When carbon emission trading meets a regulated industry: Evidence from the electricity sector of China*

Jing Cao† Mun S. Ho‡ Rong Ma§ Fei Teng¶

June 2021

Abstract

This paper provides retrospective firm-level evidence on the effectiveness of China's carbon market pilots in reducing emissions in the electricity sector. We show that the carbon emission trading system (ETS) has no effect on changing coal efficiency of regulated coal-fired power plants. Although we find a significant reduction in coal consumption associated with ETS participation, this reduction was achieved by reducing electricity production. The output contraction in the treated plants is not due to their optimizing behavior but is likely driven by government decisions, because the impacts of emission permits on marginal costs are small relative to the controlled electricity prices and the reduction is associated with financial losses. In addition, we find no evidence of carbon leakage to other provinces, but a significant increase in the production of non-coal-fired power plants in the ETS regions.

Keywords: Carbon Market, Emission Trading, Power Plant, Electricity Generation

*We thank the editor and two anonymous referees, as well as Jingbo Cui, Xiaomeng Cui, Ying Fan, Kathrine von Graevenitz, Stephen Jarvis, Guojun He, Andreas Lange, Mingquan Li, Kamiar Mohaddes, Peter Nilsson, Yun Qiu, Wolfram Schlenker, Qu Tang, Ulrich Wagner, Chunhua Wang, Haitao Yin, Da Zhang, Junjie Zhang, and Jinhua Zhao, for their comments and suggestions. We thank the participants at the 2019 workshop on environmental and energy economics at Shanghai Jiao Tong University, the workshop at Jinan University, the EAERE 2019 Summer School, the 2019 Resource Security and Economic Science Workshop at Xiamen Univerisity, the 2020 China Energy Modeling Forum, and the 2021 Annual Conference of Government and Economics at Tsinghua University. This paper was supported by the National Key Research and Development Program of China under grant numbers 2020YFA0608603 and 2017YFA0603602, the National Natural Science Foundation of China under grant numbers 71690244 and 71461010701, and the grant to Harvard China Project for "China 2030/2050: Energy and Environmental Challenges for the Future" by the Harvard Global Institute.

†School of Economics and Management, Hang Lung Center for Real Estate, Tsinghua University, Beijing, China. Email: caojing@sem.tsinghua.edu.cn.

‡Harvard China Project on Energy, Economy and Environment, School of Engineering and Applied Sciences, and Resources for the Future, Washington, DC, USA. Email:munho@seas.harvard.edu.

§Corresponding author. School of Economics and Management, Beihang University, Beijing, China. Email: rongma@buaa.edu.cn.

¶Institute of Energy, Environment and Economy, Tsinghua University, Beijing, China. Email: tengfei@tsinghua.edu.cn.

1 Introduction

Given the concerns over climate change due to greenhouse gases from human activities, as described by the IPCC (2013), there has been an intense effort to design and implement carbon mitigation policies. To complement traditional "command-and-control" regulations, governments are developing market-based policies such as carbon taxes and emission trading. These carbon pricing instruments, and other policies such as innovation subsidies, are expected to reduce reliance on fossil fuels and help the switch to clean alternatives by inducing directed technology change (Acemoglu et al. 2012, 2016).

The largest carbon-emitting industry in the world is the electricity sector,[1] making it the obvious target for an emission reduction policy. However, due to its natural monopoly characteristics, in most countries the electricity sector is subject to strict governmental regulations. In addition to the regulations on prices and pollutant emissions commonly applicable to such sectors, governments often impose strict regulations on generation and distribution. Although some economies such as the European Union (EU), the U.S., and Japan have been restructuring their electricity sectors to introduce market elements in generation, in most countries the industry is still largely controlled by dispatch commands from governments, especially in developing economies.

This paper exploits China's pilot carbon markets as a quasi-experiment to investigate the effects of carbon emission trading on promoting emission reduction in the electricity sector. China has initiated carbon market pilots in seven areas of the country since 2013 and planned to begin a national carbon market for the electricity sector in 2021. Using a micro-level dataset encompassing nearly all power plants in China, we estimate the causal impact of the pilot carbon markets on the electricity sector.

While these pilots cover only six provinces of China, they are large and important markets. According to the World Bank's Carbon Pricing Dashboard they cover 575 million tons of CO_2, second only to the EU Emission Trading System's 1726 million tons.[2] We only focus on the electricity sector in this paper, but that is the dominant source of coal combustion in these provinces. The national carbon emission trading system (ETS) will initially cover more than 2,200 power plants and their CO_2 emissions are expected to be around 4 billion metric tons

[1] Global CO_2 emissions from the electricity and heat generation sector in 2018 were 13.978 billion metric tons, accounting for 40% of total global emissions, according to statistics from the International Energy Agency.

[2] The data from the Carbon Pricing Dashboard is available at their web page: https://carbonpricingdashboard.worldbank.org/map_data.

(International Carbon Action Partnership 2021). This will be the world's largest carbon market where the covered power plants are responsible for half of the industrial CO_2 emissions in China and more than 10% of global CO_2 emissions.[3] The covered CO_2 emissions are even greater than the total industrial greenhouse gas emissions of the U.S. (3.148 billion tons of CO_2e in 2019).[4] It is thus of great importance to understand the likely impact of the ETS in China.

The central question addressed by this paper concerns how effective the pilot carbon markets were in reducing the emissions of China's electricity sector. Did the pilot markets lead to a reduction in CO_2 emission intensity or total emissions? The ETS imposes constraints on CO_2 emissions of regulated plants. If these constraints are binding, the plants will incur incremental costs according to the levels of their CO_2 emissions, and thus may have an incentive to reduce emissions.

However, electricity generation by power plants is governed by commands from provincial authorities, which are coordinated with the regional and national dispatch organizations governing inter-provincial flows. Until recently there were no daily spot markets in generation, only some limited markets in long-term contracts between large generators and large consumers, and scattered generation rights markets.[5] The long-dominant principle in operation is "fair dispatch," which allocates annual electricity generation quotas to each plant based on its class of generators regardless of cost or efficiency. Daily (real-time) dispatch decisions are guided by these plans. The annual output and fuel consumption of each plant - coal-fired, hydro, or other renewable - thus depends on these electricity system plans, and the actual daily dispatch decisions and plant level operating decisions under the ETS. More recently, the central government ordered local planning authorities to take energy conservation and emission reduction into account when they make electricity dispatch plans.

Since the only viable way to reduce CO_2 emissions for coal-fired power plants in the short run is to reduce coal consumption,[6] by improving coal efficiency, reducing output, or retiring coal plants, we use the plant-level data to identify effects of the ETS pilots on coal intensity and

[3] According to the CO_2 emission inventories from China Emission Accounts and Datasets (CEADs), the industrial sectors (mining, manufacturing, and utilities) of China emitted 8.072 billion metric tons of CO_2 in 2018. China's total CO_2 emissions from fuel combustion in 2019 is 11.5 billion tons, while the global total is 38 billion tons (Crippa et al. 2020).

[4] According to the Environmental Protection Agency of the U.S., the greenhouse gas emissions of the U.S. are 6.558 billion tons of CO_2e in 2019, with 25% of them from electricity production and 23% from non-electricity industrial sectors.

[5] A description of the electricity system and the reforms is given in Ho et al. (2017).

[6] Carbon capture and sequestration (CCS) was not an option at the time of the pilots. China had only about 20 CCS facilities in operation or under construction in 2018 (Global CCS Institute 2018).

total coal consumption by means of difference-in-differences (DiD) regressions. The impacts on electricity generation and operating hours are also investigated in order to explore the drivers of changes in coal consumption. To compare the ETS-treated plants with a more comparable group, we further match them with non-regulated coal-fired power plants that have the most similar ex-ante coal consumption, which is the metric used to determine ETS enrollment. We also employ the generalized synthetic control method with interactive fixed effects to capture unobserved time-varying confounders from common shocks. A major concern of CO_2 control programs is leakage - the possibility that other regions will step up production and offset the reductions in the control region. Therefore, we also examine spillover effects of the ETS pilots on non-pilot regions and on non-fossil-fuel power plants. Finally, coal combustion releases CO_2 and conventional air pollutants, and we discuss the implications for emission reduction of CO_2 and conventional air pollutants.

This study's contributions are threefold. First, we provide the first retrospective firm-level evidence for the impacts of China's carbon markets on fossil fuel consumption and CO_2 emissions. Since China is the world's largest CO_2 emitter, the effectiveness of its mitigation policies is likely to be the major factor in determining the success of global efforts to address climate change. Carbon emission trading is one of the country's major policies, but the effectiveness of carbon markets remains an issue of intense debate. Policymakers want to promote the transition towards cleaner sources of energy, but uncertainty regarding policy and future carbon prices hinders decisions on clean technology investment (Acemoglu and Rafey 2019), possibly offsetting the effects of carbon prices that are in place. There are many difficult design issues in implementing a carbon price. For example, the allocation of initial free allowances is seen as crucial to obtaining support from the regulated entities, and the optimal allowance allocation in emission trading schemes depends on various distributional goals (see Fowlie and Perloff 2013, Meunier et al. 2014, 2018, and Dardati 2016 for relevant discussions).

Existing studies of China's carbon markets have discussed topics such as allowance allocation (Lin and Jia 2018), effects on regional economic development (Fan et al. 2017, Liu et al. 2017) and co-pollutant emissions (Li et al. 2018). Those studies use simulations, mostly by computational general equilibrium (CGE) models, to study the effects of carbon markets, relying on the fundamental assumption that the carbon markets impose binding constraints on the production and emissions of regulated firms. There are, however, far fewer empirical studies on the effectiveness of China's carbon markets. Cui et al. (2018, 2020) and Zhu et al. (2019) note this deficiency in empirical research, however, they examine the effects on patents and financial performance rather than the actual efficacy in terms of emission reduction. Our empirical study fills this gap and provides empirical evidence for the effectiveness of carbon markets in China. We find no effect of the ETS pilots on improving coal efficiency, but we show a significant decline in coal consumption associated with the ETS pilots; a reduction mainly achieved by output contraction instead of efficiency improvement.

Our second contribution to the literature is adding to the understanding of how emission trading schemes in a regulated industry may operate differently from an unregulated, marketized, one. Although there has been a surge of empirical studies of carbon markets during the very recent years, such studies focus on either unregulated manufacturing sectors (Moore et al. 2019, Naegele and Zaklan 2019) or the electricity sector of the U.S., which operates a spot market for generators (Borenstein et al. 2018, Fell and Maniloff 2018). In an economy with spot markets where generators make bids based on their marginal costs, a carbon price will raise the marginal costs for coal plants and thus affect their bids, especially in off-peak hours. In many other countries, including China, where the electricity sector is not market-oriented but strictly regulated by government, the carbon price may act differently. In China, much of the generation assets and all the transmission assets are run by state-owned enterprises (SOEs). Compliance decisions of the power plants in carbon markets are affected by both plant profit maximization and government regulations (Fowlie 2010), making the operation of an ETS in the regulated electricity sector much more complicated than in unregulated sectors.

Goulder et al. (2019) use numerical simulations to analyze the impacts of China's national ETS on the electricity sector and show that the allowance allocations based on industry benchmark emission intensities and plant-level output will subsidize electricity generation and reduce the cost-effectiveness of the ETS. Although China started a gradual marketization reform of the electricity sector in 2015, 70% of electricity in 2018 was still generated subject to dispatch commands and sold at administered prices (China Electricity Council 2019). Even among the electricity traded under long-term contracts, planning authorities are able to adjust actual production to increase the usage of clean power sources and reduce emissions.[7] Our empirical analysis shows that the observed reductions in coal consumption and output are more likely to be driven by government commands rather than plant incentives, since the effects of the carbon price on marginal costs are small relative to the controlled electricity price, and the reductions

[7]Basic rules for intermediate and long-term electricity transactions. http://www.gov.cn/xinwen/2017-01/12/content_5159156.htm.

are associated with financial losses. Although the coal consumption and output of ETS plants fell after they participated in the carbon markets, the evidence indicates that the reductions are not due to plant responses to the carbon price, but to government decisions on electricity generation.

Finally, although climate change is a global problem, current efforts to mitigate CO_2 emissions only apply to regional subsets of emitters (Naegele and Zaklan 2019). Due to the loss in competitiveness of regulated producers, in an open economy, production and the associated emissions will be shifted to unregulated regions, resulting in emission leakage (Fowlie et al. 2016, Böhringer et al. 2017, Fell and Maniloff 2018). Our third contribution to the literature is that we find no evidence that China's ETS pilots induced carbon emission leakage to other regions, possibly due to the strict regulatory hierarchy of the electricity sector. We also show that, concurrent with the output contraction in the ETS treated coal-fired plants, the electricity planning authorities, which are subject to targets for energy conservation and emission reduction, significantly increase the utilization of non-coal-fired plants. This implies a noticeable transition towards clean energy sources and links this paper to the energy transition literature.

Carbon pricing may be an important instrument to induce a transition from dirty to clean inputs (Acemoglu et al. 2012), even though this transition may be a slow process (Acemoglu et al. 2016) and can be impeded by policy uncertainty (Acemoglu and Rafey 2019). The elasticity of substitution between clean and dirty energy inputs at the industry level is estimated to be greater than one in some studies, indicating favorable conditions for an energy transition.[8] Although recent studies have documented significant effects of carbon markets on low-carbon innovation using patent data (Calel and Dechezleprêtre 2016, Cui et al. 2018, Zhu et al. 2019), there is little empirical evidence about the energy transition in China.

The remainder of this paper is organized as follows. Section 2 provides a background on carbon markets in China and the electricity sector. Section 3 discusses our identification strategy and the micro-level data of national power plants. Section 4 presents the empirical results. Section 5 concludes.

[8] See Papageorgiou et al. (2017). Cao et al. (2020) also estimated energy substitution elasticities that are greater than one for many industries in China.

2 Background of China's ETS and electricity system

2.1 Features of China's carbon markets

As one of the major initiatives implemented to meet the China CO_2 emission reduction targets, in 2011 the National Development and Reform Commission (NDRC, the powerful planning agency) proposed carbon emission trading markets, and launched seven carbon market pilots in Beijing, Tianjin, Shanghai, Chongqing, Shenzhen, Hubei, and Guangdong in 2013 and 2014. The first four are large municipalities under direct administration of the central government, the last two are provinces, and Shenzhen is a special economic zone in Guangdong.

Five of these carbon market pilots are in the economically dominant East China, while Hubei is in Central China and Chongqing is in the west. Firms in electricity and energy-intensive manufacturing sectors such as cement and petrochemicals are the main participants in these markets. Transportation, construction, and some service sectors are also included in some pilots. We focus on the impact of the ETS pilots on the electricity sector, which accounts for more than 40% of annual CO_2 emissions in China[9] and is planned to be the first sector covered by the upcoming national carbon market. Regulated firms are required to submit an accounting of their CO_2 emissions in March of each year. Third parties examine the emission records in April, and in early July the records are compared with emission permits held by the firm. Various penalties are imposed if emissions exceed the permits, including, but not limited to, a fine of three times the prevailing ETS prices for excess emissions and a halved allocation of allowances in the following year. Non-compliant firms are also banned from obtaining any benefits of preferential policies from central and local governments.

Initial free allowances are mainly allocated in two ways, based on historical emissions or on benchmark emission intensities (CO_2 per unit output of the best, or benchmark, firm in each capacity category). Using historical emissions to determine allocations could incentivize firms to adjust output to meet their emission requirements. This method also reduces mitigation incentives; if firms reduce their CO_2 emissions via technology upgrades, they will subsequently be allocated fewer allowances. On the other hand, using benchmark intensities assumes high comparability in products from different firms in a given industry, which is not the case for most manufacturing sectors. Therefore, in most pilots only the electricity sector has allowances

[9] According to data from the CEADs, China emitted 9,621 million metric tons of CO_2 in 2018, 4,509 million metric tons of them from the electricity sector.

allocated based on industry benchmarks. One peculiarity of allocation based on benchmark intensity is that the number of free permits is equal to the product of benchmark intensity and output over the compliance period. This is equivalent to an output subsidy at the margin and discourages output reduction as a means to meet the emission requirements (Goulder et al. 2019).

Figure 1 displays the monthly average ETS permit price (US$/metric ton of CO_2) and total trading volumes (metric tons of CO_2) of the seven pilots. The price rose dramatically before 2014 but dropped gradually until the middle of 2015, after which it stabilized at around US$ 3. This price level is considerably lower than estimates of the social cost of carbon,[10] and somewhat lower than the EU ETS price before its reforms in 2018.[11] In contrast, trading volumes witnessed a more than seven-fold increase, from 14.6 million metric tons in 2014 to 124.2 million metric tons in 2019. The trading volumes were unevenly allocated within each year, with most transactions concentrated in the few months just before reporting due dates. This could be the result of the system working as intended. If the regulated firms had managed to significantly reduce their CO_2 emissions, they would not need to buy many permits and would only make a few trades before the due date to avoid penalties. However, this trading pattern could also be explained by the unimportance of this issue to the regulated firms. For example, the average permit price in 2016 was 3.32 US$/metric ton of CO_2, whereas the average on-grid electricity price for coal-fired power plants is 51.73 US$/MWh.[12] This suggests that for each unit of electricity generated by coal plants, the permit price is only 6.36% of the electricity sale price.[13] This is the marginal cost, for emissions exceeding the free allowances; the average net change in revenue due to the carbon price is much smaller. In our dataset from the China Electricity Council (CEC), the total electricity generation revenues of the ETS treated power plants were 25.9 billion US$ in 2016,[14] but the aggregate value of transactions for ETS permits from all regulated firms in all pilot markets was only 0.212 billion US$ in the same year, less than 1% of the power generation revenues. With the generous free allowances and low realized prices of the permits, the regulated firms have little incentive to worry much about reducing

[10]For example, Ricke et al. (2018) estimate the social cost of carbon for China to be US$ 24, eight times the ETS price.

[11]The EU allowance settlement price remained around €5 from 2013 to 2017, after which the price rose to around €20 due to the reforms by the European Commission (Bayer and Aklin 2020).

[12]The national average on-grid electricity price for coal-fired power plants is obtained from the National Energy Administration.

[13]The average CO_2 emission intensity per unit output for coal-fired power plants was 0.99 kg CO_2/kWh in 2016, calculated using the CO_2 emission data from the CEADs and electricity generation data from the CEC.

[14]The electricity generation revenues are calculated by the products of the total amount of electricity generation in the CEC dataset and the national average on-grid electricity price for coal-fired power plants.

CO_2 emissions. Buying a few permits just before the due date was a low-cost option, reducing output to sell permits is a low-profit option. The actual efficacy of the ETS is thus largely an open question requiring empirical investigation.

