. This may result from two potential reasons. First, considering the increasing cost burden of power plants in China, the reduction of efficiency could be due to the lack of active efforts for improving production and operational capacity (Zhang and Adom, 2018). Second, with the development of technology especially in pilot power plants, the optimal cost efficiency is supposed to be higher and lead to the lower cost efficiency of power plants in non-pilot provinces.

The ETS treatment effect of each separate pilot province is then compared to determine the significance of the treatment effect. We undertook the placebo test to test the validity of the synthetic control analysis. Appendix Table 7 shows the p-values that denote the proportion of placebo effects from the control units that have posttreatment RMSPE at least as great as the treated unit (Galiani and Quistorff, 2017). The comparison of the significance of the provincial treatment effect reveals that the ETS significantly improves cost efficiency in Shanghai, Guangdong, and Tianjin; however, there was no positive effect on cost performance of thermal power plants in Chongqing and Hubei.

There are several potential reasons for the difference. According to information on carbon exchanges in the pilot provinces, the carbon market in Chongqing is the least active, with lower trading volume and poorer transaction transparency. The allowance allocation in Chongqing is based on firms' self-declaration and allows for ex-post adjustment, resulting in lower compliance pressure. The compliance rate of the Chongqing carbon market in 2013–2014 was only 70%, which is much lower than the other pilots and supports the low ETS effectiveness in Chongqing. Given the better trading volume and liquidity in the Hubei carbon market, the insignificant positive effect in Hubei could be partially explained by our mechanism analysis. For example, for carbon dependence, Hubei is the only pilot province in central China and its heavy industrial structure means it has the highest carbon intensity among all pilots (Cao et al., 2021), which may increase its cost burden when adapting to the carbon trading reform requirements and cause a low ETS effectiveness on cost performance.

One main assumption of SCM analysis is that the intervention has no effect on the cost performance before the treatment period, which has been discussed in the event study analysis. Another assumption is that the cost performance of the non-pilot units is not affected by the ETS pilot policy intervention in the pilot provinces, known as the assumption of no interference between units (Abadie et al., 2010). In the context of our analysis, several potential ways may result in the violation of this "no interference" assumption. One concern is that the implementation of ETS policy may raise the awareness of carbon reduction in non-pilot provinces and induce similar responsive measures, contaminating the donor pool. Since the national unified carbon emissions trading market was officially announced at the end of 2017, it is expected that the preparation of national carbon emission trading would not severely affect the untreated power plants during the research period. However, previous findings showed the exist spillover effects of ETS on improving the green total factor productivity and reducing carbon emission in non-pilot cities and provinces (Li et al., 2022; Yang et al., 2022; Zhu et al., 2022). Although there is no enough evidence indicating its influence on plant-level financial performance in non-pilot provinces, it is still possible that these factors could contaminate the donor pool and further lead to underestimation of the cost efficiency improvement for treated power plants. If this is what actually happens, our study provides a relatively conservative estimate of the ETS policy effect. Another concern is that the power enterprises may choose the strategy to transfer some high-polluting operation from plants in pilot provinces to those in non-pilot provinces. This is not a serious concern as the power supply and demand situation within each province were quite different, and the power plants need to strictly obey the local grid dispatch regulations. Moreover, China's inter-provincial power trading was not mature during our research period, which makes it less possible for the trading or other similar coping strategies between power plants. Therefore, it is expected that this concern would not seriously affect the results.

To additionally figure out the question that whether our SCM estimations could be driven by chance, we then conduct placebo tests by considering cases that if we had treated other non-pilot plants randomly instead of plants in pilot provinces. In the calculations undertaken in the analyses above, we consider the characteristics of each separate power plant in the treated provinces. Moreover, as a robustness check, we regard the power plants in the treated provinces as one unit; specifically, we calculate the mean value of all variables and create a plant that represents the mean status of all power plants in each treated province. We then adopt the SCM again and obtain the placebo test results. The results are similar, in that there is significantly improved cost efficiency in Guangdong, Shanghai, and Tianjin but not in Chongqing and Hubei (Appendix Figure 1).

5.3 Cost saving

Based on the results of the synthetic control method, Figure 3(a)**[[fig 3 about here]]** shows the comparison of the ETS treatment effect between different pilot provinces from 2011 to 2017. Specifically, we calculate the average treatment effect of the ETS on power plants' cost efficiency in each pilot province from 2013 to 2017, as the treatment effect is statistically significant after 2013. The estimated average annual cost efficiency improvement is 9.34 percentage points in

Guangdong, 9.31 in Shanghai, and 5.76 in Tianjin. The cost saving from cost efficiency improvements can be speculated using the following equation:

$$Cost\ savings\ =\ Cost\ efficiency\ improvement\ \times Total\ cost$$

The cost savings calculated using the above equation are shown in Figure 3(b). As the treatment effect of Hubei is not statistically significant, the cost savings of Chongqing and Hubei are shown in grey in Figure 3(b). The cost saving for thermal power plants in each pilot is different when both total cost and cost efficiency improvement are considered. The carbon emission trading achieves annual cost savings of about 0.33 million RMB for each thermal power plant in Guangdong, which accounts for 9.11% of the total cost, 0.52 million RMB per plant (8.90% of total cost) annually in Shanghai, and 0.28 million RMB per plant (5.56% of total cost) annually in Tianjin. In sum, the ETS-induced cost efficiency improvement of power plants in these three pilot provinces saved a total of around 5.95 million RMB per year. Therefore, the total cost savings in Shanghai, Guangdong, and Tianjian during the five-year period 2013–2017 was approximately 29.75 million RMB, accounting for 29.94% of the total cost in 2017.

It should be noted that the cost saving discussed above is only the direct economic cost saving based on the plant-level analysis of cost efficiency. Other benefits, such as environmental and health benefits of emission reductions, and employment benefits may also be significant. For example, Guo et al., (2020) estimated that China's ETS has led to the reduction in production-based emissions by 6.5 Mt CO_2 and consumption-based emissions by 4.6 Mt CO_2 over the post-treatment period of 2011-2015. Assuming that one ton of CO_2 reduction could generate $147 in the national average health co-benefits (Wang et al., 2021), the health co-benefits with ETS implementation could be estimated as approximately $1.6 billion. Moreover, Zhang and Zhang et al. (2020) found the implementation of China's ETS in 2013 has increased annual rural residents' income by about 752.6 RMB and increased the ratio of rural employment to total employment by 2.35% over the period of 2014-2017, which accounts for 9.5% of the income of rural residents and 7.11% of rural employment. Therefore, the actual cost saving of ETS including those from indirect benefits could be much larger than our estimates.