2.2 Electricity system regulation and emissions

Given that non-thermal power plants generate almost no CO_2, all the plants regulated in the ETS are thermal power plants, mostly coal-fired. Thermal power plants had long dominated electricity generation in China. The proportion of electricity generation from thermal power remained at about 80% from the 1970s until 2012, after which it began a gradual decline due to the rapid growth of nuclear and wind power. Nevertheless, thermal power is still dominant, with a 72% share of total electricity generation in 2016.[15]

Unlike countries with access to cheap gas, coal is the most prevalent source of thermal power in China, contributing 91% of thermal power in 2018.[16] The intense use of coal generation makes the electricity sector the largest coal-consuming sector in China. Since 1985, coal consumption in the power sector has increased steadily, with its share of total industrial coal consumption rising from 28% in 1985 to 50% in 2013. However, after 2013, the trend was reversed, and electricity coal consumption fell for the first time since the 1970s. Total CO_2 emissions from electricity and other industrial sectors follow these trends in coal consumption. CO_2 emissions from electricity generation increased by 230% from 1,218 million metric tons in 2000 to 4,062 million metric tons of CO_2 in 2013, but following coal consumption, fell slightly in 2014 and 2015.[17]

Given this substantial level of coal combustion, the electricity sector was also the largest emitter of industrial sulfur dioxide (SO_2) and nitrogen oxides (NO_x) in the earlier years. However, in contrast with the then unregulated CO_2 emissions, emissions of SO_2 and NO_x started to fall as a result of more stringent air pollution rules and enforcement. With the enforced operation of desulfurization and denitrification equipment, the electricity sector's SO_2 emissions dropped nearly 60% from 2006 to 2015, and NO_x emissions fell 45% in the four years before 2015. Despite these considerable reductions, the electricity sector remains a major contributor to these air pollutants among all industrial sectors.

The unique feature of the electricity sector is its size combined with regulation. As a public

[15] Data source: China Electricity Yearbook.

[16] The data on electricity generation from coal and other thermal power is obtained from the CEC.

[17] Data source: CEADs.

utility in many countries, including China, it is strictly regulated. The regulatory system in China is unique given the dominant role of state-owned enterprises and the institution of "decentralized authoritarianism"[18] where economic governance is delegated to provincial governments. Electricity transmission and distribution in China are monopolized by two state-owned grid companies, the State Grid Corporation of China and the China Southern Power Grid, and their provincial subsidiaries. The provincial planning authorities, including the provincial Development and Reform Commissions and the Economic and Information Commissions, are responsible for the design and negotiations of annual electricity generation plans. Annual base production of each unit is allocated according to a "fair dispatch" formula since 1987; this assigns generators of the same class the same annual electricity generation quota to grant an equal opportunity for cost recovery on investments.[19] Dispatch agencies in grid companies then design real-time unit commitment schedules so that actual utilization averaged over the year matches the base generation allocated.

Power plants follow these schedules to produce electricity and will be warned and disconnected from electricity grids for violations of the schedules. They are also entitled to submit their proposals on their planned amount of electricity generation for next year. In the mid-2000s a limited amount of "direct contracting" was introduced whereby large consumers could enter long-term contracts with large generators. However, the great majority of dispatch decisions is ultimately determined by provincial-level generation planning. These fair-dispatch plans do not follow least-cost rules but are made by bargaining among different stakeholders (state-owned generators, the state grid, the central planning agency, and the provincial planning agency), subject to technical requirements for system reliability (for a further discussion, see Ho et al. 2017).

In the 2000s, the power shortages of the 90s were replaced by excess capacity, and at the same time air pollution problems became more severe, due to the enormous levels of coal combustion. Various reforms of the power system were tried, including generation rights trading, "energy conservation dispatch" and direct contracting. In response to the high use of fossil fuels, a push towards renewable energy was also started. These reforms were not entirely successful, with provincial governments promoting their own generators (and tax base) and limited inter-provincial trades which were intended to bring renewable power from the north and west to

[18]Xu (2011) gives a comprehensive analysis of the institutions affecting economic development and reforms in China.

[19]Rules on Operation of Power Grids. http://www.gov.cn/gongbao/content/2007/content_751791.htm.

the load centers in the east. As a result, the fair allocation plan remains dominant, with energy conservation and emission reduction also taken into account by the planning authorities and dispatch agencies to some degree. For example, to promote renewable energy, grid companies can offer preemption, and commit to purchasing all electricity generated by renewable energy firms.[20] The most recent master plan for the electricity sector covering 2016 to 2020 further commands that energy conservation and emission reduction should form one of the major goals of electricity planning and dispatch.[21]

In 2015, China began implementing major electricity market reforms, promoting long-term and intermediate markets, auxiliary services markets, and setting up pilot spot markets.[22] Taking the long-term contracts arranged on these markets into consideration, provincial planning authorities design electricity generation plans and dispatch agencies make real-time commitment schedules accordingly. They are also entitled to adjust the contracts to improve grid reliability and increase the use of clean power sources, that is, they maintain dominant control over electricity generation. The government did not start to relax the electricity system planning until 2017.[23] Under this vertical hierarchy of control, the efficacy of carbon emission trading relies on multiparty decisions of stakeholders and the outcomes are not obvious.

Figure 2 shows the annual CO_2 emissions of the electricity sector from each of the pilot regions (colored lines)[24] and the non-ETS provinces (grey lines). Except for Chongqing and Hubei, the other four pilot regions witnessed, on average, an 11% decrease in emissions from the electricity sector from 2014 to 2017. This coincides with the period when the ETS pilots are in operation. For Hubei, emissions remained stable and for Chongqing, emissions surged by 22% in that period. For Guangdong and Shanghai, their emissions also picked up in 2017. Given this complex behavior, more careful empirical examination is therefore required to assess the effectiveness of the ETS pilots.

[20] Order of the State Electricity Regulatory Commission (July 25, 2007), "Regulatory measures for grid company full integration of renewable electricity." http://www.gov.cn/ziliao/flfg/2007-08/01/content_702636.htm.

[21] NDRC (Dec 22, 2016), "The 13th Five-Year Plan for electricity power development." http://www.gov.cn/xinwen/2016-12/22/content_5151549.htm.

[22] China initiated spot market pilots at eight provinces in 2017 and 2018, including Inner Mongolia, Shanxi, Gansu, Shandong, Zhejiang, Fujian, Sichuan, and Guangdong.

[23] Announcement of National Energy Administration and NDRC, "Orderly relaxation of the electricity generation and consumption planning." https://www.ndrc.gov.cn/fzggw/jgsj/yxj/sjdt/201704/t20170410_986939.html.

[24] The data is obtained from the CEADs, which includes Shenzhen in its province, Guangdong.

3 Empirical Methodology

3.1 Identification strategy

3.1.1 Difference-in-differences estimation

To identify the causal effect of the ETS on participating firms in China, we exploit the carbon market pilots started in the seven municipalities and provinces around 2013. For brevity we use the terms pilot provinces and non-pilot provinces, although some of the pilot areas are municipalities not under a provincial government. Major CO_2 emitting firms in the pilot provinces were compulsorily enrolled in the emission trading markets, whereas less important firms in these areas and all firms in non-pilot provinces were not subject to the permit requirements. This differentiated assignment of carbon market participation and the timing of the pilot initiation enable us to exploit the policy as a quasi-experiment. Specifically, in our baseline analysis, we compare the changes in the outcome variables of interest for the regulated coal-fired power plants (treatment group), to the corresponding changes in the coal plants in non-pilot provinces (control group) during the same period, before and after carbon market initiation. The specification for our difference-in-differences (DiD) estimation is:

$$y_{it} = \beta ETS_i \times TP_t + \alpha Z_{ct} + \eta_i + \delta_{gt} + \epsilon_{it} \tag{1}$$

where y_{it} is the outcome variable of interest, ETS_i is a dummy variable that equals one if power plant i is enrolled in the ETS and zero otherwise, TP_t is a dummy variable that equals one for the years when the ETS pilots are in operation and zero otherwise, Z_{ct} is a set of control variables, η_i represents plant-level fixed effects, and δ_{gt} represents region-year-level fixed effects.[25]

We use coal-fired power plants in non-pilot provinces as the control group and exclude non-covered firms in pilot provinces because treatment assignment is not random but depends on past coal consumption and CO_2 emissions at the plant level. The covered power plants are large coal consumers and CO_2 emitters, and the non-covered coal-fired plants in pilot provinces are mainly small-scale plants and outdated plants that are scheduled to be phased out shortly after 2013.[26] In most pilots, the cutoff for ETS participation is 10,000 metric tons of coal per year,

[25]In our sample, almost all treatment plants are covered by the ETS from the start of the carbon markets. Six plants that were not in the first year of the ETS were later included, and we exclude them from our regression sample due to possible endogeneity in the timing of coverage.

[26]For example, Shanghai Zhabei Power Plant and Guangdong Mei County Power Plant were not covered by the ETS because they were to be shut down in 2015 and 2016.

which is appropriate for manufacturing firms but is a very low level for power plants, and we note that only about 30 coal-fired power plants that are still in operation in 2017 in the pilot regions are not covered during this period. Because treatment assignment for plants in the pilot regions is endogenously determined by their past coal consumption, direct comparisons of the covered and non-covered plants in the pilot regions could therefore lead to erroneous estimates due to selection bias. In robustness checks in Appendix A, we also employ the generalized synthetic control method to construct more comparable counterfactuals for the treated plants using the within-province variation.

This choice of control group allows us to compare the treated plants with similar coal-fired power plants in non-pilot provinces. However, using the between-province variation for identification is susceptible to confounding variables that parallel the ETS pilots. To alleviate this concern, we use time-varying regional fixed effects, δ_{gt}. We group provinces to the six regions of China, that is, North China, Northeast China, East China, South Central China, Southwest China, and Northwest China.[27] These divisions are based on geographic proximity and derived from earlier administrative areas of China. Although they were officially dissolved in the 1950s, it still constitutes the first digit of current administrative division codes and many current administrative tasks are still allocated by these six regions, such as the military administrative regions and the national anti-pollution campaigns. More importantly, the regional divisions also largely overlap with the regional electricity grids. Electricity supply to local residents and enterprises is mainly controlled by the State Grid Corporation of China (SGCC) and the China Southern Power Grid Company (CSPGC). CSPGC oversees electricity supply in Guangdong, Guangxi, Yunnan, Guizhou, Hainan, Hong Kong, and Macau. The other provinces are mainly under the administration of five regional subsidiaries of the SGCC (North, Northeast, East, Central, Northwest) which cover similar administrative divisions. Controlling for the region-year fixed effects means that we are comparing the treated plants with plants in nearby non-pilot provinces from the same division and the same year. This absorbs time-varying variations at the division (and higher) level and uses only variations within divisions for identification.

In addition, we consider a rich set of city-year covariates Z_{ct} to control for factors that could affect plant-level electricity production, including the logarithm of electricity consumption, GDP, population, industrial gross output, number of industrial firms, and the value-added to GDP

[27] North China includes Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia. Northeast China includes Heilongjiang, Jilin, Liaoning. East China includes Shanghai, Zhejiang, Jiangsu, Shandong, Anhui, Jiangxi, Fujian. South Central China includes Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan. Southwest China includes Sichuan, Guizhou, Yunnan, Chongqing, Tibet. Northwest China includes Shaanxi, Gansu, Ningxia, Qinghai, Xinjiang.

ratios for the secondary and tertiary sectors.[28] The city-level variables are largely exogenous in our specification because demand for electricity at each plant is driven by regional economic factors but the variation in the electricity generation of a single power plant is unlikely to change the city's conditions under the hierarchy of electricity sector regulation.

Coal-fired power plants are major emitters of air pollutants such as SO_2 and NO_x and provincial governments set pollutant discharge fees to control them. These fees were replaced by environmental taxes in 2018. Around both 2010 and 2015, most provinces raised their discharge fees to deal with increasingly severe air pollution. For example, Tianjin raised discharge fees on SO_2 emissions from 0.63 to 1.26 RMB/kg in 2011 and further to 6.30 RMB/kg in 2015. To exclude confounding effects from discharge fee changes, we control for discharge fee rates for sulfur dioxide and nitrogen oxides emissions by province and year. The same measures on the discharge fees are also used by Gowrisankaran et al. (2020) to study the effects on productivity and emissions.

In 2012 provinces were, for the first time, assigned targets for reducing CO_2 intensity (CO_2 emissions per unit GDP) by the 12th Five-Year Plan (2011 to 2015). These reduction targets, differentiated by provincial economic development levels, ranged from 10% to 19% initially, and were raised after 2015. We use these provincial carbon intensity targets[29] to control for the different stringency of general CO_2 regulations across provinces. In order to further control for the stringency of environmental regulations at a more detailed level, we follow Chen et al. (2018) and use the proportion of the text of annual city government work reports that is devoted to environmental regulations. We collect more than 3,000 government work reports for 270 cities from 2005 to 2017. The proportion of environment-related text is defined as the ratio of total words in environment-related sentences to total words of the work report.[30] This measure is in the same spirit of using text as data (Grimmer and Stewart 2013) and similar indices have also been constructed to measure uncertainty (e.g., Baker et al. 2016, Gulen and Ion 2015, Handley and Li 2020).

[28] The data on city-year-level covariates are obtained from the China City Statistical Yearbook. The secondary sector covers mining, manufacturing, utilities and construction. The primary sector covers agriculture and the tertiary sector covers all other industries (mainly services and government).

[29] For years before 2012, the targets are assigned to be zero for all provinces.

[30] Following Chen et al. (2018), we define environment-related sentences as the sentences that contain any of the following words: pollution (*wuran*), environment (*huanjing*), environmental protection (*huanbao*), energy consumption (*nenghao*), emission reduction (*jianpai*). The Chinese word for environment, *huanjing*, may refer to many different concepts and we exclude the sentences that refer to other meanings, such as development environment, social environment, economic environment, legal environment, business environment, and external or internal environment.

3.1.2 Matched DiD estimation

The validity of the DiD estimator relies on the assumption that the treatment and control plants, in the same division and during the same year, would have followed parallel trends of the outcome variables of interest in the absence of the ETS pilots. Even though we use between-province variation for identification, the treated plants are not necessarily comparable to coal-fired power plants in non-pilot provinces due to the existence of small-scale plants in the control group. To address this concern, we follow Cicala (2015) to use matched DiD estimations by matching the treated plants with the coal-fired power plants that have the most similar coal consumption in 2012, the year before any ETS pilots started. Specifically, for each treated plant, we find 10 coal-fired power plants with the closest coal consumption in 2012 within 300 miles of the treated plant and in the same geographic division. Since the cutoffs for ETS participation in the pilot provinces are largely determined by coal consumption, the matched plants would have been incorporated into the ETS had they been located in the pilot regions. In order to avoid treated plants being matched with a plant that only appears in our sample for a few years, we restrict the matching procedure to plants that are in the sample for at least seven years. We allow for gaps in the time series in order to avoid dropping too many observations when constructing a balanced panel. Since our sample period is from 2005 to 2017 (without 2013), this restriction suggests that we match the treated plants with other plants that exist for at least three years before the start of ETS pilots.

For robustness checks, we consider alternative matching procedures in a separate appendix, [31] including using different numbers of matched plants, having fewer years of existence when restricting the sample, and using a different matching variable. We also provide balance checks in the Online Appendix to show that the differences in pre-treatment periods between treated plants and the matched sample are not statistically significant. After constructing the matched sample, we follow Cicala (2015) to use the inverse of the number of matches as regression weights for each matched untreated plant.[32] Figure 3 shows the geographic distribution of the treated plants (red triangles), matched plants (blue dots) and other coal-fired power plants (yellow dots). The treated plants are located in four municipalities and two provinces and are surrounded by matched plants from nearby provinces.

[31] A separate appendix to this paper provides robustness checks and supplementary analyses. We will refer to this as the Online Appendix when referencing additional material.

[32] The weights assigned to treated plants are equal to 1, and 0 to unmatched plants.

3.1.3 Generalized synthetic control

The matched DiD estimator is used to construct a more balanced control group in order to alleviate selection bias at the plant level. However, we still need to consider the possibility of uncontrolled confounders even after we include a rich set of covariates. To further address this concern, we employ the generalized synthetic control (GSC) method. Starting with Abadie and Gardeazabal (2003), synthetic control approaches have drawn much recent attention from researchers (e.g., Abadie et al. 2010, 2015, Chernozhukov et al. 2017, Arkhangelsky et al. 2020). Xu (2017) generalizes this approach to multiple treated units and further develops the GSC method. Bayer and Aklin (2020) use this method to evaluate the effects of the European Union's ETS. Similarly, we modify equation (1) and use the GSC method to estimate the following equation

$$y_{it} = \beta ETS_i \times TP_t + \lambda_i' f_t + \alpha Z_{ct} + \delta_{gt} + \epsilon_{it} \tag{2}$$

where $f_t = (f_{1t}, \ldots, f_{rt})$ is an $r \times 1$ vector of unobserved factors common to all units, and $\lambda_i = (\lambda_{i1}, \ldots, \lambda_{ir})$ is a vector of unknown factor loadings specific to unit i.

The inclusion of interactive fixed effects $\lambda_i' f_t$ relaxes the conventional strict exogeneity assumption of DiD estimators because they can capture a wide range of unobservables, including the confounders that are common shocks with heterogeneous impacts.[33] For example, the economic slowdown that began in China in 2011 may reduce electricity demand by more in highly developed regions than in poorer regions, and national anti-pollution policies impose particularly stringent regulations in some developed regions.

We follow Xu (2017) to estimate equation (2) in three steps to calculate the treated counterfactuals and estimate the average treatment effect on the treated plants.[34] Since the GSC method relies on more periods of pretreatment data to estimate the interactive fixed effects, we also restrict the GSC estimations to power plants that are in the sample for at least 7 years.

In the Online Appendix, we also use the synthetic difference-in-differences method proposed by Arkhangelsky et al. (2020) as a robustness check for the GSC estimators.

[33]The interactive fixed effects $\lambda_i' f_t$ can capture any unobserved variables that can be decomposed to the multiplicative form $U_{it} = a_i \times b_t$ (Xu 2017).

[34]The first step is to use observations of the control group to estimate α, f_t, and $\lambda_i^{control}$. The second step is to use pretreatment observations of the ETS treated plants, and $\hat{\alpha}$ and $\hat{f}_t$ obtained from the first step, to estimate λ_i^{treat} for each treated unit. The last step is to calculate the treated counterfactuals and estimate ATT based on $\hat{\alpha}$, $\hat{f}_t$, $\hat{\lambda}_i^{treat}$.

3.1.4 Key variables of interest

Our primary purpose is to examine the effectiveness of the pilot ETS in reducing CO_2 emissions in the electricity sector. Since information regarding plant-level CO_2 emissions is not available in our dataset, we instead consider plant-level coal intensity (the ratio of coal consumption to generated electricity) and coal consumption. CO_2 emissions are normally not measured directly but imputed from coal consumption. Unlike sulfur dioxide and nitrogen oxides, which can be substantially abated by desulfurization and denitrification equipment, CO_2 emissions are much more difficult to capture and store. Appendix Figure A1 shows that SO_2 and NO_x emission intensities of fossil fuel consumption in the electricity sector have been reduced considerably while CO_2 emission intensity remains almost unchanged during the last decade. Although we could use the national average CO_2 intensity (emissions per ton of coal) to calculate CO_2 emissions, we stick to coal consumption because our primary purpose is to investigate the efficacy of the ETS, not to quantify the CO_2 mitigation effects.

To further understand the underlying mechanisms for changes in coal consumption, we also examine the effects of the ETS pilots on electricity generation and generator operating hours. The relation between coal consumption and annual output of electricity depends on the number of hours, the operating intensity (unit load) during each of those hours, the number of times that output is ramped up and down, and other operational conditions.

3.2 Data

The main dataset used in our empirical analysis is the power plant data collected by the China Electricity Council (CEC), which is the national association for the electricity industry founded with the approval of the State Council. Our dataset covers more than 10,000 power plants from 2005 to 2017, with detailed information on plant-level annual electricity generation, operating hours, generator capacities, coal intensity, coal consumption, names of plants, and locations. All power plants with installed capacity of 6 megawatts (MW) or higher are covered by this dataset. Since this is quite a low threshold for coal-fired power plants even in 2005, this dataset covers nearly all coal plants in China. For instance, in 2012, the total installed capacity for plants above 6 MW is 753.82 gigawatts (GW), accounting for 99.86% of the country's total 754.88 GW coal capacity.[35]

[35]The data for installed capacities is obtained from the 2012 report of the CEC.

We obtain the lists of firms participating in the ETS pilots from the local Development and Reform Commissions of the pilot provinces and municipalities. For about 170 regulated power generation companies in the ETS firm lists, we manually search for their company names and aliases in the CEC power plant dataset.[36] Given that almost all regulated power plants are coal-fired plants, we retain coal-fired power plants in our sample and exclude other types of power plants (e.g., gas-fired, hydropower, nuclear, and wind power plants) to ensure the comparability between treatment and control groups. We also exclude the observations with missing values for the key variables (coal intensity, coal consumption, and electricity generation) to ensure the reliability of estimation results. Data for 2013 is missing from our sample because the CEC did not report plant-level information for that year. Although omitting 2013 reduces the sample size, it also reduces potential biases since most of the pilot provinces (Beijing, Tianjin, Shanghai, and Guangdong) started their carbon markets in the second half of 2013; the annual data would reflect the production behavior of treated plants with and without the ETS. Inclusion of data for 2013 could thus cause a downward or upward estimation bias, depending on whether that year was classified as a treatment or control period. Our data cleaning procedures leave us with 209 regulated power plants and 2,809 unregulated coal-fired power plants with 197 unregulated plants in pilot provinces.[37]

Table 1 reports summary statistics for the power plant dataset after data cleaning. For treated plants, the average annual coal consumption is 894,820 metric tons, average electricity generation is 3,014 gigawatt-hours (GWh), average coal intensity is 307 grams/kilowatt-hour (g/kWh), average operating hours are 4,672 hours per year, and average installed capacity is 672.56 MW. In our dataset, treated plants account for 94% of all electricity generation by coal-fired power plants in pilot provinces during the period when the ETS are in operation. Significant differences exist between regulated plants and other plants, especially for the non-regulated plants in pilot provinces. The average coal consumption of regulated plants is 65% and 231% higher than unregulated plants in non-pilot and pilot provinces, respectively. The differences in

[36] For example, Zhongshan Thermal Power Generation Corporation Ltd is recorded using its full name in the ETS list, but is recorded as Zhongshan Thermal Power Plant in the CEC dataset. We use "Zhongshan Thermal Power" as the keyword to search in the CEC dataset. For the unmatched companies in the ETS lists, we further search for their aliases online and use these aliases to match with the CEC dataset. For example, China Resources Yichang Power Generation Corporation Ltd is recorded using its full name in the ETS list, but has the alias Runchang Power Plant in the CEC dataset. After these procedures, fewer than 20 power generation firms in the ETS lists remain unmatched with the CEC dataset.

[37] Most of the unregulated coal-fired power plants in the ETS pilot provinces only exist in the years before 2013 in our sample. Only about 30 power plants are left unregulated in 2017. The number of regulated power plants is larger than the number of electricity generation companies in the ETS firm list because some companies have multiple plants.

output are even greater (72% higher than plants in non-pilot provinces and 267% higher than unregulated plants in pilot provinces). The regulated plants are also more efficient since their coal intensities are 14% and 23% lower than unregulated plants in non-pilot and pilot provinces, respectively, possibly due to their larger scale. Moreover, the operating hours of treated plants are merely 1.1% higher than the plants in non-pilot provinces but are 22% greater than the unregulated plants in pilot provinces. This indicates that the unregulated plants in pilot provinces are less favored by local planning authorities and are probably in the process of being phased out.

For robustness checks, in the online appendix we use alternative firm-level data on coal intensity and consumption from the Ministry of Finance and the State Taxation Administration, and self-reported data on CO_2 intensity and emissions. We use information on firm-level business status to identify the exit of power plants; that data is obtained from the National Enterprise Credit Information Publicity System which is maintained by the State Administration for Market Regulation. The publicity system reports comprehensive firm information, such as its legal representative, registration number, registration date, status, administrative licenses, penalties, and shareholders.

In addition, we consider the air quality co-benefits of the ETS pilots in the Online Appendix. We use geographically gridded air pollutant concentration data from the U.S. National Aeronautics and Space Administration (NASA). We follow Karplus et al. (2018) and use the daily observation data of SO_2 and NO_2 concentrations from the Ozone Monitoring Instruments of Aura satellites with resolution at $0.25° \times 0.25°$. We calculate annual average concentrations based on the daily observations. The data for annual $PM_{2.5}$ concentrations is provided by the Socioeconomic Data and Applications Center (SEDAC) which utilizes the GEOS-Chem atmospheric model with satellite data on aerosol optical depth from MODIS, MISR and SeaWiFS to estimate gridded ground-level annual $PM_{2.5}$ concentrations. Following Karplus et al. (2018), we draw a circle with a radius of 35 km centered at each power plant and take the average of gridded air pollutant concentrations covered by the circle as the pollutant concentrations of that plant.

4 Empirical Results

4.1 Main results

Table 2 reports the main estimation results. Column (1) shows the changes in coal intensity associated with ETS participation. The DiD estimator in Panel A shows that the coefficient for coal intensity is only 0.024, which is not statistically or economically significant. This suggests that compared with non-regulated coal-fired power plants in nearby provinces, the ETS treated plants did not improve their coal efficiency after joining the ETS pilots. Panel B reports the matched DiD estimator using a more comparable control group. The coefficient (0.015) remains not statistically significant, and is somewhat smaller than the DiD estimate in Panel A. The GSC estimator in Panel C uses interactive fixed effects to control for heterogeneous impacts from common shocks and now the coefficient for coal intensity (0.039) becomes a bit larger than the estimates in Panels A and B, but it is still statistically insignificant. Therefore, the insignificant coefficients for coal intensity in all three panels strongly indicate that in our sample period, the ETS pilots of China have a negligible effect on the coal efficiency of participating power plants. This is consistent with our discussions on the ETS price in section 2.1 and suggests that the low permit price and generous free allowances fail to induce participating firms to improve their energy efficiency.

By contrast, Column (2) shows a significant decrease in coal consumption associated with the ETS pilots. The DiD estimator in Panel A implies a 16.1% fall in coal consumption of the treated plants, and the effects estimated by matched DiD and GSC are even greater than that from the DiD estimator (-0.222 and -0.207). All the estimates are statistically significant at the 1% level. This implies that the ETS-treated plants experienced a substantial reduction in coal consumption after joining the ETS pilots.

Given the negligible change in coal intensity, the significant decrease in coal consumption from the treated plants should imply a considerable reduction in electricity production from them. To examine this, Columns (3) and (4) of Table 2 show the changes in electricity generation and generator operating hours after participating in ETS pilots. The estimates on electricity generation are negative and statistically significant at the 1% level in all Panels A-C, suggesting significant reductions in the output of regulated plants. This is consistent with the results in Columns (1) and (2), because the demand for coal of each power plant is derived from electricity production. When the difference in the change in coal intensity is negligible, the viable way to lower coal consumption for the ETS plants is to reduce output. Meanwhile, the coefficients in Column (4) for hours are negative but are smaller in magnitude and statistically insignificant, except for the GSC estimator. This implies that the reduction in operating hours associated with ETS participation is, if anything, small. Therefore, the observed reduction in output is mainly driven by a fall in operation intensity rather than reduction in operating hours. This is probably because the cost of ramping up from a cold start is usually higher than that of reducing operation intensity given the same amount of output reduction.

Figure 4 plots the time path of the changes in coal intensity (a-b), coal consumption (c-d), electricity generation (e-f), and operating hours (g-h) for the regulated plants relative to the control plants constructed by the matched DiD estimator (left column) and the GSC estimator (right column), together with their 95% confidence bands. For both methods, the pre-ETS estimates for coal intensity are centered around zero and are not statistically significant, and most post-ETS estimates for coal intensity remain statistically insignificant, except for the GSC estimator in the first post-ETS year. Nevertheless, the post-ETS estimates for coal consumption and output are negative and most are statistically significant, while the pre-ETS estimates are also centered around zero and statistically insignificant. These time trends confirm the substantial reductions in coal consumption and output associated with ETS participation. The pre- and post-ETS estimates on operating hours are not statistically significant, except for the first two years after the ETS are in operation, when the estimates are significantly negative.

Overall, these results indicate that China's ETS pilots did not successfully induce regulated power plants to improve their coal efficiency. We indeed observe a significant reduction in coal consumption from the treated plants, but this decrease is achieved by reducing their electricity generation, instead of upgrading their generators for greater efficiency.

4.2 Potential confounders

We have noted that the highly regulated nature of the electricity sector means that ETS participants may be subject to some other environmental regulations that coincide with the ETS pilots. This section discusses potential confounding policies and examines whether they drive the main results.

Ultra-low emission standards. The first parallel policy we consider is the ultra-low emission standards (ULES). In 2014, the Ministry of Environmental Protection issued a work plan that required all eligible coal-fired power plants in the country to achieve ultra-low emission standards for particulates, sulfur dioxide, and nitrogen oxides by 2020 (Tang et al. 2019).[38] More specifically, the policy commands coal-fired power plants above 300 MW (used for public electricity generation, not own-use) to achieve the new emission standards by 2017, 2018, and

[38] The policy requires the emission concentrations of particulates, sulfur dioxide, and nitrogen oxides to be no greater than 10, 35, and 50 mg/m^3, respectively.

2020 in the east, central, and west regions of China, respectively. Plants need authentication of meeting the ULES from local governments and approval for environmental impact assessment reports for their generator upgrades undertaken to meet the ULES. We identify the power plants that achieved the ULES by authentication reports and approvals for completed ULES upgrades issued by local governments.

National Specially Monitored Firms. Another possible confounding policy is the National Specially Monitored Firms (NSMF) program (Zhang et al. 2018). Firm environmental performance is typically monitored by provincial or other local authorities but the NSMF program requires major polluting firms to be directly supervised by the central government and monitored in real time by continuous emissions monitoring systems. We obtain the lists of firms monitored in this way each year from the Ministry of Environmental Protection and add a dummy $NSMF$ to control for the policy.

"Green" dispatch pilots. We also consider the energy-saving and emission-reducing dispatch that was initially piloted in five provinces (Guangdong, Guangxi, Yunnan, Guizhou, and Hainan) in 2010 before it was introduced to all provinces under the 13th Five-Year Plan (2016-2020). We use the interaction of $GreenDispatch_p$ (a dummy variable to denote the five "green" dispatch pilot provinces) and T_{2010} (a dummy variable to denote years after 2010) to control for this policy.

Table 3 reports the estimation results controlling for the ULES, NSMF, and "green" dispatch policies. Consistent with the main results in Table 2, the coefficients on $ETS_i \times TP_t$ for coal intensity remain statistically insignificant for all three estimators in Panels A-C, but all the coefficients for coal consumption and output are negative and statistically significant (at the 5% level for the DiD estimators and at the 1% level for the matched DiD and GSC estimators). Furthermore, their magnitudes are also similar to those in Table 2. This implies that the main results are not driven by these three policies. The coefficients on the ULES dummy are statistically positive for coal consumption, output, and operating hours in Panels A and B. This suggests that after achieving the emission standards, ULES plants were granted more operating hours and produced more electricity compared with non-ULES plants. Meanwhile, the coefficients on the ULES dummy for coal intensity are quite small and become statistically insignificant for the matched DiD estimators, implying that the plants achieved the ULES mainly by using scrubbers rather than improving coal efficiency. The coefficients on the NSMF dummy are significantly positive in Columns (2)-(4) of Panel A, but become insignificant in Panel B except for output when the NSMF plants are compared to other plants with similar coal consumption in 2012. The green dispatch pilots also have significantly negative effects on electricity generation, coal consumption, and operating hours according to the DiD estimators, although the effects become insignificant for the matched DiD estimators.

Plant exit. Since 2006, China has phased out many high-polluting and outdated facilities in the electricity sector.[39] To examine whether the closing of power plants biases the main results, Columns (1)-(4) of Table 4 report the estimation results using only plants that remain in operation in the last year of our sample (2017). The number of observations for DiD estimators falls by 40% compared with Table 2, while those for matched DiD estimators and GSC estimators fall by only 20% because they are conducted using plants that exist for at least seven years in the sample period. For all three panels, we find the coefficients on coal intensity are not significant. Moreover, conforming with the main results, the coefficients on coal consumption and output remain significantly negative, and for most estimators, the magnitudes of effects are somewhat larger than the main results in Table 2, implying substantial reductions in coal consumption and output of the treated plants even when compared with the plants that were not shut down.

It may be the case that some plants were still operating in the last year of the sample, but were scheduled to cease operating in the coming years. The production in such plants may have been affected by these plans, for example if their output quotas were reduced prior to their closure. To address this concern, for the power plants in our sample, we obtain their business status in June 2020,[40] that is, more than two years after the last year of our sample, and further exclude the plants that had been deregistered by that time, had their business licenses cancelled, or had relocated. This results in excluding about 10% of the samples in the three panels. The estimation results after excluding these plants, presented in Columns (5)-(8) of Table 4, are consistent with the main results. The coefficients on coal consumption and output remain significantly negative, and the coefficients on coal intensity are quite small and not statistically significant, except for the GSC estimator in Column (5), which is positive and significant at the 5% level.

To examine the role of exit and entry in these estimated ETS effects, we employ the Dynamic Olley-Pakes Decomposition (DOPD) proposed by Melitz and Polanec (2015) to identify the contributions to coal intensity and coal consumption from entrants, exiters, and survivors,

[39] Notice of the State Council (Mar 20, 2006), "Accelerating the structural adjustment of industries with overcapacity." http://www.gov.cn/zwgk/2006-03/20/content_231376.htm.

[40] We obtain the business status information from the National Enterprise Credit Information Publicity System as described in section 3.2.

separately for ETS pilot provinces[41] and non-pilot provinces. Appendix Figure A2(a)-(c) show the contributions to coal intensity (ETS provinces in dashed lines, non-ETS in solid lines).[42] For both pilot provinces and other provinces, their output-weighted coal intensity declined significantly from 2005 to 2017. Both regions witnessed a more than 15% reduction in the coal intensity of surviving plants, while the reductions contributed by entrants and exiters are about only 2%. The similar time trends in coal intensity for pilot and other provinces are consistent with the insignificant effect of the ETS on coal efficiency. Meanwhile, Figure A2(d) shows that the contribution from surviving plants to output-weighted coal consumption in pilot provinces declined more than the plants in other provinces after 2014, but Figure A2(e) shows that the entrants in both regions have a parallel post-treatment trend in coal consumption. Furthermore, exiters in both regions contribute positively to coal consumption because their exit increases output quotas allocated to the remaining plants, and they also have a parallel post-treatment trend. This suggests that the observed reduction in coal consumption in Table 2 is mainly driven by the surviving plants.

4.3 Channels

In the main results, we observe a significant reduction in coal consumption, induced by production shrinkage rather than coal efficiency improvement. To understand why the ETS pilots cause output reductions, we examine the possible channels in Tables 5 and 6.

On-grid electricity prices are typically well above the marginal costs of coal-fired power plants to allow them to recover their substantial fixed investment costs. These fixed prices are in sharp contrast to countries with spot markets and fluctuating prices. With the trivial ETS prices noted in section 2.1, plants have no incentive to reduce output as long as their marginal costs after joining the ETS remain below on-grid prices. In addition, all pilot regions, except Chongqing, allocate free allowances to coal-fired power plants by benchmark emission intensities and plant-level output. This could offset the incentive for ETS treated plants to reduce output because allocated free allowances would be reduced by the current period's output reductions (Goulder et al. 2019). Therefore, the observed reduction is more likely to be caused by commands from the electricity planning authorities.

[41] We include the non-regulated plants in pilot provinces because there were hardly any exits among the ETS treated plants.

[42] Figure A2 is based on decomposition results by the DOPD, so no confidence interval is provided and the parallel pretreatment trends shown by the matched DiD and GSC estimators in Figure 4 do not necessarily exist.

To confirm that the output contraction is caused by planning authorities rather than decisions of the power plants, we examine the relation between power plants' profitability and reductions in output. Although power plants consume less coal due to output reductions, their fixed costs are unchanged, which include not only capital equipment costs but also much of their labor costs. This implies that lower output reduces profits. Hence, power plants are unlikely to willingly reduce their output. The CEC dataset contains no information on profits, so to examine this relation we obtain plant-level annual net profits of treated plants from other data sources. For listed power generation companies, we obtain profit information for each power plant from their annual reports for the period from 2005 to 2017. For other firms, we obtain the information from a firm-level dataset from the State Taxation Administration (STA) and the Ministry of Finance (MOF), which jointly collect information on financial outcomes, taxation, and energy use of about 2 million firms from 2007 to 2015 (see Liu and Mao 2019 for further details). In total, we obtain the information on profits for 758 power plants and 3,276 observations, of which 37% report negative profits.[43]

We estimate equation (1) again, adding a dummy variable $Loss_{it}$, which equals one if plant i reports negative profits for year t, and zero otherwise, and its interaction with $ETS_i \times TP_t$. The results are given in Table 5.[44] In Panels A and B, we find that the coefficients of OLS and matched estimators on ETS participation now become smaller in magnitude than those in Table 2 and are not statistically significant in all columns. The coefficients on $Loss_{it}$ are mostly negative but not statistically significant. However, the coefficients on the triple interactions are significantly negative for coal consumption, output, and operating hours. In addition, Panel C reports the results of GSC estimators with ETS participation and $Loss_{it}$ as additional covariates. The coefficients on the triple interaction remain negative and statistically significant for coal use, output, and hours, and their magnitudes are close to the OLS estimators. The large and negative coefficients suggest that treated power plants that had significant reductions in coal consumption and output are the plants that report negative profits. These significant financial losses strongly indicate that the output contraction of the treated plants is unlikely to be voluntary due to firm optimizing behavior given the relation between on-grid electricity prices and marginal costs. Therefore, the reductions in coal consumption and output are more likely to be caused by the planning authorities. During the 13th Five-Year-Plan, energy conservation and emission

[43]This ratio is close to the data disclosed by CEC. According to the Annual Development Report of the China's Electricity Sector, published by the CEC in 2019, 43.8% of coal-fired power plants report negative profits in 2018.