6. DISCUSSION AND CONCLUSION

This study examined the effects of China's carbon emissions trading policy on the production costs of thermal power plants. We conducted a DID analysis between plants in pilot and non-pilot provinces after the ETS announcement and also after the ETS formal implementation. The results showed that China's ETS policy seemed to initially marginally reduce power plants' cost efficiency following the announcement in 2011, and then significantly improve the cost efficiency after the implementation in 2013. We also discussed under what conditions the ETS pilot was effective in saving power plants' costs. It was found that a higher degree of marketization, stricter environmental policy enforcement, and lower carbon dependence help to increase the effectiveness of the ETS on cost performance. Provincial results from synthetic control analysis also show that cost efficiency was enhanced for power plants in Shanghai, Guangdong, and Tianjin, leading to significant cost savings for those pilot power plants. However, this positive effect was not found for pilot plants in Chongqing and Hubei provinces.

Based on our analysis, there are several implications for promoting carbon market reforms. First, carbon emission trading is a promising instrument for use in achieving the carbon neural commitment in a cost-effective way. As China's carbon ETS for the power sector has been expanded nationwide since 2021, the future national market is expected to witness even larger gains due to the enhanced cost efficiency of participants. The specific ETS implementation, such as the quotas and how they are allocated, need to be carefully considered, as participants' enthusiasm for emissions reduction should be encouraged to the greatest extent.

Second, different regional conditions need to be considered in the governance of the carbon emission trading market. Specific measures are needed to promote regional marketization development, conduct strict environmental enforcement, and develop low-carbon industries to reduce carbon dependency, as they support the carbon trading system. Meanwhile, considering the significant role of these different localized factors, it is suggested to pay more attention on the effectiveness of the national ETS in the western and central region of China where the economy is not well developed but carbon emissions are heavy. It is necessary to consider their cost burden and introduce more incentive tools and risk management tools that could encourage polluters to participate and help them to create a virtuous cycle. In turn, participants' positive carbon reduction actions could accelerate the transformation of the whole industry structure.

Third, for entities involved in the carbon ETS, our study sends a positive signal that active participation in the trading market is beneficial for their long-term sustainability. Specifically, ETS requirements not only help to keep carbon emissions within necessary limits and address corporate social responsibility, but also lead to potential higher cost efficiencies through application of efficient and clean technology, equipment, or procedures. Therefore, early and active participation in the carbon trading market is a key measure for firms to achieve a balance between commercial value and social value.

This research is limited in several aspects and presents several directions for future research. First, we estimated the plant-level cost performance based on observed total cost and calculated cost efficiency considering data availability. More detailed and precise measurement of the internal processes for cost efficiency change in pilot plants can be explored. Second, although we have explored the potential cost strategies of power plants, firm-level response strategies of power enterprises have not been discussed. Future studies could combine the specific cost strategy of the power enterprises under the carbon ETS policy to better identify their response actions. Third, this study only discussed the cost savings of ETS implementation before 2017 due to the lack of more detailed plant-level data. With the development of China's ETS, the change in carbon price and carbon quotas could affect the cost performance of power plants. It is also worth identifying whether cost efficiency improvements could be sustainable in the long term, and how long this benefit will last in offsetting part of the carbon compliance cost.

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Table 1: Descriptive Statistics

Variable	Definition	Units	Obs	Mean	Std. Dev.	Min	Max
	Explained variable						
lntcost	Total cost, in log form	Yuan	1102	15.5867	1.2402	11.7027	25.7815
costeff	Cost efficiency	--	1102	0.8353	0.0958	0.1485	0.9848
	Covariates (Plant level)						
lnoutput	Annual power output, in log form	billion KWH	1102	4.5254	0.5669	3.1781	9.0366
lnpe	Standardized energy price calculated by total energy cost/ energy consumption, in log form	Yuan	1102	6.8322	1.3416	5.1218	22.2862
lnpl	Standardized labor price calculated by total labor cost/ the amount of labor, in log form	Yuan	1102	8.7139	1.1575	5.4438	21.2946
klr	Capital-labor ratio	%	1102	0.3842	0.8155	0.0309	7.5000
Lnerso2	SO_2 emission per unit of power output, in log form	10,000 tonnes	1102	8.5916	0.4792	3.6442	9.0867
	Covariates (Provincial level)						
lpergdp	GDP per capital, in log form	100 million yuan	1102	10.5358	0.5698	8.7165	11.8212
indratio	Value-added of the secondary industry /GDP	%	1102	0.4127	0.0650	0.2352	0.5738
fdi_r	Foreign direct investment/GDP	%	1102	0.0043	0.0078	0.0000	0.1038
lindinvest	Investment in the treatment of industrial pollution, in log form	10,000 yuan	1102	12.3952	0.7419	10.5117	14.1637
epustd	Economic policy uncertainty index	--	1102	22.5105	15.4700	0.3348	86.2528
ltotalpat	Number of total patent application, in log form	Number	1102	10.5919	1.5414	6.5088	13.3500
market	Market index	--	1102	8.0675	1.8171	4.1380	11.2330
lpenalty	Number of environmental administrative penalty cases, in log form	Number	1102	8.0506	1.0741	4.2195	10.5567
carbongdp	Carbon emission per GDP	10,000 tonnes/yuan	1102	2.4588	1.6343	0.5943	8.6053

Table 2: Baseline analysis

	DV=total cost			DV=cost efficiency		
	(1)	(2)	(3)	(4)	(5)	(6)
$ETS_{announce}$	-0.0459		0.0082	-0.0041		-0.0237
	(0.0758)		(0.0667)	(0.0232)		(0.0262)
$ETS_{implement}$		-0.0917	-0.0961*		0.0220	0.0348**
		(0.0656)	(0.0509)		(0.0152)	(0.0157)
Plant-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Provincial controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Plant fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.2818	1.2571	1.2174	1.0632	0.9715	1.0865
	(2.9885)	(2.8314)	(3.0040)	(0.9226)	(0.8888)	(0.9250)
Observations	1102	1102	1102	1102	1102	1102
Within R^2	0.9237	0.9239	0.9239	0.0910	0.0927	0.0940

Note: This table reports baseline estimates of ETS effect on total cost and cost efficiency for pilot power plants. Cols.1-3 report the estimate for total cost and cols.4-6 report the estimate for cost efficiency. Plant-level controls include *lnoutput*, *lnpe*, *lnpl*, *klr and lnerso2*. Provincial controls include *lpergdp, indratio, fdi_r, lindinvest, epustd, market, lpenalty, ltotalpat* and *carbongdp.* Year and plant fixed effects are controlled. Standard errors clustered by plant are reported in parentheses, * p<0.1, ** p<0.05, *** p<0.01.