[44]In Table 5 and later tables, except Table A5 that uses province-level data, we add control variables for the ULES, NSMF, and green dispatch pilots.

reduction has been targets of electricity dispatch in all provinces. Therefore, the planning authorities in pilot provinces may reduce the electricity generation of the coal-fired ETS-treated plants over their likely objection.

An alternative explanation to the substantial output contraction from plants with negative profits is that their coal efficiency is so low that their marginal costs are above on-grid electricity prices. In our sample, their average coal intensity is 301 g/kWh during the period from 2015 to 2017, which is only 5.187% greater than the average intensity of plants with non-negative profits in the same period. Meanwhile, the average coal cost for ETS plants is 84.734 US$/ton in that period,[45] and their average on-grid electricity price is 64.224 US$/ MWh. With the 288 g/kWh average coal intensity, the marginal revenues (the on-grid electricity price) are more than twice their marginal costs (coal costs per unit output). Therefore, even for these plants with negative profits and high coal intensity, they should have no incentive to voluntarily reduce output.

A possible concern about the results in Table 5 is that the purchase of permits might increase operating costs of treated plants and reduce their profits. To show that the permit costs cannot drive the substantial output contraction, we first calculate marginal profits of ETS plants using the average on-grid electricity prices for coal-fired power plants in each province from the National Energy Administration, and the coal cost per unit output. In Figure 5 we graph the distributions of these marginal profits for the ETS plants, separately for 2015, 2016 and 2017. Although coal prices increased by more than 20% during 2015-2017, and the average marginal profits fell from 42.798 to 32.715 US$/MWh, the marginal profits of all treated plants are positive (solids lines in Figure 5). Even for the least efficient plants, their marginal profits are still about 7 US$/MWh in 2017 when the coal price was at a peak in that period.

We next use the average carbon emission intensity in the electricity sector[46] to calculate CO_2 emissions per unit output for the treated plants, and then use permit prices in each ETS market to measure their permit costs per unit output. To illustrate the largest possible impacts of permit costs on marginal profits, we assume that plants are given no free allowances and have to purchase permits for all of their emissions. We subtract the permit costs from their marginal profits and present the adjusted distributions by dashed lines in Figure 5. The average permit cost

[45]We obtain city-level free on board (FOB) prices of thermal coal for 75 cities from the China Coal Market (http://www.cctdcoal.com/). Plant-level coal costs are measured by these FOB prices from the nearest city, plus rail transportation costs. The transportation costs are calculated from the distance to each plant and the benchmark railway freight charges for coal transportation, which are set by the NDRC.

[46]The average CO_2 emission intensity is calculated using the total CO_2 emissions of the electricity sector from the CEADS, and the sector's total coal consumption for that year from the China Environment Statistical Yearbook.

for the treated plants is 1.868 US$/MWh. Thus, even assuming no revenues from free allowances, their marginal profits only decrease by 5% on average and remain positive for all plants. This implies that increasing production is still profitable for the ETS-treated plants. Therefore, the direct effects of the ETS on profits are not large enough to turn marginal profits negative, and are unlikely to induce treated plants to substantially reduce their output.

To assure that the observed output decrease is not driven by a profit maximizing response of treated plants to the ETS pilots, we run our main regressions with annual average permit prices ($Price_{pt}$) as an additional explanatory variable. The results are given in Appendix Table A1. If the treated plants respond to the increased cost due to carbon prices by reducing output, we should expect greater output reduction with higher ETS prices. However, Table A1 shows that, conditional on ETS participation, the coefficients of ETS prices are quite small in magnitude and not statistically significant in all columns, while the coefficients of $ETS_i \times TP_t$ remain statistically negative for coal consumption and output. This suggests that the reductions in coal consumption and output are not responsive to changes in ETS prices, confirming that the reductions are more likely due to planning agency decisions.

The electricity marketization reforms that started in 2015 were intended to relax regulations on electricity prices and production. The newly established electricity markets mainly cover intermediate and long-term contracts, and planning authorities still have a dominant influence on real-time generation, especially in the early stages of the reforms before the introduction of spot markets. To examine the effects of these reforms, we first define a marketization ratio as the ratio of electricity sold on markets to total provincial electricity consumption.[47] We use the ratio in 2017 to separate provinces into two groups - high-marketization and low-marketization[48] - and then estimate the heterogenous effects of the ETS pilots for them separately. Table 6 presents the estimation results, Columns (1)-(4) for the high-marketization group and Columns (5)-(8) for the low. For both groups, all estimators on coal consumption and output remain significantly negative. Although the effects in high-marketization provinces are smaller than those in low-marketization provinces according to DiD and GSC estimators in Panels A and C, the differences are quite small and the effects are even larger for high-marketization provinces using the matched DiD estimators. This implies substantial reductions in coal and output of ETS-treated plants in both

[47]The data is obtained from the China Electricity Council.

[48]The high-marketization group includes Anhui, Fujian, Guangdong, Guangxi, Guizhou, Henan, Hubei, Jiangsu, Inner Mongolia, Liaoning, Ningxia, Qinghai, Shanxi, Sichuan, Yunnan, Zhejiang. The low-marketization group includes Beijing, Chongqing, Gansu, Hainan, Hebei, Heilongjiang, Hunan, Jiangxi, Jilin, Shaanxi, Shandong, Shanghai, Tibet, Tianjin, Xinjiang.

groups. Furthermore, all estimates on coal intensity are not statistically significant, suggesting that even in high-marketization provinces, the ETS pilots did not induce treated plants to improve their coal efficiency. Therefore, the reforms did not seem to change the influence of planning authorities on the production of ETS treated plants during the sample period. Although the marketization reforms promoted long-term and intermediate contracts, planning authorities and dispatch agencies maintained the dominant control over electricity generation through real-time commitment schedules. The introduction of some spot market pilots since 2018 could relax some regulations from planning authorities but this is out of our sample period.

4.4 Additional heterogeneity

Heterogeneity by coal intensity. If the reductions in coal consumption and output are forced by planning authorities, they may reduce output more in the plants with higher coal intensity in order to achieve greater CO_2 emission reduction. To examine whether the ETS pilots have heterogeneous effects differing by coal intensity, we classify power plants into four groups based on their coal intensity in 2012 and estimate with all three sets of estimators (DiD, matched DiD, GSC) for the four groups. Appendix Table A2 presents the estimation results. For each estimator there are four columns; Columns (1), (5) and (9) report results for the highest coal intensity group, (2), (6), and (10) report results for the second highest intensity group, etc. Consistent with our expectations, we find largest reductions in coal consumption in the two least efficient groups. The reduction in output is also largely concentrated in these two groups, except that the matched DiD estimator for the second most efficient group is also significantly negative. These results suggest that the least coal-efficient groups experience the biggest reductions in coal consumption and output. Moreover, all estimates for coal efficiency are not statistically significant, conforming with the main results.

Heterogeneity by ownership. We next consider if state ownership affected the response to the ETS. Using ownership information from the Wind database[49] for listed electricity generation companies and in the STA-MOF dataset for other firms, we identify the types of ownership for 1,115 coal-fired power plants in the main dataset. Of these, about 75% are state-owned plants (SOPs). Appendix Table A3 shows the effects of the ETS pilots on SOPs and non-SOPs separately. We find that for both SOPs and non-SOPs, the estimates on coal intensity are not

[49] The Wind database, maintained by Wind Information Co. Ltd, is like Bloomberg in the U.S. that collects financial data of listed firms.

statistically significant in all columns. The DiD and matched DiD estimators on coal consumption are significantly negative for SOPs, while the GSC estimators are not statistically significant. Meanwhile, for non-SOPs, the effects are statistically significant and much greater in magnitude, ranging from -38.3% to -55.1% for coal consumption and -30.6% to -50.6% for output. The results suggest that both SOPs and non-SOPs seem to experience output contraction after joining the ETS, but the latter bear the largest reductions in electricity generation and coal consumption. Compared with SOPs, non-SOPs generally have less bargaining power when planning authorities cut their output. This is also consistent with the heterogeneous effects by coal intensity, since the non-SOPs are generally smaller in scale and have higher coal intensity than the SOPs.

Heterogeneity by pilot regions. The six pilot regions differ substantially in their ETS market design, such as sector coverage and market liquidity. Appendix Figure A3(a) shows that Beijing has the highest carbon price. The coverage of the Beijing ETS is the most comprehensive, with most covered companies in the service sector which are allocated proportionally fewer allowances compared with firms in other covered sectors. The low supply of emission permits may account for the high prices in that market. For trading volumes, Appendix Figure A3(b) shows that the volumes for Guangdong and Hubei are much greater than other regions due to their carbon market size. The price and trading volumes for Chongqing remain relatively low over this period, except when volumes surged in 2017. The lack of trading in the Chongqing ETS is likely due to excessive allowance supply. The initial allowances in Chongqing were allocated according to total emission limits and self-reported allowance demands. This could induce firms to exaggerate their demands to obtain more allowances. Most participating firms thus have no need to trade with others to meet their permit requirements.

Appendix Table A4 reports estimation results for each pilot region, comparing the treated plants with coal-fired power plants from non-pilot provinces in the same regional division.[50] For all pilot regions, the estimates on coal intensity remain statistically insignificant, confirming that there is no improvement in coal efficiency associated with ETS participation. For Beijing and Tianjin, we find the estimates on coal consumption and output are negative and large in magnitude but are not statistically significant except for the GSC estimates on coal consumption. The lack of statistical power may be caused by the small number of treated power plants in the two regions. For Shanghai and Guangdong, all estimators for coal consumption and output are negative, and are both economically and statistically significant.

[50]We do not separate Shenzhen from Guangdong due to the small number of covered coal-fired power plants in Shenzhen.

Meanwhile, all estimates for Hubei are statistically insignificant. Although Figure A3(b) shows that the Hubei ETS had the largest trading volumes in 2015, it was subsequently surpassed by Guangdong. By 2019, the trading volumes in Guangdong were five-times greater than in Hubei. In fact, the demand for emission permits in Hubei had been low from 2016 to 2018. The daily ETS price change was limited in the range from -1% to 10% by the Hubei government in 2016.[51] This limit reduced market liquidity and the ETS price declined gradually until 2018. After that, the price began to rise, but this period is not covered by the CEC sample. For Chongqing, all estimates are also statistically insignificant, and this is consistent with the low level of activity in the Chongqing ETS market. Overall, the results in Table A4 imply considerable heterogeneity across the pilot regions. Guangdong and Shanghai seem to effectively curb coal consumption of thermal power plants by reducing power output. The effects in Beijing and Tianjin are estimated to be large but lack statistical power. No apparent changes are observed in Hubei and Chongqing, indicating that their planning authorities did not noticeably force ETS treated plants to reduce fossil fuel consumption and carbon emissions during this period.

4.5 Spillover effects

Our estimation results document significant declines in coal consumption, resulting from reductions in electricity generation from coal plants in the ETS pilots. The reduction in output amounts to 116 billion kWh from 2014 to 2017 in the pilot provinces according to the DiD estimator in Table 2. This accounts for 12% of total electricity generation in these provinces in 2017. What could the pilot provinces do to accommodate this reduction in coal power output? One option is to increase electricity imports from nearby provinces. This would mean that electricity generation in neighboring provinces could be affected by the ETS pilots. However, the validity of our DiD estimator relies on the stable unit treatment value assumption (SUTVA). If the coal-fired power plants in nearby provinces increase their electricity production to supply the pilot regions, this will violate the SUTVA and cause over-estimation of the ETS effects on coal consumption.

To examine whether there is any significant carbon leakage to neighboring provinces, we exclude the power plants in pilot regions from the estimation sample and treat the coal-fired power plants in neighboring provinces as the new treatment group, with the remaining coal-fired power plants as the control group. We construct another interaction term $Neighbor_p \times$

[51] Hubei Emission Exchange notice (July 15, 2016), "Adjusting the limits of HBEA Daily Trading Range for Carbon Emission Permit Trades." http://www.hbets.cn/index.php/index-view-aid-1181.html.

TP_t, where $Neighbor_p$ is a dummy variable denoting the neighboring provinces of ETS pilot regions. The matched DiD estimators for this test sample are constructed by matching the power plants in neighboring provinces with 10 coal-fired power plants that have the most similar coal consumption in 2012 from the other non-pilot provinces in the same geographic division. Table 7 reports the estimation results. All coefficients on the new interaction term are not statistically or economically significant. This implies that there is no evidence that the ETS pilots cause carbon leakage to coal-fired power plants in nearby provinces. Despite the recent marketization, the power sector in China is still under strict regulations. Although power plants in the nearby provinces have a cost advantage, their ability to sell electricity to nearby regions is limited by various frictions such as the slow development of inter-province electricity markets, tariffs imposed by different regional grids, and excess capacity. The absence of carbon leakage is likely the result of the strict regulatory regime and the far-reaching authority of provincial governments.

An alternative explanation for the findings in Table 7 is that the pilot regions increase electricity imports not only from nearby provinces but also from provinces further away. Unfortunately, it is difficult to examine this spillover effect on such power plants using our DiD specifications because we are unable to find a suitable control group for them. Instead, we test this channel using provincial-level data for bilateral electricity imports and exports, obtained from the CEC, with the following specification:

$$EL_{pqt} = \beta PilotProvince_{pq}^{type} \times TP_t + \alpha X_{pt} + \gamma X_{qt} + \eta_{pq} + \delta_t + \epsilon_{pqt} \tag{3}$$

where EL_{pqt} is the logarithm of traded electricity exported by province p to province q in year t, $PilotProvince_{pq}^{IM}$ is a dummy variable that equals one if the importer q is an ETS pilot province, $PilotProvince_{pq}^{EX}$ is a dummy variable that equals one if the exporter p is an ETS pilot province, η_{pq} and δ_t represent exporter-importer fixed effects and year fixed effects, X_{pt} and X_{qt} denote province-year-level control variables for exporters and importers, including the logarithm of electricity consumption, GDP, population, industrial output, number of industrial firms, the ratios of secondary industry value-added to GDP and tertiary industry value-added to GDP,[52] pollution fee rates for sulfur dioxide emissions and nitrogen oxides emissions, and CO_2 mitigation targets.

We estimate equation (3) in separate tests with $PilotProvince_{pq}^{IM} \times TP_t$ and $PilotProvince_{pq}^{EX} \times TP_t$ as the main regressors. The equation is estimated with positive bilateral flows only, and with all possible bilateral flows for robustness. Columns (1)-(4) of Appendix Table A5 report the

[52]The province-year-level control variables are obtained from the China Statistical Yearbook.

OLS estimation results. Columns (1) and (2) compare the changes in electricity imports of pilot provinces after the ETS started with the changes in non-ETS provinces, (1) for positive flows only and (2) for all bilateral flows. For both columns, the coefficients of $PilotProvince_{pq}^{IM} \times TP_t$ are small and insignificant. This suggests that there were negligible differences between the changes in electricity imports for pilot provinces and for other provinces. Columns (3) and (4) examine the responses to the ETS in electricity exports for pilot provinces. Although the magnitude of the effect is much larger in Column (3) than Column (1), the coefficients on $PilotProvince_{pq}^{EX} \times TP_t$ are not statistically significant, implying that there is no significant change in the electricity exports of the pilot provinces. Columns (5)-(8) of Table A5 report the results using GSC estimators; they are also statistically insignificant. These results imply no evidence of carbon leakage to non-pilot provinces.

Another spillover effect we consider is a switch to non-fossil fuel generators in the pilot provinces to replace the reduced coal power. We examine this effect by using triple difference estimations with data for all power plants. Specifically, we use the dummy variable $NonCoal_i$ to denote "clean" power plants, which equals to one if plant i is a non-coal-fired power plant. $PilotProvince_p$ denotes the pilot provinces. We use the triple interaction term $NonCoal_i \times PilotProvince_p \times TP_t$ to compare the difference between "clean" power plants and coal-fired power plants, between pilot and other provinces, and between the periods before and after the ETS pilots are in operation. We control province-year and plant type (NonCoal)-year fixed effects to ensure coefficients on the triple interaction term are not driven by any time-varying unobservables at the province or plant type levels. As further robustness checks, we also conduct a 1-to-10 match for the non-coal-fired power plants in pilot provinces by matching them with the non-coal-fired plants in other provinces that had the most similar generation capacity in 2012, and run GSC estimations after controlling province-year and plant type-year fixed effects.

Table 8 shows that the coefficients on this triple interaction term are positive and statistically significant for electricity generation and operating hours. This implies that when the pilot provinces reduced output from the ETS treated coal-fired plants, they also expanded the generation from clean power plants. Their output and operating hours rise by 19.4% and 24.6%, respectively, according to the DiD estimator. The effects on generation capacity are not significant; this is not very surprising given that China generally had excess generation capacity at that time (Ren et al. 2019). These results imply a transition towards clean energy in the ETS pilot regions. Although we find no evidence that the ETS pilots improved coal efficiency, Table

8 indicates that an increase in utilization of non-coal-fired power plants occurred in the pilot regions. However, since the output contraction from the treated plants is unlikely to be voluntary, as suggested by our discussions in section 4.3 above, the observed transition to clean energy is most likely due to government decisions.

The reductions in coal-fired electricity supply in pilot provinces could also induce manufacturing firms to use more self-generated electricity. To examine this, we use a sample of coal-fired power plants from manufacturing firms, which are covered by the CEC dataset but not used in our previous analysis, and investigate how changes in their outcome variables are associated with the ETS pilots. Appendix Table A6 presents the estimation results. We find that none of the coefficients of $PilotProvince_p \times TP_t$ is statistically significant, implying that the ETS pilots have negligible effects on their electricity generation and coal use for generating electricity. China has been tightening regulations for self-generation from manufacturing firms since they are less efficient and emit more air pollution per unit output. These plants in the ETS pilot provinces are also under strict regulations and are restricted from expanding their electricity production.

A large portion of power plants in China are owned by several large power generation corporations. In a free electricity market, if ETS-treated plants in a power generation group reduce their output in response to the emission trading, that group might increase the output of untreated plants elsewhere as compensation. This would result in a shift of electricity production from treated to untreated plants in the same power generation corporation. To examine this, we count the number of ETS treated plants for each power generation group g, denoted as $NumTreated_g$,[53] and interact it with the time dummy TP_t. If production is shifted from treated to untreated plants in the same group due to ETS, we expect more shifted production to the untreated plants in groups with more ETS-treated plants. Appendix Table A7 reports the estimation results after dropping observations of plants in pilot provinces, and compares the changes of the non-ETS plants in the power generation groups with some ETS-treated plants to the changes of other non-ETS plants. Columns (1)-(4) report the OLS estimators, and Columns (5)-(8) report the matched estimators by matching the plants with positive $NumTreated_g$ (i.e. non-ETS plants in a group with ETS-treated plants) to 10 other plants that have the closest coal consumption in 2012. We find that in all columns the coefficients of $NumTreated_g \times TP_t$ are quite small and statistically insignificant. This suggests that the electricity production of

[53]For robustness checks, we also normalize $NumTreated_g$ using the total number of coal-fired plants in power generation group g, and find that the coefficients of $NumTreated_g \times TP_t$ remain statistically insignificant.

untreated plants in power generation groups with some ETS-treated plants do not increase significantly compared with the production of other untreated plants. This is consistent with the strict regulations of the electricity sector in China. Power production is under the control of electricity planning authorities, and power plants are not very free to change their output.

4.6 Implications for emission mitigation

In the main results in section 4.1, we find a substantial reduction in coal consumption in the ETS-treated plants. The CO_2 emissions should fall in parallel given the stable carbon emission intensity. We quantify the implied CO_2 emission changes in Table 9. The average annual coal consumption of each ETS treated plant is 0.894 million metric tons. Therefore, the DiD estimation results in Table 2 suggest that the coal consumption falls by an average of 0.144 million metric tons (95% C.I.: (-0.251,-0.037)) for each treated plant. The reductions implied by the matched DiD and GSC estimators are even greater, at 0.199 and 0.185 million metric tons, respectively. Since the average carbon emission intensity in the thermal power sector of China is 2.337 metric tons of CO_2/metric ton of coal in 2017, the induced CO_2 emission reduction is 0.337 million metric tons according to the DiD estimators. If we use the social cost of carbon for China of 24 US$/metric ton from Ricke et al. (2018), then the monetized benefits from the induced change in carbon emissions come to 8.080 million US$ per plant. If we consider all ETS treated plants, according to the DiD estimators, the reductions in coal consumption, CO_2 emissions, and social costs of carbon are 30 million metric tons, 70 million metric tons, and 1,689 million US$ in total over 2014 to 2017, respectively.

The reduction in coal combustion also has obvious co-benefits in terms of reducing conventional air pollution. These air quality improvements are discussed in the online appendix.

5 Conclusion

Exploiting China's carbon ETS pilots as a quasi-experiment, we utilize a micro-level dataset of national power plants to empirically identify effects of the ETS in a highly regulated electricity sector with no spot markets for power generation. We find the ETS pilots have no effect on coal efficiency of the power plants obliged to enroll in the ETS. A reduction of more than 16% in coal consumption is associated with ETS participation, but this reduction is mainly achieved through lower electricity generation rather than efficiency improvement. This finding is robust to testing for a variety of potential confounding factors, and to alternative datasets and empirical specifications that we examined.

We show that the reduction in output is more likely to be caused by government commands from electricity planning authorities rather than by the optimizing decisions of the plants since the marginal cost of additional production under the ETS is still lower than the on-grid price. We also find that these plants suffer financial losses from the output reductions. ETS plants are allocated free permits primarily based on industry benchmarks, and the prices of emission permits were low; these suggest that they are unlikely to voluntarily reduce output. Non-state-owned power plants, plants with lower coal efficiency, and plants located in Shanghai and Guangdong experience greater, and more statistically significant, reductions in coal consumption and output compared to the other plants in the ETS. These results imply that the planning authorities seemed to change electricity planning to reduce the coal consumption of regulated plants, in particular, the non-state-owned and low-efficiency plants. Considering that the ETS failed to improve energy efficiency in this highly regulated sector, at least in the short run, CO_2 emission reduction is probably largely contingent on decisions of the powerful planning authorities and not individual generators.

For unregulated coal-fired power plants in provinces neighboring the pilot regions, we detect no significant change in coal consumption and electricity generation. Neither electricity imports nor exports for the pilot provinces witnessed any significant change after the ETS pilots began. The lack of evidence of carbon leakage may be attributed to the hierarchy of dispatch control; provincial organizations have the greatest authority in real-time dispatch, while inter-provincial electricity dispatch is controlled by regional agencies and subject to various institutional and market frictions. We find significant increases in electricity generation and operating hours of non-coal-fired plants in the pilot provinces. This indicates that electricity planning authorities, in at least some of the ETS areas, reduced output from the treated coal plants and increased the utilization of non-coal-fired power plants. This implies that, if emission reduction is an important target for provincial planning authorities, then they may shift electricity dispatch from the coal-fired carbon market participants to “clean” power plants, concurrently promoting the energy transition.

Simple calculations show that the implied CO_2 emission reduction from the coal consumption decline amounts to more than 70 million tons. In addition, we find substantial reductions in SO_2 concentration and moderate reductions in NO_2 and $PM_{2.5}$ concentrations in the areas around the treated plants. This provides empirical evidence for the air quality benefits of the observed reduction in coal consumption.

An important question pertains to the incentives of electricity planning authorities. The growing importance of energy-saving and emission-reducing dispatch may have contributed to their decisions to reduce the output of ETS treated plants. Meanwhile, provincial Development and Reform Commissions (DRCs) is the main authority for provincial electricity planning, and are also responsible for the operation of ETS pilots. Our discussions with government officials in charge of provincial electricity planning in the pilot regions indicate that the large ETS plants are often the prime targets when the planning authorities intend to reduce industrial emissions. Reducing their CO_2 emissions would, at the minimum, show the higher authorities that the local DRC-run ETS pilots achieved the implicit aim of emission reduction. Furthermore, the ETS and expectations of more strict regulations and higher permit prices in future may help planning authorities cut the self-proposed output of the regulated coal-fired plants. Nevertheless, whatever the incentives of planning authorities were, our empirical analysis reveals that the reduction in coal consumption of ETS plants is not achieved by the market incentives of emission trading, but by government commands.

Although the electricity sector is still under strict control by the various levels of government in China, it has been under gradual marketization reforms. It remains unclear how power plants would respond to an ETS if they were given greater flexibility in deciding their own levels of electricity generation, or even allowed to participate in spot markets. In particular, the upcoming national carbon market will also adopt the allowance allocation rule based on industry benchmarks and output (Goulder et al. 2019). Under this tradable performance standard, plants could be incentivized to increase their output. Whether more efficient plants would be raising output relative to the least efficient plants in a more deregulated environment is the key question for future ETS experimentation and empirical research.

References

[1] A. Abadie, A. Diamond, and J. Hainmueller, "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program," *Journal of the American Statistical Association*, vol. 105, no. 490, pp. 493–505, 2010.

[2] ——, "Comparative politics and the synthetic control method," *American Journal of Political Science*, vol. 59, no. 2, pp. 495–510, 2015.

[3] A. Abadie and J. Gardeazabal, "The economic costs of conflict: A case study of the basque country," *American Economic Review*, vol. 93, no. 1, pp. 113–132, 2003.

[4] D. Acemoglu, P. Aghion, L. Bursztyn, and D. Hemous, "The environment and directed technical change," *American Economic Review*, vol. 102, no. 1, pp. 131–66, February 2012.

[5] D. Acemoglu, U. Akcigit, D. Hanley, and W. Kerr, "Transition to clean technology," *Journal of Political Economy*, vol. 124, no. 1, pp. 52–104, 2016.

[6] D. Acemoglu and W. Rafey, "Mirage on the horizon: Geoengineering and carbon taxation without commitment," *National Bureau of Economic Research*, 2019.

[7] D. Arkhangelsky, S. Athey, D. A. Hirshberg, G. W. Imbens, and S. Wager, "Synthetic difference in differences," *arXiv. org*, 2020.

[8] S. R. Baker, N. Bloom, and S. J. Davis, "Measuring economic policy uncertainty," *Quarterly Journal of Economics*, vol. 131, no. 4, pp. 1593–1636, 2016.

[9] P. Bayer and M. Aklin, "The european union emissions trading system reduced CO2 emissions despite low prices," *Proceedings of the National Academy of Sciences*, vol. 117, no. 16, pp. 8804–8812, 2020.

[10] C. Böhringer, K. E. Rosendahl, and H. B. Storrøsten, "Robust policies to mitigate carbon leakage," *Journal of Public Economics*, vol. 149, pp. 35–46, 2017.

[11] S. Borenstein, J. Bushnell, F. A. Wolak, and M. Zaragoza-Watkins, "Expecting the unexpected: Emissions uncertainty and environmental market design," *National Bureau of Economic Research*, 2018.

[12] R. Calel and A. Dechezleprêtre, "Environmental policy and directed technological change: Evidence from the European carbon market," *Review of Economics and Statistics*, vol. 98, no. 1, pp. 173–191, 2016.

[13] J. Cao, M. S. Ho, and R. Ma, "Analyzing carbon pricing policies using a general equilibrium model with production parameters estimated using firm data," *Energy Economics*, vol. 92, p. 104958, 2020.

[14] Z. Chen, M. E. Kahn, Y. Liu, and Z. Wang, "The consequences of spatially differentiated water pollution regulation in China," *Journal of Environmental Economics and Management*, vol. 88, pp. 468 – 485, 2018.

[15] V. Chernozhukov, K. Wuthrich, and Y. Zhu, "An exact and robust conformal inference method for counterfactual and synthetic controls," *arXiv. org*, 2017.

[16] China Electricity Council, *Anuual Development Report of China's Electricity Sector*. China Building Materials Press, 2019.

[17] S. Cicala, "When does regulation distort costs? lessons from fuel procurement in us electricity generation," *American Economic Review*, vol. 105, no. 1, pp. 411–44, 2015.

[18] M. Crippa, D. Guizzardi, M. Muntean, E. Schaaf, E. Solazzo, F. Monforti-Ferrario, J. Olivier, and E. Vignati, *Fossil CO_2 emissions of all world countries - 2020 Report*. Publications Office of the European Union, 2020.

[19] J. Cui, J. Zhang, and Y. Zheng, "Carbon pricing induces innovation: Evidence from China's regional carbon market pilots," *AEA Papers and Proceedings*, vol. 108, pp. 453–57, 2018.

[20] ——, "Effects of carbon market on firm's competitiveness: evidence from the regional experiments of China," *Working paper*, 2020.

[21] E. Dardati, "Pollution permit systems and firm dynamics: how does the allocation scheme matter?" *International Economic Review*, vol. 57, no. 1, pp. 305–328, 2016.

[22] Y. Fan, J. Wu, Y. Xia, and J. Liu, "How will a nationwide carbon market affect regional economies and efficiency of CO_2 emission reduction in China?" *China Economic Review*, vol. 38, pp. 151 – 166, 2016.

[23] H. Fell and P. Maniloff, "Leakage in regional environmental policy: The case of the regional greenhouse gas initiative," *Journal of Environmental Economics and Management*, vol. 87, pp. 1 – 23, 2018.

[24] M. Fowlie, "Emissions trading, electricity restructuring, and investment in pollution abatement," *American Economic Review*, vol. 100, no. 3, pp. 837–69, June 2010.

[25] M. Fowlie and J. M. Perloff, "Distributing pollution rights in cap-and-trade programs: are outcomes independent of allocation?" *Review of Economics and Statistics*, vol. 95, no. 5, pp. 1640–1652, 2013.

[26] M. Fowlie, M. Reguant, and S. P. Ryan, "Market-based emissions regulation and industry dynamics," *Journal of Political Economy*, vol. 124, no. 1, pp. 249–302, 2016.

[27] Global CCS Institute, *The Global Status of CCS - 2018*. Global CCS Institute, 2018.

[28] L. H. Goulder, X. Long, J. Lu, and R. D. Morgenstern, "China's unconventional nationwide co 2 emissions trading system: The wide-ranging impacts of an implicit output subsidy," *National Bureau of Economic Research*, 2019.

[29] G. Gowrisankaran, M. Greenstone, A. Hortaçsu, M. Liu, C. Shen, and B. Zhang, "Discharge fees, pollution mitigation, and productivity: Evidence from Chinese power plants," *Working paper*, 2020.

[30] J. Grimmer and B. M. Stewart, "Text as data: The promise and pitfalls of automatic content analysis methods for political texts," *Political Analysis*, vol. 21, no. 3, pp. 267–297, 2013.

[31] H. Gulen and M. Ion, "Policy uncertainty and corporate investment," *Review of Financial Studies*, pp. 523–564, 2016.

[32] K. Handley and J. F. Li, "Measuring the effects of firm uncertainty on economic activity: New evidence from one million documents," *National Bureau of Economic Research*, 2020.

[33] M. Ho, Z. Wang, and Z. Yu, *China's Power Generation Dispatch*. Resources for the Future, 2017.

[34] International Carbon Action Partnership, *Emissions Trading Worldwide: Status Report 2021*. Berlin: adelphi, 2018.

[35] IPCC, *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press, 2013.

[36] V. J. Karplus, S. Zhang, and D. Almond, "Quantifying coal power plant responses to tighter SO_2 emissions standards in China," *Proceedings of the National Academy of Sciences*, vol. 115, no. 27, pp. 7004–7009, 2018.

[37] M. Li, D. Zhang, C.-T. Li, K. M. Mulvaney, N. E. Selin, and V. J. Karplus, "Air quality co-benefits of carbon pricing in China," *Nature Climate Change*, vol. 8, no. 5, pp. 398–403, 2018.

[38] B. Lin and Z. Jia, "Impact of quota decline scheme of emission trading in China: A dynamic recursive CGE model," *Energy*, vol. 149, pp. 190 – 203, 2018.

[39] Y. Liu and J. Mao, "How do tax incentives affect investment and productivity? firm-level evidence from china," *American Economic Journal: Economic Policy*, vol. 11, no. 3, pp. 261–91, 2019.

[40] Y. Liu, X.-J. Tan, Y. Yu, and S. Qi, "Assessment of impacts of Hubei pilot emission trading schemes in China – a CGE-analysis using TermCO2 model," *Applied Energy*, vol. 189, pp. 762 – 769, 2017.

[41] M. Melitz and S. Polanec, "Dynamic olley-pakes productivity decomposition with entry and exit," *RAND Journal of Economics*, vol. 46, no. 2, 2015.

[42] G. Meunier, J.-P. Montero, and J.-P. Ponssard, "Output-based allocations in pollution markets with uncertainty and self-selection," *Journal of Environmental Economics and Management*, vol. 92, pp. 832 – 851, 2018.

[43] G. Meunier, J.-P. Ponssard, and P. Quirion, "Carbon leakage and capacity-based allocations: Is the EU right?" *Journal of Environmental Economics and Management*, vol. 68, no. 2, pp. 262–279, 2014.

[44] N. Moore, P. Grosskurth, and M. Themann, "Multinational corporations and the EU emissions trading system: The specter of asset erosion and creeping deindustrialization," *Journal of Environmental Economics and Management*, vol. 94, pp. 1 – 26, 2019.

[45] H. Naegele and A. Zaklan, "Does the EU ETS cause carbon leakage in European manufacturing?" *Journal of Environmental Economics and Management*, vol. 93, pp. 125 – 147, 2019.

[46] C. Papageorgiou, M. Saam, and P. Schulte, "Substitution between clean and dirty energy inputs: A macroeconomic perspective," *Review of Economics and Statistics*, vol. 99, no. 2, pp. 281–290, 2017.

[47] M. Ren, L. G. Branstetter, B. K. Kovak, D. E. Armanios, and J. Yuan, "Why has China overinvested in coal power?" *National Bureau of Economic Research*, 2019.

[48] K. Ricke, L. Drouet, K. Caldeira, and M. Tavoni, "Country-level social cost of carbon," *Nature Climate Change*, vol. 8, no. 10, pp. 895–900, 2018.

[49] L. Tang, J. Qu, Z. Mi, X. Bo, X. Chang, L. D. Anadon, S. Wang, X. Xue, S. Li, X. Wang *et al.*, "Substantial emission reductions from chinese power plants after the introduction of ultra-low emissions standards," *Nature Energy*, vol. 4, no. 11, pp. 929–938, 2019.

[50] C. Xu, "The fundamental institutions of China's reforms and development," *Journal of Economic Literature*, vol. 49, no. 4, pp. 1076–1151, 2011.

[51] Y. Xu, "Generalized synthetic control method: Causal inference with interactive fixed effects models," *Political Analysis*, vol. 25, no. 1, p. 57–76, 2017.

[52] B. Zhang, X. Chen, and H. Guo, "Does central supervision enhance local environmental enforcement? quasi-experimental evidence from China," *Journal of Public Economics*, vol. 164, pp. 70–90, 2018.

[53] J. Zhu, Y. Fan, X. Deng, and L. Xue, "Low-carbon innovation induced by emissions trading in China," *Nature Communications*, vol. 10, no. 1, p. 4088, 2019.

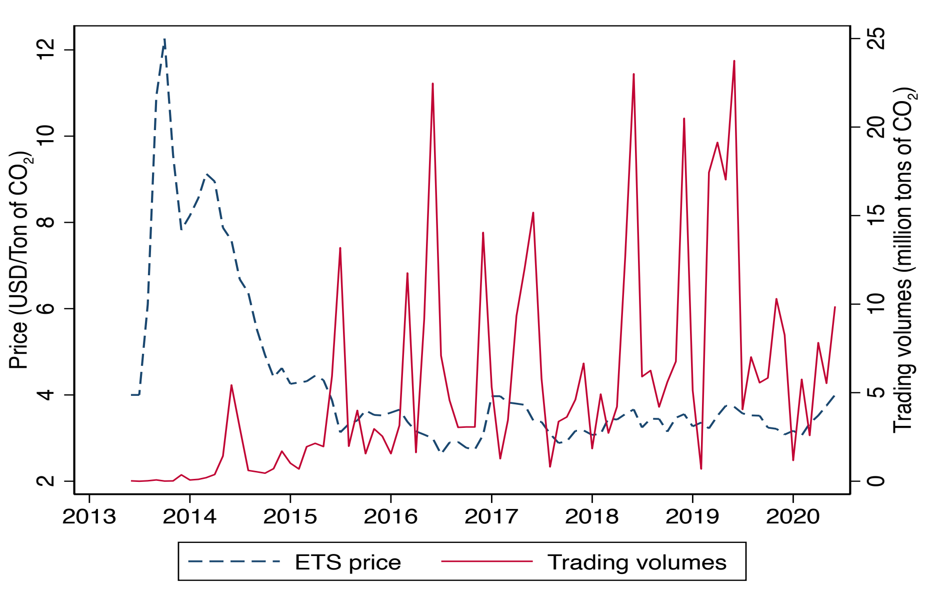


Figure 1: National monthly average ETS price and monthly trading volumes

Note: The data is calculated from prices and trading volumes of each ETS pilots, which are collected from the Wind database.