Table 3: Heterogeneity analysis with different impact mechanisms

	DV=Total cost			**DV=Cost efficiency**		
Impact Mechanism	Marketalization	Penalty	Carbongdp	Marketalization	Penalty	Carbongdp
	(1)	(2)	(3)	(4)	(5)	(6)
$ETS_{announce}$	0.0072	0.0132	0.0121	-0.0235	-0.0248	-0.0248
	(0.0673)	(0.0668)	(0.0671)	(0.0263)	(0.0262)	(0.0263)
$ETS_{implement}$	1.4250**	0.5513**	-0.3325**	-0.1969*	-0.1033	0.1027**
	(0.6625)	(0.2681)	(0.1520)	(0.1092)	(0.0697)	(0.0420)
$ETS_{implement}$#	-0.1485**	-0.0767**	0.2848*	0.0226*	0.0163**	-0.0819*
Mechanism	(0.0658)	(0.0325)	(0.1618)	(0.0115)	(0.0082)	(0.0428)
Plant-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Provincial controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Plant fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.5775	1.1334	1.0029	1.0316	1.1044	1.1481
	(2.9151)	(2.9998)	(3.0278)	(0.9204)	(0.9249)	(0.9261)
Observations	1102	1102	1102	1102	1102	1102
Within R^2	0.9246	0.9243	0.9242	0.0958	0.0963	0.0968

Note: This table reports heterogeneous estimates of ETS effect on total cost and cost efficiency for pilot power plants with different impact mechanisms. Cols.1-3 report the estimate for total cost and cols.4-6 report the estimate for cost efficiency. Plant-level controls include *lnoutput*, *lnpe*, *lnpl*, *klr* and *lnerso2*. Provincial controls include *lpergdp*, *indratio*, *fdi_r*, *lindinvest*, *epustd*, *market*, *lpenalty*, *ltotalpat* and *carbongdp*. Year and plant fixed effects are controlled. Standard errors clustered by plant are reported in parentheses, * p<0.1, ** p<0.05, *** p<0.01.

Figures

Figure 1: Effects of carbon emission trading policy from event study

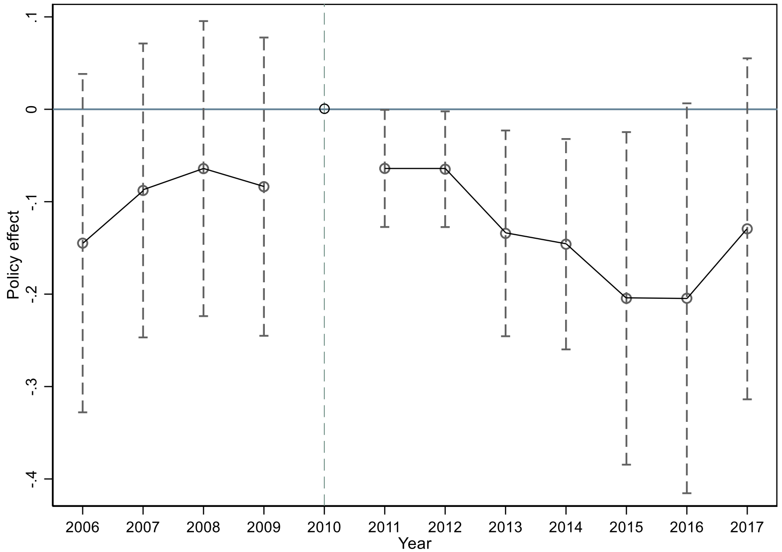


Figure 1(a) Total cost

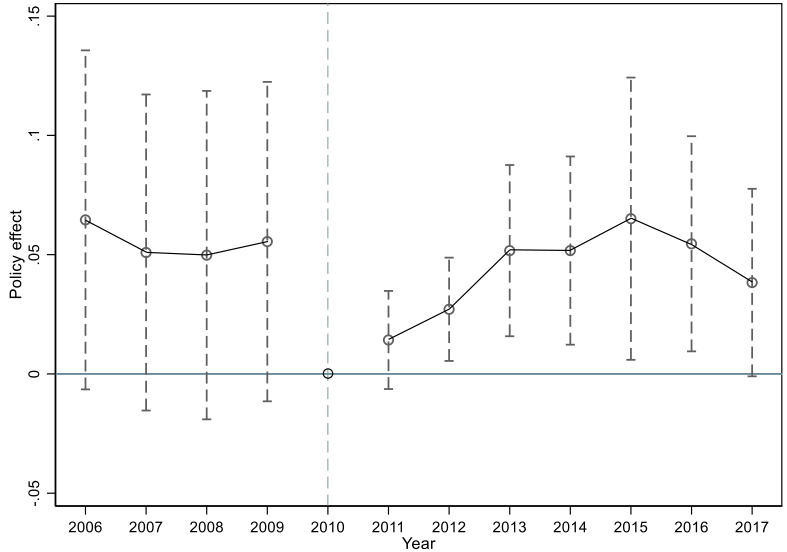
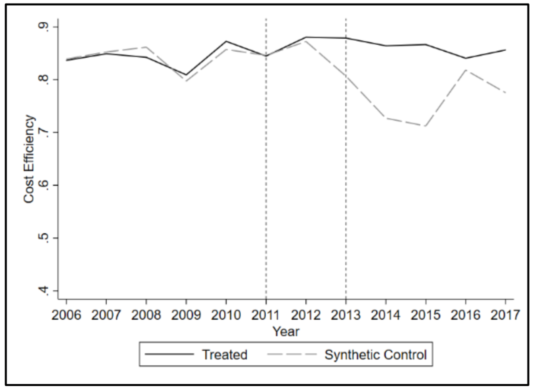