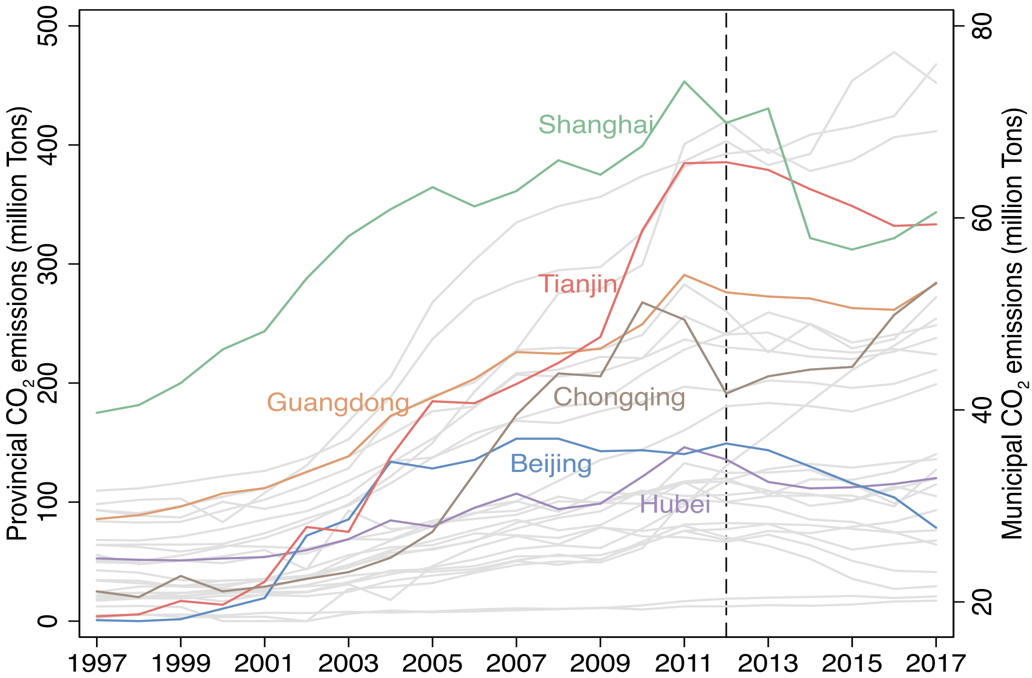


Figure 2: Provincial/Municipal CO_2 emissions of the electricity sector (million tons)

Note: The data is collected from the China Emission Accounts and Datasets (CEADs).

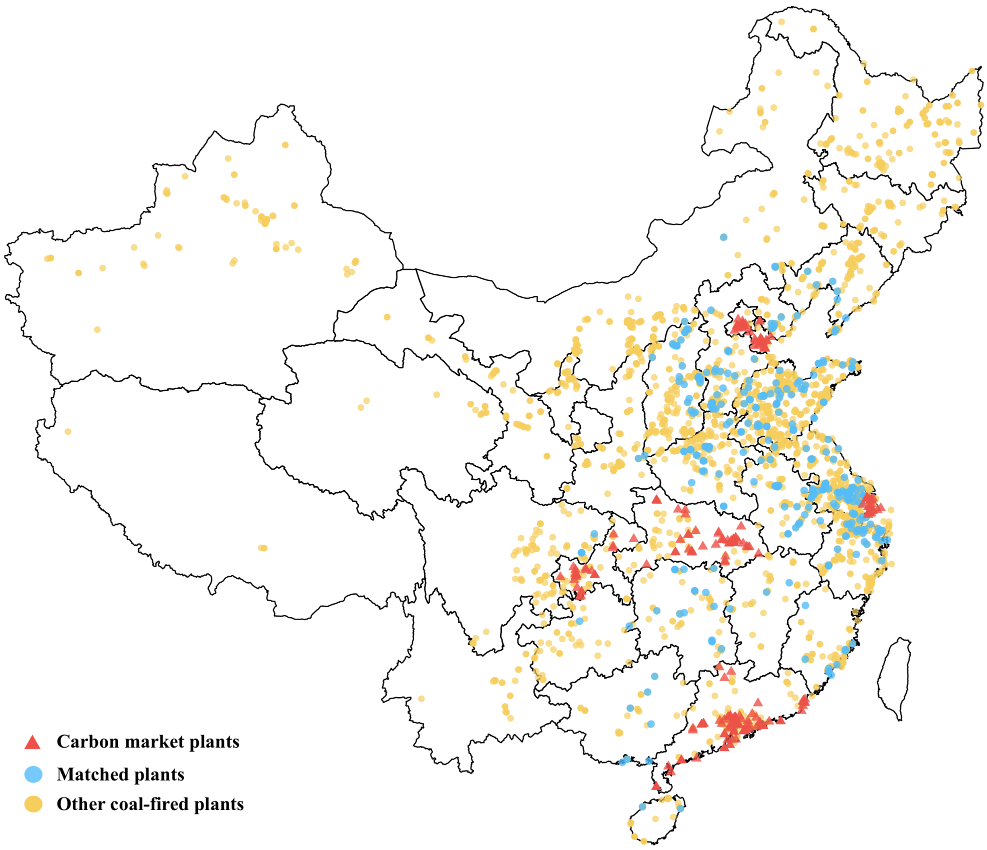
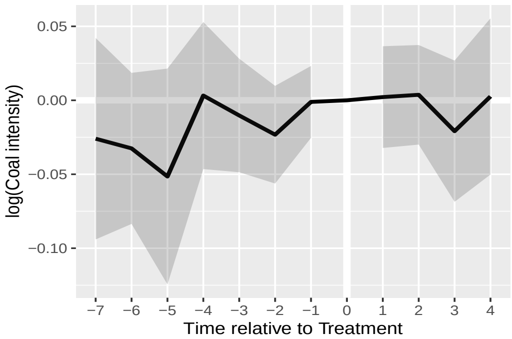
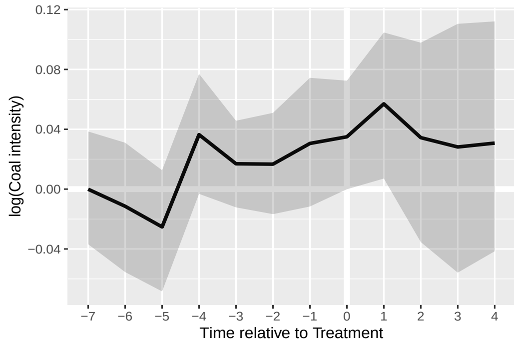


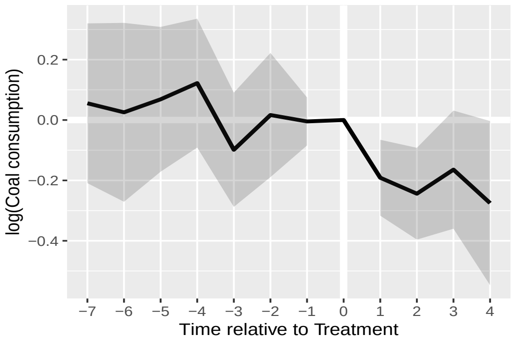
Figure 3: Geographical distribution of coal-fired power plants



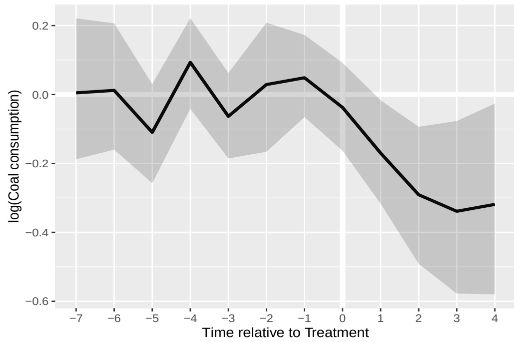
(a) Matched DiD: Coal intensity



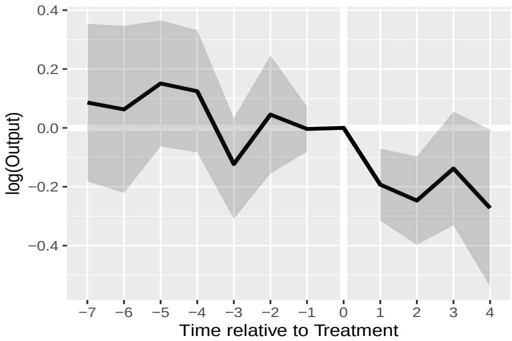
(b) GSC: Coal intensity



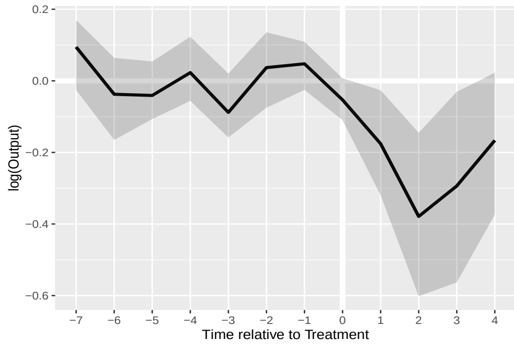
(c) Matched DiD: Coal consumption



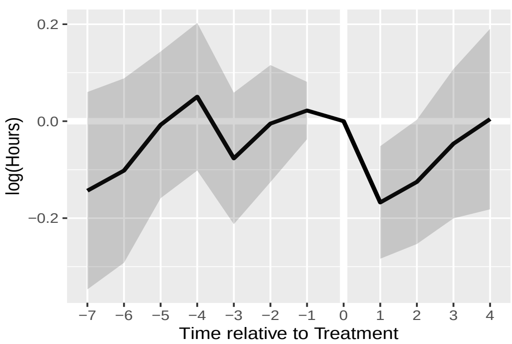
(d) GSC: Coal consumption



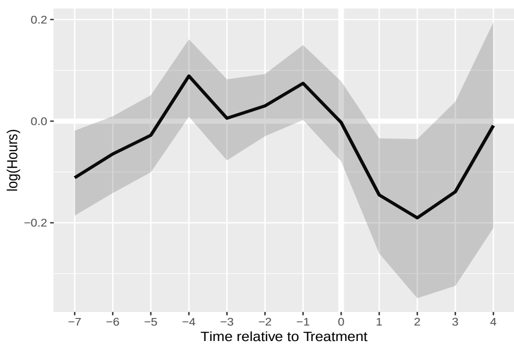
(e) Matched DiD: Output



(f) GSC: Output



(g) Matched DiD: Operating hours



(h) GSC: Operating hours

Figure 4: Trends of coal intensity, coal consumption, output, and operating hours

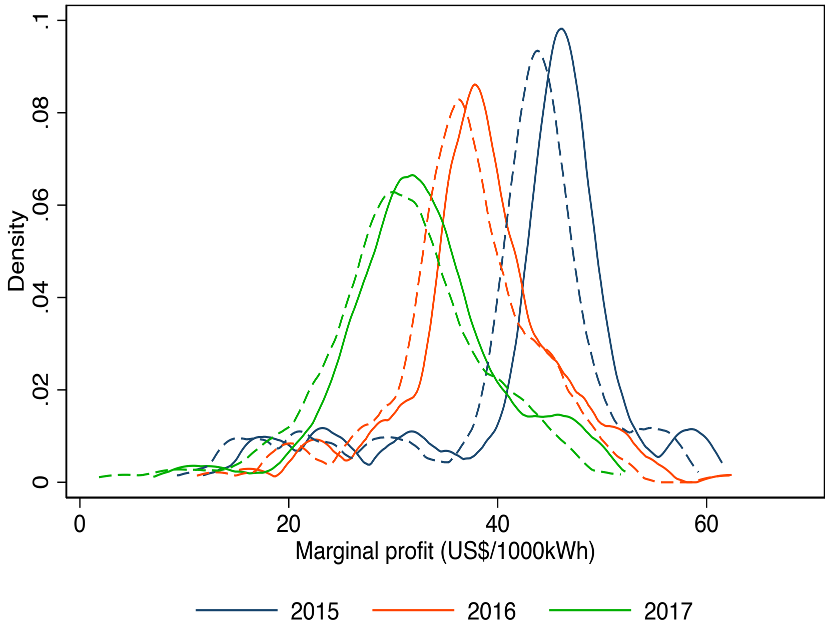


Figure 5: Distributions of marginal profits for ETS-treated plants

Note: The solid lines represent marginal profits without ETS, i.e. differences between on-grid electricity prices and coal costs per unit output. The dash lines represent marginal profits with ETS under the assumption of no initial allowances.

Table 1: Summary statistics

Variable	Obs	Mean	SD	Median	Min	Max
Panel A: Treatment plants						
Coal	1,510	894,820	857,379	657,825	1,241	6,376,944
Output	1,510	301,391	290,347	220,019	533	2,147,119
Hours	1,503	4,672	1,806	4,902	206	8,263
Intensity	1,510	307	66	304	140	749
Capacity	1,501	672,562	565,550	600,000	6,000	4,072,000
Panel B: Control plants in non-pilot provinces						
Coal	15,196	540,939	858,310	103,745	171	13,005,995
Output	15,196	175,404	286,002	29,270	379	4,306,621
Hours	15,098	4,622	1,946	4,851	206	8,656
Intensity	15,196	356	129	326	141	865
Capacity	15,018	377,461	576,690	60,000	1,900	6,120,000
Panel C: non-covered plants in pilot provinces						
Coal	696	270,445	543,879	78,542	47	4,148,993
Output	696	82,056	178,886	18,208	13	1,378,403
Hours	683	3,784	2,251	3,823	209	8,132
Intensity	696	398	138	353	29	981
Capacity	648	197,518	338,693	72,000	3,000	1,980,000

Note: $Coal$ is the coal consumption (metric tons). $Output$ is the electricity generation (10,000 kWh). $Hours$ represents the generator operation hours (hours). $Intensity$ is the coal intensity, i.e. coal consumption per electricity generation (gram/kWh). $Capacity$ is the installed capacity (kW).

Table 2: Effects of the ETS pilots on coal use and electricity production

	(1) log(Intensity)	(2) log(Coal)	(3) log(Output)	(4) log(Hours)
		Panel A: DiD estimators		
ETS×TP	0.024	-0.161***	-0.185***	-0.056
	(0.015)	(0.061)	(0.060)	(0.047)
#Plants	2,821	2,821	2,821	2,814
#ETS plants	209	209	209	209
Observations	16,638	16,638	16,638	16,526
R-squared	0.660	0.913	0.926	0.657
		Panel B: Matched DiD estimators		
ETS×TP	0.015	-0.222***	-0.237***	-0.075
	(0.020)	(0.082)	(0.081)	(0.061)
#Plants	489	489	489	489
#ETS plants	177	177	177	177
Observations	4,414	4,414	4,414	4,383
R-squared	0.634	0.907	0.917	0.623
		Panel C: GSC estimators		
ETS×TP	0.039	-0.207***	-0.216***	-0.125**
	(0.025)	(0.078)	(0.074)	(0.056)
#Plants	1,150	1,150	1,150	1,150
#ETS plants	117	117	117	117
Observations	10,869	10,869	10,869	10,802

Note: The dependent variables in Columns (1)-(4) are the logarithms of coal intensity, coal consumption, output, and operating hours. ETS_i is a dummy variable that equals one if power plant i is enrolled in the ETS. TP_t is a dummy variable that equals one for the years when the ETS pilots are in operation. Fixed effects are at the plant level and the region-year level. Control variables are the logarithm of city-year level electricity consumption, GDP, population, industrial outputs, number of industrial firms, value added to GDP ratios for the secondary and tertiary sectors, province-year level pollution fee rates on sulfur dioxides emissions and nitrogen oxides emissions, CO_2 mitigation targets of provincial governments, and environment-related text proportion of cities' annual government work reports to control for environmental regulation stringency. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Potential confounders: ULES, NSMF, and green dispatch pilots

	(1) log(Intensity)	(2) log(Coal)	(3) log(Output)	(4) log(Hours)
	Panel A: DiD estimators			
ETS×TP	0.022	-0.127**	-0.149**	-0.034
	(0.014)	(0.060)	(0.059)	(0.045)
ULES	0.016*	0.106***	0.091**	0.071***
	(0.009)	(0.037)	(0.035)	(0.024)
NSMF	-0.000	0.179***	0.179***	0.073***
	(0.010)	(0.032)	(0.030)	(0.020)
GreenDispatch×T_{2010}	0.012	-0.175**	-0.187**	-0.113*
	(0.019)	(0.083)	(0.082)	(0.063)
#Plants	2,821	2,821	2,821	2,821
#ETS plants	209	209	209	209
Observations	16,638	16,638	16,638	16,526
R-squared	0.660	0.913	0.926	0.658
	Panel B: Matched DiD estimators			
ETS×TP	0.008	-0.225***	-0.233***	-0.065
	(0.020)	(0.077)	(0.077)	(0.059)
ULES	0.003	0.152**	0.149**	0.113**
	(0.021)	(0.060)	(0.058)	(0.045)
NSMF	-0.016	0.110	0.126*	0.081
	(0.015)	(0.076)	(0.072)	(0.053)
GreenDispatch×T_{2010}	0.032	0.017	-0.015	-0.044
	(0.030)	(0.120)	(0.120)	(0.087)
#Plants	489	489	489	489
#ETS plants	177	177	177	177
Observations	4,414	4,414	4,414	4,383
R-squared	0.634	0.907	0.917	0.623
	Panel C: GSC estimators			
ETS×TP	0.039	-0.219***	-0.216***	-0.108**
	(0.025)	(0.066)	(0.062)	(0.051)
#Plants	1,150	1,150	1,150	1,150
#ETS plants	117	117	117	117
Observations	10,869	10,869	10,869	10,802

Note: The dependent variables in Columns (1)-(4) are the logarithms of coal intensity, coal consumption, output, and operating hours. ETS_i and TP_t are defined in Table 2. $ULES_{it}$ is a dummy variable that equals one if the plant i achieves the ultra-low emission standard in year t. $NSMF_{it}$ is a dummy variable that equals one if the plant i is regulated by the NSMF policy in year t. $GreenDispatch_p$ is dummy variable that equals one if the province p is a pilot province of energy-saving dispatch. T_{2010} denotes the years after 2010. Fixed effects are at the plant level and the region-year level. Control variables are the same as those in Table 2. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Potential confounder: plant exit

	Plants that remain in the sample in 2017				Omitting plants that exited by business registration			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(Intensity)	log(Coal)	log(Output)	log(Hours)	log(Intensity)	log(Coal)	log(Output)	log(Hours)
Panel A: DiD estimators								
ETS×TP	0.015	-0.225***	-0.240***	-0.125***	0.016	-0.228***	-0.244***	-0.109**
	(0.016)	(0.064)	(0.063)	(0.046)	(0.018)	(0.068)	(0.066)	(0.046)
#Plants	1,464	1,464	1,464	1,462	1,331	1,331	1,331	1,329
#ETS plants	186	186	186	186	174	174	174	174
Observations	10,231	10,231	10,231	10,181	9,160	9,160	9,160	9,113
R-squared	0.606	0.919	0.928	0.641	0.617	0.918	0.927	0.638
Panel B: Matched DiD estimators								
ETS×TP	0.012	-0.247***	-0.259***	-0.103	0.015	-0.226***	-0.241***	-0.084
	(0.019)	(0.086)	(0.086)	(0.064)	(0.020)	(0.087)	(0.087)	(0.061)
#Plants	381	381	381	381	352	352	352	352
#ETS plants	164	164	164	164	151	151	151	151
Observations	3,641	3,641	3,641	3,619	3,324	3,324	3,324	3,304
R-squared	0.672	0.909	0.919	0.616	0.694	0.908	0.918	0.618
Panel C: GSC estimators								
ETS×TP	0.032	-0.283***	-0.119**	0.214	0.041**	-0.296***	-0.176*	0.234
	(0.020)	(0.064)	(0.105)	(0.157)	(0.020)	(0.066)	(0.116)	(0.183)
#Plants	801	801	801	801	713	713	713	713
#ETS plants	99	99	99	99	87	87	87	87
Observations	7,991	7,991	7,991	7,951	7,057	7,057	7,057	7,020

Note: Columns (1)-(4) report the estimation results on plants that remain in the sample in 2017. Columns (5)-(6) report the estimation results by further omitting the plants that exited according to their business registration information in 2020. The dependent variables in Columns (1)-(4) and Columns (5)-(8) are the logarithms of coal intensity, coal consumption, output, and operating hours. ETS_i and TP_t are defined in Table 2. Fixed effects are at the plant level and the region-year level. Control variables are the same as those in Table 2. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Possible channel for ETS effects: profitability

	(1) log(Intensity)	(2) log(Coal)	(3) log(Output)	(4) log(Hours)
		Panel A: OLS estimators		
ETS×TP×Loss	-0.034	-0.517**	-0.483**	-0.285**
	(0.029)	(0.216)	(0.217)	(0.130)
ETS×TP	0.006	-0.132	-0.138	-0.078
	(0.016)	(0.090)	(0.090)	(0.083)
Loss	0.004	-0.048	-0.052	-0.058**
	(0.012)	(0.037)	(0.035)	(0.026)
#Plants	758	758	758	754
#ETS plants	82	82	82	82
Observations	3,276	3,276	3,276	3,247
R-squared	0.658	0.939	0.948	0.738
		Panel B: Matched estimators		
ETS×TP×Loss	-0.021	-0.446*	-0.426*	-0.259*
	(0.032)	(0.233)	(0.232)	(0.142)
ETS×TP	0.036	-0.137	-0.173	-0.114
	(0.026)	(0.118)	(0.115)	(0.100)
Loss	-0.012	-0.057	-0.045	-0.066
	(0.018)	(0.074)	(0.079)	(0.041)
#Plants	216	216	216	216
#ETS plants	63	63	63	63
Observations	1,167	1,167	1,167	1,161
R-squared	0.754	0.940	0.946	0.677
		Panel C: GSC estimators		
ETS×TP×Loss	-0.039	-0.515***	-0.477***	-0.347***
	(0.038)	(0.171)	(0.158)	(0.084)
#Plants	183	183	183	183
#ETS plants	53	53	53	53
Observations	1,281	1,281	1,281	1,275

Note: The dependent variables in Columns (1)-(4) are the logarithm of coal intensity, coal consumption, output, and operating hours. ETS_i and TP_t are defined in Table 2. $Loss_{it}$ is a dummy variable that equals one if the plant i reports negative profits in year t. Fixed effects are at the plant level and the region-year level. Control variables are the same as those in Table 2 and confounding policies including the ULES, NSMF, and green dispatch pilots. Standard errors are clustered at the plant level. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Possible channel for ETS effects: marketization

	High-marketization provinces				Low-marketization provinces			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(Intensity)	log(Coal)	log(Output)	log(Hours)	log(Intensity)	log(Coal)	log(Output)	log(Hours)
Panel A: DiD estimators								
ETS×TP	0.009	-0.294***	-0.303***	-0.070	0.024	-0.367***	-0.391***	-0.220**
	(0.016)	(0.072)	(0.071)	(0.057)	(0.033)	(0.102)	(0.101)	(0.099)
#Plants	1,355	1,355	1,355	1,353	1,442	1,442	1,442	1,437
#ETS plants	122	122	122	122	87	87	87	87
Observations	7,823	7,823	7,823	7,760	8,639	8,639	8,639	8,592
R-squared	0.674	0.909	0.924	0.617	0.644	0.912	0.926	0.681
Panel B: matched DiD estimators								
ETS×TP	0.024	-0.335***	-0.359***	-0.086	0.029	-0.326**	-0.354**	-0.147
	(0.018)	(0.083)	(0.082)	(0.063)	(0.038)	(0.143)	(0.145)	(0.108)
#Plants	235	235	235	235	231	231	231	231
#ETS plants	105	105	105	105	72	72	72	72
Observations	2,175	2,175	2,175	2,162	2,067	2,067	2,067	2,051
R-squared	0.606	0.914	0.928	0.622	0.637	0.889	0.900	0.616
Panel C: GSC estimators								
ETS×TP	-0.078	-0.258***	-0.320***	-0.152**	0.014	-0.320***	-0.326***	-0.311**
	(0.650)	(0.094)	(0.090)	(0.071)	(0.040)	(0.090)	(0.108)	(0.166)
#Plants	501	501	501	501	649	649	649	649
#ETS plants	72	72	72	72	45	45	45	45
Observations	4,776	4,776	4,776	4,739	5,603	5,603	5,603	5,575

Note: The dependent variables in Columns (1)-(4) and Columns (5)-(8) are the logarithms of coal intensity, coal consumption, output, and operating hours. Columns (1)-(4) are for plants in the 8 provinces with high marketization ratios. Columns (5)-(8) are for plants in the provinces with low marketization ratios. ETS_i and TP_t are defined in Table 2. Fixed effects are at the plant level and the year level. Control variables are the same as those in Table 2 and confounding policies including the ULES, NSMF, and green dispatch pilots. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Spillover effects for provinces neighboring ETS pilots

	(1) log(Intensity)	(2) log(Coal)	(3) log(Output)	(4) log(Hours)
		Panel A: DiD estimators		
Neighbor×TP	0.019	-0.079	-0.049	-0.014
	(0.015)	(0.055)	(0.047)	(0.029)
#Plants	2,612	2,612	2,612	2,605
#Neighboring plants	1,380	1,380	1,380	1378
Observations	15,196	15,196	15,196	15,092
R-squared	0.670	0.914	0.927	0.645
		Panel B: Matched DiD estimators		
Neighbor×TP	0.022	-0.135	-0.075	-0.014
	(0.023)	(0.088)	(0.086)	(0.057)
#Plants	1,723	1,723	1,723	1,719
#Neighboring plants	1,003	1,003	1,003	1,000
Observations	10,138	10,138	10,138	10,047
R-squared	0.695	0.910	0.922	0.655
		Panel C: GSC estimators		
Neighbor×TP	0.010	0.088	0.055	-0.113
	(0.013)	(0.070)	(0.083)	(0.087)
#Plants	1,273	1,273	1,273	1,273
#Neighboring plants	554	554	554	554
Observations	8,669	8,669	8,669	8,264

Note: The dependent variables in Columns (1)-(4) are the logarithms of coal intensity, coal consumption, output, and operating hours. $Neighbor_i$ is a dummy variable that equals one if plant i is a coal-fired power plant in the provinces next to the ETS pilots. TP_t is a dummy variable that equals one at the years when the ETS pilots are in operation. Fixed effects are at the plant level and the region-year level. Control variables are the same as those in Table 2 and confounding policies including the ULES, NSMF, and green dispatch pilots. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Effects of the ETS pilots on clean electricity production

	DiD estimators			Matched DiD estimators			GSC estimators		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	log(Output)	log(Hours)	log(Capacity)	log(Output)	log(Hours)	log(Capacity)	log(Output)	log(Hours)	log(Capacity)
PilotProvince×	0.194**	0.246***	0.045	0.326***	0.304***	0.051	0.349***	0.232***	0.099***
NonCoal×TP	(0.084)	(0.053)	(0.041)	(0.106)	(0.061)	(0.055)	(0.085)	(0.050)	(0.030)
#Plants	9,029	9,010	9,342	2,001	1,996	2,004	3,097	3,155	3,364
#Treated clean plants	397	396	398	258	255	258	114	111	114
Observations	48,839	49,254	51,842	15,963	16,094	16,399	35,019	35,492	36,970
R-squared	0.883	0.699	0.981	0.912	0.704	0.976	-	-	-

Note: The dependent variables in Columns (1)-(3) and Columns (4)-(6) are the logarithms of output, operating hours, and production capacity. $NonCoal_i$ is a dummy variable for "clean" power plants, which equals to 1 if plant i is a non-coal power plant. $PilotProvince_p$ equals to 1 if province p is a pilot province. TP_t is a dummy variable that equals one at the years when the ETS pilots are in operation. Fixed effects are at the province-year level, the plant type-year (NonCoal×Year) level, and the plant level. Control variables are the same as those in Table 2 and confounding policies including the ULES, NSMF, and green dispatch pilots. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Implied changes in CO_2 emissions and social costs from estimated reductions in coal use

	Per ETS treated plant			All ETS treated plant		
	DiD	Matched DiD	GSC	DiD	Matched DiD	GSC
Coal consumption changes (million tons)	-0.144	-0.199	-0.185	-30	-42	-39
	(-0.251,-0.037)	(-0.342,-0.055)	(-0.322,-0.048)	(-52,-8)	(-72,-11)	(-67,-10)
CO2 emission changes (million tons)	-0.337	-0.464	-0.433	-70	-97	-90
	(-0.587,-0.087)	(-0.8,-0.128)	(-0.753,-0.113)	(-123,-18)	(-167,-27)	(-157,-24)
Social costs (million USD)	-8.080	-11.142	-10.389	-1689	-2329	-2171
	(-14.081,-2.08)	(-19.208,-3.076)	(-18.062,-2.716)	(-2943,-435)	(-4015,-643)	(-3775,-568)

Note: Changes in coal consumption are calculated based on the main results in Table 2. In brackets are the 95% confidence intervals.

Appendix Figures and Tables

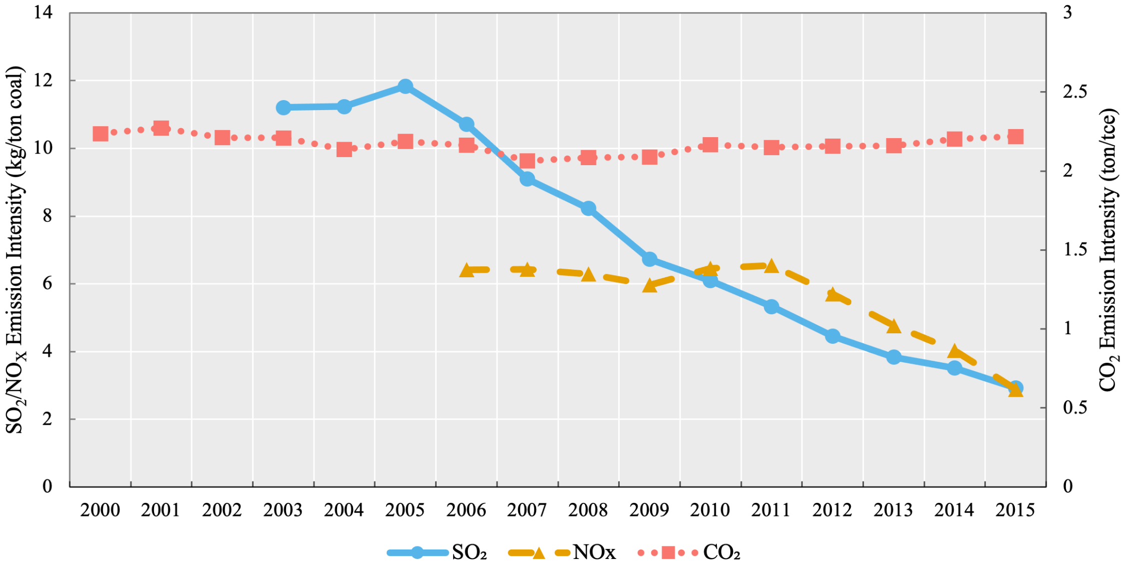
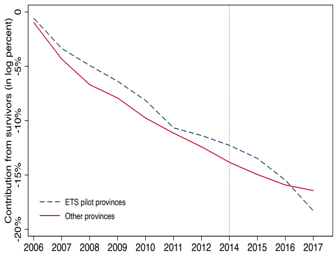
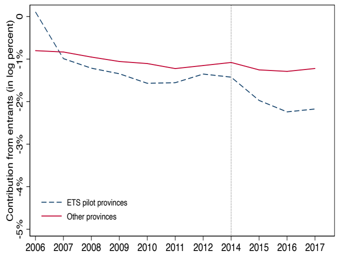


Figure A1: Emission intensities of China's electricity sector

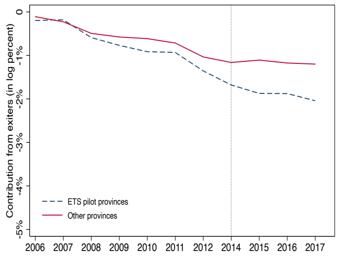
Note: Emission intensity is defined as the ratio of emission quantity to fossil fuel consumption including coal, oil and natural gas (in tonne of coal equivalent). SO_2 and NO_x emissions are collected from the China Statistical Yearbook on Environment. CO_2 emissions are collected from the China Emission Accounts and Datasets (CEADs). Coal consumption is collected from the China Energy Statistical Yearbook.



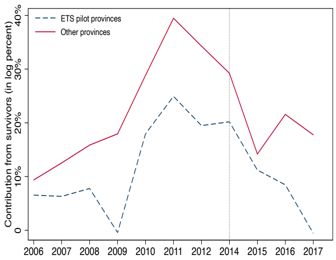
(a) Survivors: coal intensity



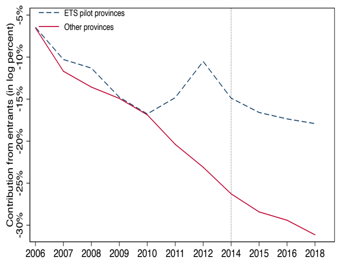
(b) Entrants: coal intensity



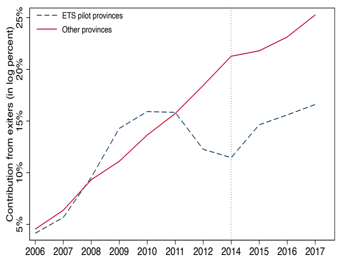
(c) Exiters: coal intensity



(d) Survivors: coal consumption

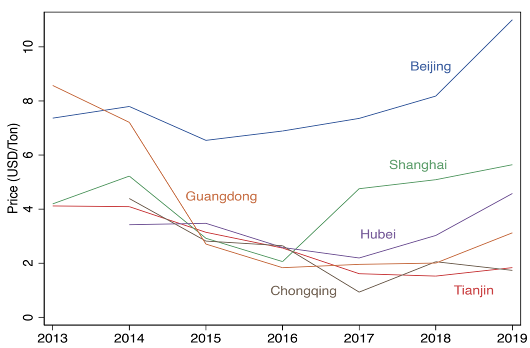


(e) Entrants: coal consumption

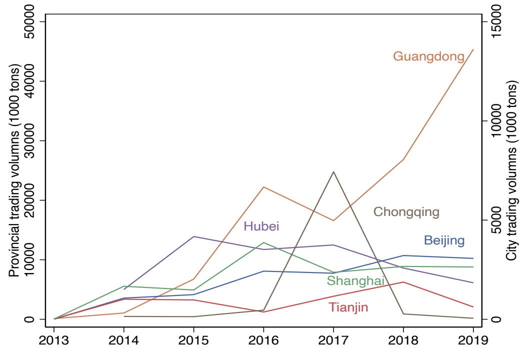


(f) Exiters: coal consumption

Figure A2: Contributions to coal intensity and consumption from survivors, entrants, and exiters



(a) Annual average ETS prices (USD per ton)



(b) Annual total trading volumes (1000 tons)

Figure A3: ETS prices and trading volumes of the six pilot regions

Note: The data is collected from the Wind database.