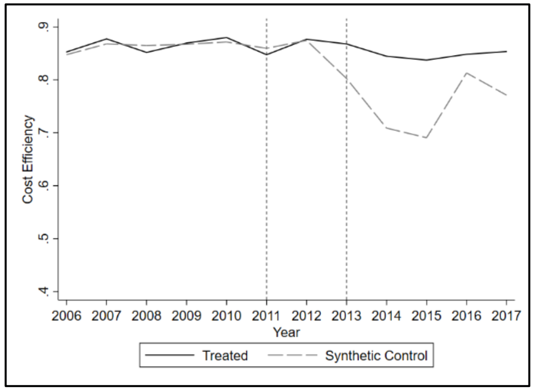
Figure 1(b) Cost efficiency

Note: Figure 1 shows the geometric illustration of ETS pilot policy using the event study method. Figure 1(a) reports the effects on total cost, and Figure 1(b) shows the effects on cost efficiency. Base year is 2010.

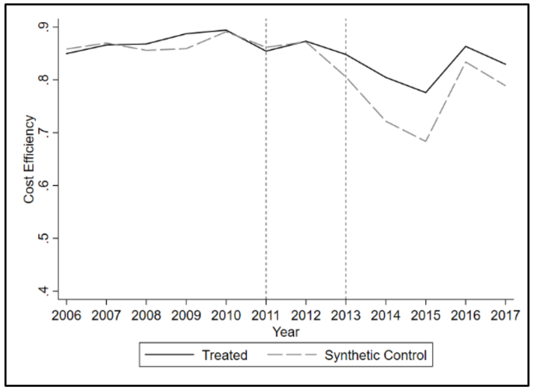
Figure 2: Treatment effects of carbon emission trading policy from synthetic control method



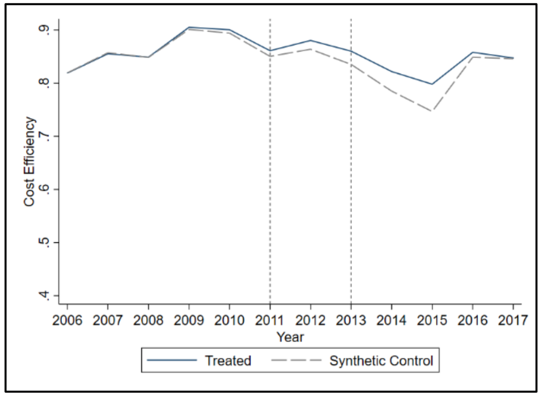
Guangdong



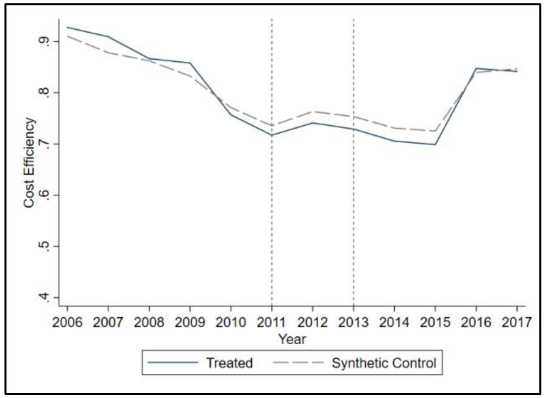
Shanghai



Tianjin



Chongqing



Hubei

Note: Figure 2 shows the change of cost efficiency due to the ETS policy on each treated province and its synthetic control unit using the synthetic control method.

Figure 3: Cost efficiency improvements and cost savings from efficiency improvements based on results from synthetic control method

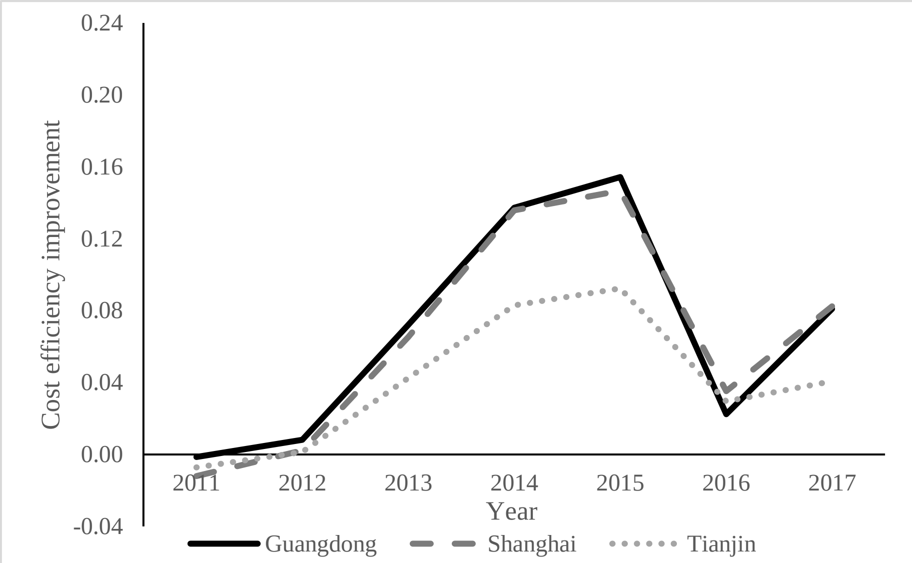


Figure 3(a) Cost efficiency improvement

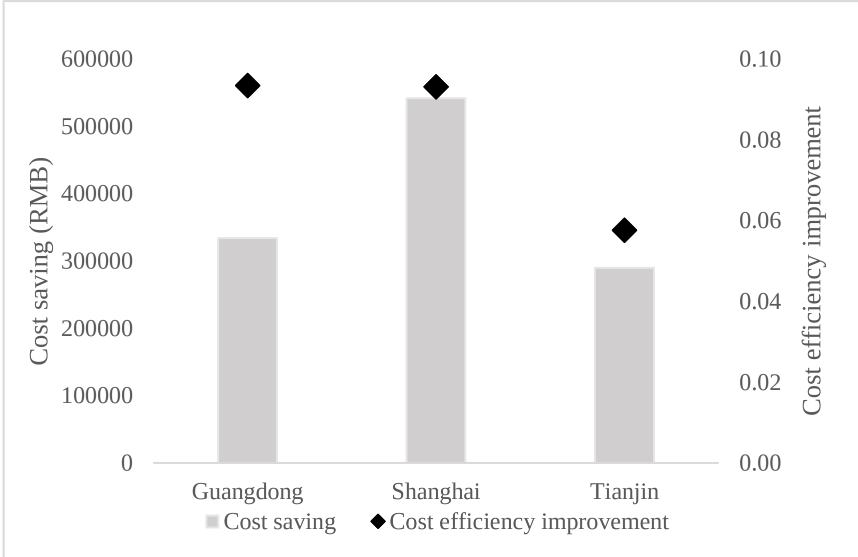


Figure 3(b) Cost saving

Note: Figure 3(a) shows the estimate for annual treatment effect for ETS in Guangdong, Shanghai and Tianjin with the synthetic control method. According to the p-values calculated by the Synth_runner package in Stata. Figure 3(b) shows the estimated average cost savings by multiplying cost efficiency by total cost of power plants.

Appendix S1: Tables

Appendix Table 1: Parallel trend test

	DV=Total cost					DV=Cost efficiency				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
*Treatment * Post$_{2007}$*	0.0629					-0.0261				
	(0.0629)					(0.0236)				
*Treatment * Post$_{2008}$*		0.0381					-0.0222			
		(0.0652)					(0.0254)			
*Treatment * Post$_{2009}$*			0.0124					-0.0215		
			(0.0740)					(0.0288)		
*Treatment * Post$_{2010}$*				0.0013					-0.0249	
				(0.0834)					(0.0290)	
*Treatment *Pretrend*					0.0055					-0.0037
					(0.0226)					(0.0108)
Constant	0.8740	0.8222	0.9138	0.9777	7.3490**	1.0830	1.1319	1.1626	1.2070	-0.4438
	(2.8835)	(2.9538)	(3.0089)	(3.0631)	(3.0079)	(0.8909)	(0.9113)	(0.9318)	(0.9444)	(1.4819)
Observations	1102	1102	1102	1102	460	1102	1102	1102	1102	460
Within R^2	0.9236	0.9236	0.9236	0.9236	0.8410	0.0920	0.0921	0.0924	0.0930	0.3238

Note: This table reports placebo test of different policy year and parallel trend test on total cost and cost efficiency for pilot power plants. Cols.1-4 and cols. 6-9 report placebo tests for total cost and cost efficiency, respectively. Columns 5 and 10 report the trend of total cost and cost efficiency during the pretreatment period, respectively. Plant-level controls include *lnoutput*, *lnpe*, *lnpl*, *klr* and *lnerso2*. Provincial controls include *lpergdp*, *indratio*, *fdi_r*, *lindinvest*, *epustd*, *market*, *lpenalty*, *ltotalpat* and *carbongdp*. Year and plant fixed effects are controlled. Standard errors clustered by plant are reported in parentheses, * p<0.1, ** p<0.05, *** p<0.01.

Appendix Table 2: Robustness analysis with PSM-DID method

	DV=Total cost				DV=Cost efficiency			
Impact Mechanism	Baseline	Marketalization	Penalty	Carbongdp	Baseline	Marketalization	Penalty	Carbongdp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ETS_{announce}$	0.1146	0.1069	0.1259*	0.1390*	-0.0570**	-0.0561*	-0.0596**	-0.0553*
	(0.0709)	(0.0695)	(0.0720)	(0.0735)	(0.0285)	(0.0282)	(0.0285)	(0.0305)
$ETS_{implement}$	-0.1450**	1.6082**	0.5908**	-0.3351**	0.0406**	-0.1713*	-0.1265*	0.1235***
	(0.0690)	(0.6820)	(0.2855)	(0.1552)	(0.0198)	(0.0973)	(0.0738)	(0.0460)
$ETS_{implement}$#		-0.1702**	-0.0877**	0.2500		0.0206*	0.0199**	-0.0990**
Mechanism		(0.0687)	(0.0343)	(0.1578)		(0.0111)	(0.0086)	(0.0443)
Plant-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-3.4167	-3.3104	-3.5079	-3.2194	1.8153**	1.8025**	1.8360**	1.7814**
	(2.7139)	(2.6308)	(2.7048)	(2.5842)	(0.7849)	(0.7725)	(0.7903)	(0.7851)
Observations	718	718	718	718	718	718	718	718
Within R^2	0.9294	0.9307	0.9302	0.9310	0.1573	0.1599	0.1626	0.1632

Note: This table reports robust estimates of ETS effect on total cost and cost efficiency for pilot power plants by adopting the PSM-DID method. The pretreatment value from 2006 to 2010 of *lpergdp*, *indratio*, *fdi_r*, *lindinvest* and *carbongdp* are selected as covariates in the propensity matching procedure. Cols.1-4 report the estimate for total cost and cols.5-8 report the estimate for cost efficiency. Plant-level controls include *lnoutput*, *lnpe*, *lnpl*, *klr* and *lnerso2*. Provincial controls include *market, lpenalty, ltotalpat* and *epustd.* Year and plant fixed effects are controlled. Standard errors clustered by plant are reported in parentheses, * p<0.1, ** p<0.05, *** p<0.01.

Appendix Table 3: Propensity score matching results

Covariates	Treated	Control	%bias	t	p>t
		Before matching			
lpergdp	10.621	10.030	130.50	11.18	0.000
indratio	0.430	0.444	-26.00	-1.93	0.055
fdi_r	0.002	0.001	72.70	6.37	0.000
lindinvest	12.068	12.171	-15.20	-1.28	0.202
carbongdp	1.523	3.383	-142.30	-9.84	0.002
		After matching			
lpergdp	10.388	10.396	-1.80	-0.11	0.915
indratio	0.441	0.440	2.30	0.16	0.874
fdi_r	0.002	0.002	-1.70	-0.12	0.904
lindinvest	12.215	12.094	18.00	1.13	0.261
carbongdp	1.717	1.711	0.50	0.06	0.948

Appendix Table 4: Robustness analysis with considering effect of SO_2 emission trading scheme

	DV=Total cost				DV=Cost efficiency			
Impact Mechanism	Baseline	Marketalization	Penalty	Carbongdp	Baseline	Marketalization	Penalty	Carbongdp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ETS_{announce}$	0.0082	0.0072	0.0132	0.0121	-0.0237	-0.0235	-0.0248	-0.0248
	(0.0697)	(0.0703)	(0.0698)	(0.0701)	(0.0274)	(0.0275)	(0.0274)	(0.0275)
$ETS_{implement}$	-0.0961*	1.4250**	0.5513*	-0.3325**	0.0348**	-0.1969*	-0.1033	0.1027**
	(0.0532)	(0.6926)	(0.2803)	(0.1589)	(0.0164)	(0.1142)	(0.0728)	(0.0439)
$ETS_{implement}$#		-0.1485**	-0.0767**	0.2848*		0.0226*	0.0163*	-0.0819*
Mechanism		(0.0688)	(0.0340)	(0.1691)		(0.0120)	(0.0086)	(0.0448)
SO2ETS	-0.6181***	-0.6027***	-0.6209***	-0.6559***	0.0625	0.0602	0.0631	0.0734
	(0.2237)	(0.2181)	(0.2223)	(0.2260)	(0.0945)	(0.0939)	(0.0944)	(0.0953)
Plant-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.6678	2.0026	1.5645	1.4471	1.0753	1.0243	1.0973	1.1387
	(2.9878)	(2.9028)	(2.9890)	(3.0162)	(0.9297)	(0.9250)	(0.9297)	(0.9310)
Observations	1102	1102	1102	1102	1102	1102	1102	1102
Within R^2	0.9640	0.9643	0.9642	0.9641	0.3210	0.3223	0.3227	0.3231

Note: This table reports robust estimates of ETS effect on total cost and cost efficiency for pilot power plants after considering effect of SO_2 emission trading scheme. Cols.1-4 report estimates for total cost and Cols.5-8 report estimates for cost efficiency. Plant-level controls include *lnoutput*, *lnpe*, *lnpl*, *klr* and *lnerso2*. Provincial controls include *lpergdp*, *indratio*, *fdi_r*, *lindinvest*, *epustd*, *market*, *lpenalty*, *ltotalpat* and *carbongdp*. Year and plant fixed effects are controlled. Standard errors clustered by plant are reported in parentheses, * p<0.1, ** p<0.05, *** p<0.01.

Appendix Table 5: Robustness analysis with considering effect of provincial CO_2 emission reduction targets

	DV=Total cost				DV=Cost efficiency			
Impact Mechanism	Baseline	Marketalization	Penalty	Carbongdp	Baseline	Marketalization	Penalty	Carbongdp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ETS_{announce}$	0.0897	0.0888	0.0930	0.0933	-0.0414	-0.0412	-0.0421	-0.0424
	(0.0638)	(0.0639)	(0.0643)	(0.0644)	(0.0273)	(0.0274)	(0.0274)	(0.0275)
$ETS_{implement}$	-0.0992*	1.4259**	0.4873*	-0.3287**	0.0354**	-0.1971*	-0.0894	0.1019**
	(0.0536)	(0.6812)	(0.2517)	(0.1459)	(0.0154)	(0.1099)	(0.0696)	(0.0405)
$ETS_{implement}$#		-0.1489**	-0.0695**	0.2765*		0.0227*	0.0148*	-0.0801*
Mechanism		(0.0675)	(0.0304)	(0.1534)		(0.0116)	(0.0081)	(0.0414)
CO2reduce	-0.0876***	-0.0876***	-0.0862***	-0.0873***	0.0190**	0.0190**	0.0187**	0.0189**
	(0.0299)	(0.0299)	(0.0299)	(0.0299)	(0.0075)	(0.0075)	(0.0075)	(0.0075)
Plant-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.9028	1.2637	0.8316	0.6956	1.1547	1.0997	1.1699	1.2147
	(2.8960)	(2.8189)	(2.8955)	(2.9180)	(0.9157)	(0.9124)	(0.9161)	(0.9167)
Observations	1102	1102	1102	1102	1102	1102	1102	1102
Within R^2	0.9265	0.9272	0.9269	0.9268	0.1071	0.1088	0.1089	0.1097

Note: This table reports robust estimates of ETS effect on total cost and cost efficiency for pilot power plants after considering effect of provincial CO_2 emission reduction targets in China's 12th and 13th Five-Year Plan. Cols.1-4 report estimates for total cost and Cols.5-8 report estimates for cost efficiency. Plant-level controls include *lnoutput*, *lnpe*, *lnpl*, *klr* and *lnerso2*. Provincial controls include *lpergdp*, *indratio*, *fdi_r*, *lindinvest*, *epustd*, *market*, *lpenalty*, *ltotalpat* and *carbongdp*. Year and plant fixed effects are controlled. Standard errors clustered by plant are reported in parentheses, * p<0.1, ** p<0.05, *** p<0.01.

Appendix Table 6: Robustness analysis with different model specifications

	Tobit model				Tobit model without plant-level control			
	Baseline	Marketalization	Penalty	Carbongdp	Baseline	Marketalization	Penalty	Carbongdp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ETS_{announce}$	-0.0237	-0.0235	-0.0248	-0.0248	-0.0196	-0.0197	-0.0207	-0.0207
	(0.0259)	(0.0259)	(0.0259)	(0.0260)	(0.0235)	(0.0236)	(0.0236)	(0.0236)
$ETS_{implement}$	0.0348**	-0.1969*	-0.1033	0.1027**	0.0340*	-0.1893*	-0.0844	0.0967**
	(0.0155)	(0.1078)	(0.0688)	(0.0414)	(0.0195)	(0.1087)	(0.0703)	(0.0455)
$ETS_{implement}$#		0.0226**	0.0163**	-0.0819*		0.0218*	0.0140*	-0.0757*
Mechanism		(0.0113)	(0.0081)	(0.0423)		(0.0116)	(0.0079)	(0.0450)
Plant-level controls	Yes	Yes	Yes	Yes	No	No	No	No
Provincial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.1378	1.0844	1.1604	1.2121	0.4153	0.3595	0.4328	0.4765
	(0.9578)	(0.9522)	(0.9572)	(0.9591)	(0.6959)	(0.6956)	(0.6939)	(0.7006)
Observations	1102	1102	1102	1102	1102	1102	1102	1102
Log Likelihood	1235.2	1236.3	1236.6	1236.9	1219.3	1220.2	1220.2	1220.6

Note: This table reports robust estimates of ETS effect on cost efficiency for pilot power plants with Tobit model and Tobit model without plant-level control. Cols.1-4 report Tobit estimates and cols.5-8 report estimates from fixed effect model without plant-level control variables. Plant-level controls include *lnoutput*, *lnpe*, *lnpl*, *klr* and *lnerso2*. Provincial controls include *lpergdp*, *indratio*, *fdi_r*, *lindinvest*, *epustd*, *market*, *lpenalty*, *ltotalpat* and *carbongdp*. Year and plant fixed effects are controlled. Standard errors clustered by plant are reported in parentheses, * p<0.1, ** p<0.05, *** p<0.01.

Appendix Table 7: Synthetic control method results

SCM	Guangdong	Shanghai	Tianjin	Chongqing	Hubei
2011	-0.0014	-0.0120	-0.0072	0.0107	-0.0182
	0.9604	0.8278	0.6046	0.5556	0.3366
2012	0.0081	0.0022	0.0014	0.0165	-0.0222
	0.7968	0.9733	0.9778	0.6889	0.5401
2013	0.0720**	0.0653	0.0425	0.0249	-0.0243
	0.0378	0.1813	0.2645	0.7778	0.8171
2014	0.1372***	0.1357**	0.0829	0.0368	-0.0255
	0.0073	0.0346	0.1538	0.8000	0.8817
2015	0.1543***	0.1467**	0.0924	0.0513	-0.0265
	0.0052	0.0365	0.1795	0.7778	0.9131
2016	0.0224**	0.0352***	0.0295**	0.0092	0.0076
	0.0470	0.0068	0.0279	0.5556	0.5767
2017	0.0810**	0.0825**	0.0407*	0.0014	-0.0051
	0.0110	0.0308	0.0992	0.9222	0.8079

Note: Synth_runner command in Stata were used to calculate the p-values of the placebo test.

Appendix Table 8: Stochastic frontier analysis results

Panel A: SFA estimations[a,e]

	DV=Total cost		
	(1)	(2)	**(3)**
lnoutput	0.2823***	0.2553***	0.2724***
	(0.0000)	(0.0000)	(0.0000)
lnpe	0.2940***	0.1519***	0.1956***
	(0.0000)	(0.0000)	(0.0000)
lnpl	0.9259***	0.9074***	0.9538***
	(0.0000)	(0.0000)	(0.0000)
klr	-0.4789***	-0.4769***	-0.4952***
	(0.0000)	(0.0000)	(0.0000)
lnerso2	0.3239***	0.1218***	0.1600***
	(0.0000)	(0.0000)	(0.0000)
Year fixed effect	Yes	Yes	Yes
Mundlak's specification	No	Yes	Yes
Region fixed effect	No	No	Yes
Constant	1.5233***	-0.3478	-0.4578*
	(0.0000)	(0.2454)	(0.2911)
Lambda	4.1754***	7.5962***	2.5824***
	(0.0000)	(0.0000)	(0.0000)
Observations	1102	1102	1102

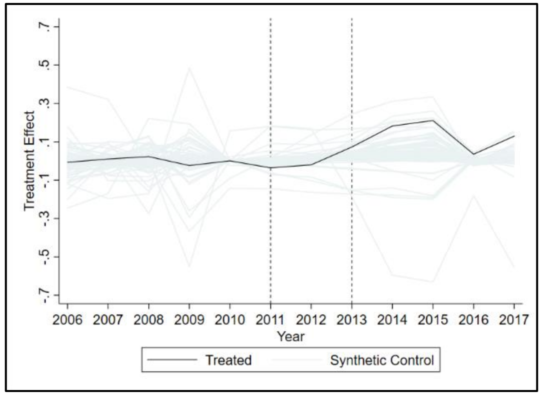
Panel B: Estimated efficiency[b]

	tre	trem	treml[d]
	(1)	(2)	(3)
Mean	0.8140	0.8352	0.8353
Minimum	0.2182	0.4518	0.1485
Maximum	0.9875	0.9914	0.9848
Standard deviation	0.1149	0.1091	0.0958
Correlation[c,e]	tre	trem	treml
tre	1	0.9298***	0.8891***
trem	0.9426***	1	0.8477***
treml	0.9509***	0.8926***	1

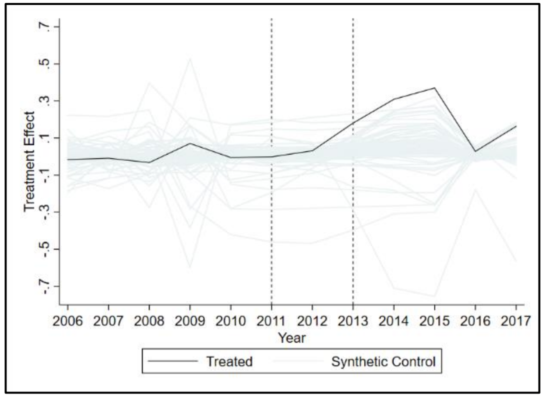
Notes: [a] Panel A reports results from SFA estimation. [b] Panel B reports descriptive statistics of estimated cost efficiency. [c] For the correlations, lower triangular cells report Pearson's correlation coefficients, upper triangular cells are Spearman's rank correlation. [d] As model (4) controls for the most fixed effects to address the possible omitted variable biases, we use the estimate efficiency (*treml*) from this model for our cost efficiency analysis. In fact, in the unreported results, we find that the use of alternative efficiency scores from other models do not affect our results. [e] Standard errors are in parentheses, * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Appendix S2: Figures

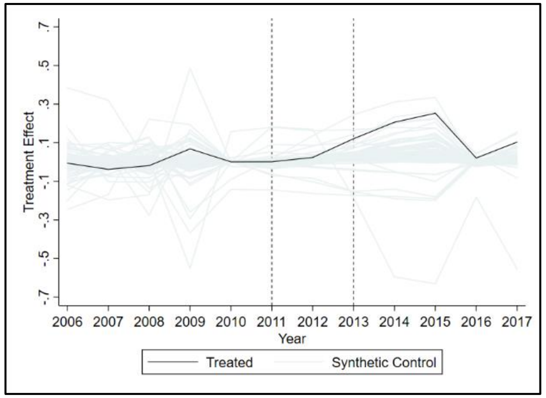
Appendix Figure 1: Placebo test for synthetic control method



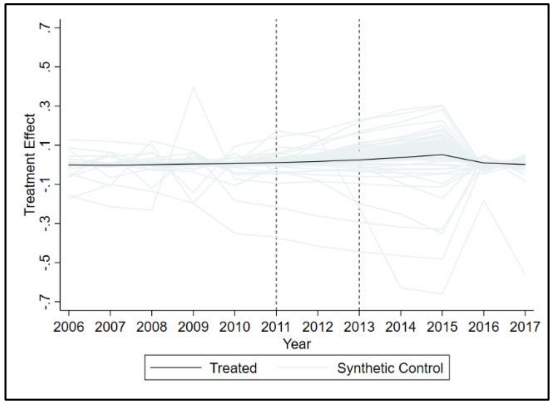
Guangdong



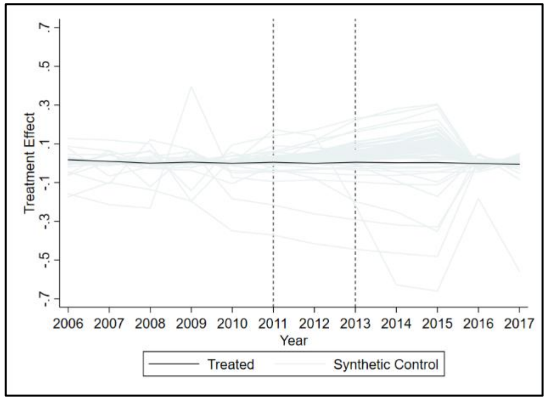
Shanghai



Tianjin



Chongqing



Hubei

Note: This figure shows the treatment effect on cost efficiency from ETS pilot policy on each treated province and the placebo tests for different synthetic control units using the synthetic control method.

Appendix S3: Stochastic Frontier Analysis

The stochastic frontier model was originally developed by Aigner et al. (1977). The basic formulation of the stochastic frontier model is:

$$y = \beta' X + v + u \tag{A.1}$$

where y is the goal attainment measured by goal attainment, and $\beta' X + v$ is the optimal frontier goal pursued by the individual, such as the minimum cost or maximal production. $\beta' X$ is the explanatory part which determines the frontier and $v \sim N[0, {\sigma_u}^2]$ denotes the stochastic part. These two parts compose the 'stochastic frontier'. u denotes the inefficiency term, where

$$u = |U| \sim N[0, {\sigma_u}^2] \tag{A.2}$$

u also refers to the amount by which the individual fails to achieve the optimal goal (frontier).

In this study, we adopt stochastic frontier analysis to estimate the cost efficiency of thermal power plants. The cost frontier is firstly constructed using the following equation:

$$TC = f(Y, X, P; \beta) e^v e^u \tag{A.3}$$

where *TC* is the minimum cost to produce the electricity power, and $f(Y, X, P; \beta)$ denotes the deterministic part for the cost frontier. Specifically, *TC* is the total cost, *Y* refers to output measured by total electricity power generation, *P* is the price of inputs, including P_L and P_E, which are the prices of capital (the installed power capacity) and labor (total employees), respectively, *X* is the vector of explanatory variables that affect the expense cost, e^v is the stochastic component of the cost frontier, and $f(Y, X, P; \beta) e^v$ denotes the optimal minimum cost and the deviation from this optimal cost due to inefficiency is captured by e^u. Following the linear function, we further control the ratio of capital to labor (*KL*), SO_2 emission per unit of power generation (*SO2*), and fixed effects of time (d_t) and region (l_j), which are measured by a vector of year dummies and region dummies[3], respectively. The modified equation can be written as follows:

$$\ln TC = \ln f\left(Y, P_L, P_E, KL, SO2, d_t, l_j; \beta\right) + V + U \tag{A.4}$$

Moreover, we also adopt Mundlak's (1978) specification here to control for potential unobserved individual heterogeneity. Mundlak (1978) put forward a method to further consider the correlation between explanatory variables and the individual specific term η_i. The unobserved characteristics from the inefficiency term can thus be

[3] A set of region dummy variables are constructed based on the divisions of North China, Northeast China, East China, South China, Southwest China, Central China, and Northwest China.

partially separated from the inefficiency term by adding this auxiliary equation into the main frontier model.

$$\eta_i = \mu_i + \gamma_i \tag{A.5}$$

$$\mu_i = \bar{M}_i \pi = \frac{1}{T}\sum_{t=1}^{T} M_{it}\pi \tag{A.6}$$

$$\gamma_i \sim iid\left(0, \sigma_\delta^2\right) \tag{A.7}$$

where M_{it} is the vector of explanatory variable, M_i is a vector of the mean value for the respective explanatory variables, and π is a vector of estimated coefficients. The persistent inefficiency term is $\gamma_i > 0$ after separating the time-invariant provincial factors that do not affect the inefficiency. Provincial factors with short-run rigidities that have an impact on the inefficiency are captured by $\mu_{it} > 0$.

The cost function with econometric specifications after adding the auxiliary equation is:

$$\ln TC = \ln f\left(Y, P_L, P_E, KL, SO2, d_t, l_j; \beta\right) + \bar{M}_i \pi + \mu_{it} + \gamma_i + \nu_{it} \tag{A.8}$$

By adopting the above equation, the overall cost efficiency can then be computed based on estimation results as in the following equation:

$$Costefficiency_{it} = \frac{TC_{it}^F}{TC_{it}} = \exp\left(-\widehat{U_{it}}\right) \tag{A.9}$$

where TC_{it}^F is the minimum expense cost of the *i*th plant at time *t* and TC_{it} is the observed total cost.