Table A1: Effects of permit prices on coal use and electricity production

	(1) log(Intensity)	(2) log(Coal)	(3) log(Output)	(4) log(Hours)
Panel A: DiD estimators				
ETS×TP	0.022	-0.196**	-0.217**	-0.064
	(0.023)	(0.092)	(0.100)	(0.076)
Prices	0.000	0.020	0.020	0.009
	(0.004)	(0.018)	(0.018)	(0.015)
#Plants	2,821	2,821	2,821	2,814
#ETS plants	209	209	209	209
Observations	16,638	16,638	16,638	16,526
R-squared	0.660	0.913	0.926	0.658
Panel B: Matched DiD estimators				
ETS×TP	0.046	-0.307***	-0.276**	-0.054
	(0.040)	(0.117)	(0.114)	(0.086)
Prices	-0.004	0.023	0.012	-0.003
	(0.006)	(0.024)	(0.023)	(0.018)
#Plants	489	489	489	489
#ETS plants	177	177	177	177
Observations	4,414	4,414	4,414	4,383
R-squared	0.462	0.907	0.917	0.625
Panel C: GSC estimators				
ETS×TP	0.039	-0.219***	-0.216***	-0.125**
	(0.025)	(0.072)	(0.065)	(0.059)
#Plants	1150	1150	1150	1150
#ETS plants	117	117	117	117
Observations	10,869	10,869	10,869	10,802

Note: The dependent variables in Columns (1)-(4) are the logarithms of coal intensity, coal consumption, output, and operating hours. ETS_i and TP_t are defined in Table 2. $Prices_{pt}$ represents the annual average permit price in pilot province p at year t, and it equals zero in non-pilot provinces and at pretreatment period in pilot provinces. Fixed effects are at the plant level and the region-year level. Control variables are the same as those in Table 2 and confounding policies including the ULES, NSMF, and green dispatch pilots. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A2: Heterogenous effects of the ETS pilots by initial coal intensity

	DiD estimators				Matched DiD estimators				GSC estimators			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
						Panel A: log(Intensity)						
ETS×TP	-0.012	0.015	0.041	-0.047	0.009	-0.003	0.061	-0.096	-0.104	0.035	0.068	0.068
	(0.037)	(0.012)	(0.032)	(0.071)	(0.046)	(0.015)	(0.046)	(0.117)	(0.106)	(0.048)	(0.057)	(0.081)
#Plants	360	320	313	356	111	127	110	75	261	272	271	241
#ETS plants	13	33	44	47	13	33	44	47	12	27	34	39
Observations	2,983	2,771	2,741	2,810	1,052	1,246	1,108	729	2,168	2,197	2,171	2,015
R-squared	0.444	0.453	0.350	0.483	0.571	0.489	0.484	0.512	-	-	-	-
						Panel B: log(Coal)						
ETS×TP	-0.274**	-0.201**	-0.051	0.029	-0.074	-0.203**	-0.167	-0.003	-0.333**	-0.271**	-0.087	0.033
	(0.133)	(0.091)	(0.119)	(0.148)	(0.173)	(0.095)	(0.144)	(0.245)	(0.151)	(0.124)	(0.264)	(0.287)
#Plants	360	320	313	356	111	127	110	75	261	272	271	241
#ETS plants	13	33	44	47	13	33	44	47	12	27	34	39
Observations	2,983	2,771	2,741	2,810	1,052	1,246	1,108	729	2,168	2,197	2,171	2,015
R-squared	0.913	0.885	0.924	0.836	0.901	0.893	0.932	0.789	-	-	-	-
						Panel C: log(Output)						
ETS×TP	-0.267**	-0.217**	-0.117	0.075	-0.083	-0.200**	-0.298*	0.093	-0.320**	-0.330***	-0.043	0.039
	(0.127)	(0.092)	(0.129)	(0.143)	(0.167)	(0.095)	(0.155)	(0.208)	(0.148)	(0.105)	(0.116)	(0.19)
#Plants	360	320	313	355	111	126	110	75	261	272	271	241
#ETS plants	13	33	44	47	13	33	44	47	12	27	34	39
Observations	2,983	2,771	2,741	2,810	1,052	1,246	1,108	729	2,168	2,197	2,171	2,015
R-squared	0.926	0.889	0.928	0.862	0.910	0.894	0.937	0.822	-	-	-	-
						Panel D: log(Hours)						
ETS×TP	-0.106	0.004	-0.134	0.115	-0.049	-0.040	-0.171	0.055	-0.139	-0.272***	0.024	0.273
	(0.088)	(0.050)	(0.130)	(0.159)	(0.134)	(0.071)	(0.139)	(0.188)	(0.103)	(0.096)	(0.215)	(0.433)
#Plants	360	319	313	381	111	127	110	75	261	272	271	241
#ETS plants	13	33	44	47	13	33	44	47	12	27	34	39
Observations	2,964	2,756	2,722	2,788	1,048	1,236	1,103	720	2,156	2,188	2,156	2,002
R-squared	0.657	0.588	0.638	0.660	0.685	0.637	0.761	0.607	-	-	-	-

Note: Columns (1), (5), and (9) report the estimation results of the group with the highest coal intensity. Columns (2), (6), and (10) are for the second highest coal intensity, Columns (3), (7), and (11) for the third highest, and Columns (4), (8), and (12) for the lowest. ETS_i and TP_t are defined in Table 2. Fixed effects are at the plant level and the region-year level. Control variables are the same as those in Table 2 and confounding policies including the ULES, NSMF, and green dispatch pilots. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Heterogenous effects of the ETS pilots by plant ownership

	DiD estimators				Matched DiD estimators				GSC estimators			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	log(Intensity)	log(Coal)	log(Output)	log(Hours)	log(Intensity)	log(Coal)	log(Output)	log(Hours)	log(Intensity)	log(Coal)	log(Output)	log(Hours)
Panel A: State-owned power plants												
ETS×TP	-0.039	-0.210**	-0.203**	0.071	-0.058	-0.229**	-0.193*	0.082	-0.013	-0.208	-0.109	-0.109
	(0.033)	(0.092)	(0.084)	(0.079)	(0.039)	(0.111)	(0.102)	(0.087)	(0.049)	(0.242)	(0.249)	(0.106)
#Plants	756	756	756	755	151	151	151	151	249	249	249	249
#ETS plants	51	51	51	51	45	45	45	45	29	29	29	29
Observations	5,051	5,051	5,051	5,023	1,408	1,408	1,408	1,400	3,536	3,536	3,536	3,521
R-squared	0.630	0.906	0.916	0.634	0.764	0.874	0.886	0.575	-	-	-	-
Panel B: Non-state-owned power plants												
ETS×TP	-0.163	-0.383**	-0.306*	-0.219	-0.148	-0.496**	-0.358*	-0.005	-0.090	-0.551**	-0.506**	-0.340**
	(0.112)	(0.158)	(0.161)	(0.148)	(0.155)	(0.191)	(0.191)	(0.249)	(0.118)	(0.241)	(0.212)	(0.187)
#Plants	249	250	249	248	48	48	48	48	197	197	197	197
#ETS plants	20	20	20	20	16	16	16	16	12	12	12	12
Observations	1,520	1,527	1,520	1,508	412	416	416	410	968	968	968	960
R-squared	0.697	0.889	0.910	0.748	0.735	0.898	0.920	0.758	-	-	-	-

Note: Columns (1)-(4) report the DiD estimators. Columns (5)-(8) report the matched DiD estimators. Columns (9)-(12) report the GSC estimators. The dependent variables in Columns (1)-(4), Columns (5)-(8), and Columns (9)-(12) are the logarithms of coal intensity, coal consumption, output, and operating hours. ETS_i and TP_t are defined in Table 2. Fixed effects are at the plant level and the region-year level. Control variables are the same as those in Table 2 and confounding policies including the ULES, NSMF, and green dispatch pilots. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A4: Heterogenous effects of the ETS pilots by pilot regions

	DiD estimators				Matched DiD estimators				GSC estimators			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	log(Intensity)	log(Coal)	log(Output)	log(Hours)	log(Intensity)	log(Coal)	log(Output)	log(Hours)	log(Intensity)	log(Coal)	log(Output)	log(Hours)
Panel A: Beijing												
ETS×TP	-0.046	-0.307	-0.261	0.011	-0.038	-0.366	-0.347	0.019	-0.095	-0.370*	-0.163	-0.163
	(0.047)	(0.196)	(0.167)	(0.147)	(0.154)	(0.306)	(0.269)	(0.229)	(0.192)	(0.228)	(0.176)	(0.211)
#Plants	464	464	464	462	73	73	73	73	185	185	185	185
#ETS plants	18	18	18	18	14	14	14	14	9	9	9	9
Observations	2,762	2,762	2,762	2,742	681	681	681	675	1,750	1,750	1,750	1,738
R-squared	0.673	0.915	0.935	0.574	0.695	0.923	0.937	0.679	-	-	-	-
Panel B: Tianjin												
ETS×TP	-0.115	-0.203	-0.088	-0.242	-0.122	-0.371	-0.250	-0.181	-0.050	-0.363**	-0.222	-0.008
	(0.088)	(0.148)	(0.111)	(0.248)	(0.091)	(0.232)	(0.216)	(0.182)	(0.100)	(0.184)	(0.161)	(0.123)
#Plants	472	472	472	470	81	81	81	81	189	189	189	189
#ETS plants	23	23	23	23	20	20	20	20	13	13	13	13
Observations	2,831	2,831	2,831	2,811	750	750	750	744	1,797	1,797	1,797	1,785
R-squared	0.653	0.918	0.937	0.575	0.660	0.925	0.938	0.677	-	-	-	-
Panel C: Shanghai												
ETS×TP	0.036	-0.302**	-0.376***	-0.183*	0.046	-0.356**	-0.407***	-0.246**	-0.046	-0.298**	-0.252*	-0.138
	(0.031)	(0.117)	(0.120)	(0.109)	(0.046)	(0.148)	(0.149)	(0.124)	(0.043)	(0.142)	(0.135)	(0.748)
#Plants	1,345	1,345	1,345	1,343	203	203	203	203	526	526	526	526
#ETS plants	28	28	28	28	24	24	24	24	18	18	18	18
Observations	7,748	7,748	7,748	7,704	2,001	2,001	2,001	1,991	4,873	4,873	4,873	4,842
R-squared	0.623	0.905	0.918	0.689	0.640	0.893	0.903	0.607	-	-	-	-
Panel D: Guangdong												
ETS×TP	0.004	-0.281***	-0.286***	-0.047	-0.019	-0.297***	-0.278***	-0.106	0.014	-0.453***	-0.415***	-0.021
	(0.018)	(0.105)	(0.107)	(0.079)	(0.027)	(0.098)	(0.094)	(0.090)	(0.029)	(0.102)	(0.100)	(0.098)
#Plants	352	352	352	351	135	135	135	135	166	166	166	166
#ETS plants	92	92	92	92	81	81	81	81	55	55	55	55
Observations	2,174	2,174	2,174	2,139	1,160	1,160	1,160	1,148	1,533	1,533	1,533	1,513
R-squared	0.531	0.826	0.853	0.581	0.435	0.873	0.895	0.647	-	-	-	-
Panel E: Hubei												
ETS×TP	0.000	0.115	0.115	-0.007	-0.010	0.042	0.052	-0.058	0.000	-0.124	-0.058	-0.185
	(0.027)	(0.132)	(0.134)	(0.081)	(0.038)	(0.195)	(0.191)	(0.115)	(0.147)	(0.177)	(0.196)	(0.143)
#Plants	290	290	290	290	81	81	81	81	126	126	126	126
#ETS plants	30	30	30	30	24	24	24	24	17	17	17	17
Observations	1,679	1,679	1,679	1,646	665	665	665	655	1,137	1,137	1,137	1,117
R-squared	0.688	0.881	0.901	0.608	0.634	0.904	0.921	0.651	-	-	-	-
Panel F: Chongqing												
ETS×TP	0.025	-0.038	-0.064	-0.077	-0.023	0.081	0.104	0.115	0.045	-0.037	0.073	0.069
	(0.027)	(0.273)	(0.270)	(0.136)	(0.040)	(0.638)	(0.640)	(0.196)	(0.042)	(0.406)	(0.391)	(0.324)
#Plants	149	149	149	149	23	23	23	23	47	47	47	47
#ETS plants	18	18	18	18	12	12	12	12	5	5	5	5
Observations	667	667	667	665	134	134	134	133	417	417	417	417
R-squared	0.811	0.880	0.904	0.644	0.772	0.790	0.802	0.741	-	-	-	-

Note: Columns (1)-(4) report the DiD estimators. Columns (5)-(8) report the matched DiD estimators. Columns (9)-(12) report the GSC estimators. The dependent variables in Columns (1)-(4), Columns (5)-(8), and Columns (9)-(12) are the logarithms of coal intensity, coal consumption, output, and operating hours. ETS_i and TP_t are defined in Table 2. Fixed effects are at the plant level and the year level. Control variables are the same as those in Table 2 and confounding policies including the ULES, NSMF, and green dispatch pilots. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A5: Inter-province electricity import and export

	DiD estimators				GSC estimators			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PilotProvince^{IM}×TP	-0.0727	-0.092			0.788	0.200		
	(0.256)	(0.108)			(0.653)	(0.410)		
PilotProvince^{EX}×TP			-0.450	-0.085			-0.075	-0.246
			(0.321)	(0.107)			(0.314)	(0.175)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer×Exporter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	985	9,048	889	9,048	908	9,048	797	9,048
R-squared	0.852	0.858	0.834	0.856	-	-	-	-

Note: The dependent variables in Columns (1)-(2) and Columns (5)-(6) are the logarithm of electricity imports. The dependent variables in Columns (3)-(4) and Columns (7)-(8) are the logarithms of electricity exports. Columns (1), (3), (5), (7) only include positive flows. Columns (2), (4), (6), (8) include all bilateral flows. Exports from pilot provinces are excluded in Columns (1)-(2) and Columns (5)-(6), and imports of pilot provinces are excluded in Columns (3)-(4) and Columns (7)-(8). $PilotProvince_{pq}^{IM}$ is a dummy variable that equals 1 if the importer q is an ETS pilot province. $PilotProvince_{pq}^{EX}$ is a dummy variable that equals 1 if the exporter p is an ETS pilot province. TP_t is a dummy variable that equals one at the years when the ETS pilots are in operation. Importer×Exporter and Year represent the importer-exporter-level and year-level fixed effects. Control variables of exporters and importers include the logarithm of electricity consumption, GDP, population, industrial outputs, number of industrial firms, value added to GDP ratios for the secondary and tertiary sectors, pollution fee rates on sulfur dioxides emissions and nitrogen oxides emissions, and CO_2 mitigation targets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A6: Spillover effects to self-generated electricity from manufacturing firms

	(1) log(Intensity)	(2) log(Coal)	(3) log(Output)	(4) log(Hours)
	Panel A: DiD estimators			
PilotProvince×TP	0.014	-0.028	-0.042	0.081
	(0.068)	(0.117)	(0.111)	(0.088)
#Plants	621	621	621	619
#Plants in pilot provinces	67	67	67	66
Observations	3,349	3,349	3,349	3,320
R-squared	0.626	0.858	0.891	0.649
	Panel B: Matched DiD estimators			
PilotProvince×TP	-0.064	-0.265	-0.225	0.001
	(0.087)	(0.208)	(0.210)	(0.150)
#Plants	148	148	148	148
#Plants in pilot provinces	46	46	46	46
Observations	1,201	1,201	1,201	1,185
R-squared	0.622	0.798	0.840	0.496
	Panel C: GSC estimators			
PilotProvince×TP	0.166	-0.064	-0.097	-0.103
	(0.158)	(0.495)	(0.384)	(0.330)
#Plants	206	206	206	206
#Plants in pilot provinces	23	23	23	23
Observations	1,884	1,884	1,884	1,869

Note: The dependent variables in Columns (1)-(4) are the logarithms of coal intensity, coal consumption, output, and operating hours. The sample covers coal-fired power plants of manufacturing firms. $PilotProvince_p$ denotes the pilot provinces, i.e. it equals to 1 if province p is a pilot province. TP_t is a dummy variable that equals one at the years when the ETS pilots are in operation. Fixed effects are at the plant level and the region-year level. Control variables are the same as those in Table 2 and confounding policies including the ULES, NSMF, and green dispatch pilots. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A7: Spillover effects to plants in the same large electricity generation corporation

	OLS estimators				Matched estimators			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(Intensity)	log(Coal)	log(Output)	log(Hours)	log(Intensity)	log(Coal)	log(Output)	log(Hours)
NumTreated×TP	0.011	0.027	0.017	-0.012	0.007	0.031	0.019	-0.003
	(0.010)	(0.017)	(0.017)	(0.012)	(0.006)	(0.020)	(0.020)	(0.015)
#Plants	2,630	2,630	2,630	2,624	677	677	677	677
#Plants in the groups	420	420	420	419	287	287	287	287
Observations	15,196	15,196	15,196	15,092	5,678	5,678	5,678	5,641
R-squared	0.671	0.912	0.927	0.653	0.533	0.925	0.939	0.591

Note: The dependent variables in Columns (1)-(4) and Columns (5)-(8) are the logarithms of coal intensity, coal consumption, output, and operating hours. Columns (1)-(4) report the OLS estimators and Columns (5)-(8) report the matched estimators. $NumTreated_{ig}$ is the number of ETS plants belonging to generation group g to which plant i belongs. TP_t is a dummy variable that equals one at the years when the ETS pilots are in operation. Fixed effects are at the plant level and the region-year level. Control variables are the same as those in Table 2 and confounding policies including the ULES, NSMF, and green dispatch pilots. Plants in the ETS provinces are excluded. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Online Appendix for
When carbon emission trading meets a regulated industry:
Evidence from the electricity sector of China

A Robustness checks

A.1 Robustness checks on matching and GSC estimators

Alternative matching estimators. In the matched DiD estimation, the treated plants are matched with 10 coal-fired untreated power plants with the closest coal consumption in 2012 following Cicala (2015). For robustness checks on this procedure, Panels A and B in Table A1 match the treated plants with 5 and 3 untreated plants with the closest coal consumption in 2012. Consistent with Panel B in Table 2, the coefficients on coal intensity remain insignificant, and all coefficients on coal consumption and output are significantly negative at the 1% level. The coefficients on operating hours also become significantly negative, although the magnitudes are much smaller than the coefficients on coal and output.

The matched plants in the main results are restricted to plants that exist for at least 7 years in our sample period. Panels C and D in Table A1 relax the restriction by matching the treated plants with the plants that exist for at least 5 and 3 years, respectively. The coefficients on coal consumption and output remain significantly negative and the magnitudes become even larger than in Table 2, while the coefficients on coal intensity remain insignificant. In addition, Panel E considers a different matching variable by matching the treated plants with 10 untreated plants with the closest average coal consumption over 2010 to 2012, and the results remain consistent with Table 2. We also compare the average characteristics between the treated plants and matched plants for our main matched DiD estimators, for the year before treatment (2012) in Panel A and for a longer pre-treatment period (from 2008 to 2012) in Panel B of Table A2. In both panels, the two groups have no significant differences in all outcome variables, suggesting that they are well balanced in the years before treatment.

Synthetic difference-in-differences estimators. For robustness checks on the GSC estimators, we use the synthetic difference-in-differences (SDID) estimators proposed by Arkhangelsky et al. (2020). SDID uses both unit and time weights to match pre-treatment trends and remains invariant to additive unit-level shifts, while the conventional synthetic method uses only unit weights and omit unit-level fixed effects. Therefore, SDID is more robust to model misspecifications and even remains consistent when the unit or time weights are poorly chosen. Since the current SDID program (version 0.0.9), provided by the authors, is applicable to balanced panels only, we restrict our sample to a balanced panel, starting from 2007. We omit 2005 and 2006 from the original sample because most ETS plants had not been established at that time. This procedure leaves us with 41 ETS-treated plants and 224 untreated coal-fired power plants. Table A3 reports the estimation results of SDID. The coefficient on coal intensity is quite small (0.012) and not statistically significant, while the coefficients on coal consumption, output, and operating hours are significantly negative, with their magnitudes greater than 10%. This confirms that the coal consumption of treated plants decreased significantly after they participated in the ETS pilots, but this fall was achieved by output contraction instead of coal efficiency improvement. Furthermore, Figure A1 shows the time trends of the outcome variables of the treated group and the counterfactual group constructed by SDID. The two groups have parallel time trends in coal consumption and output before 2013, but after that, the treated group witnessed larger falls in these variables (Figure A1(b) and (c)). For operating hours and coal intensity, the two groups share almost identical trends before 2013, but after that the hours of the treated plants decrease substantially compared with the counterfactual group (Figure A1(d)), while their difference in the changes of coal intensity is almost negligible (Figure A1(a)).

A.2 Robustness checks on other potential confounders

Huai-River-Qinling policy. We have considered possible confounders including ULES, NSMF, green dispatch pilots, and plant exit in section 4.2. For robustness, we consider whether the winter heating policy, often called the Huai-River-Qinling policy, could affect electricity generation and incidentally bias the main results. This policy allows centralized heating for residents in northern China (north of the Huai-River-Qinling boundary) during the cold months but disallows it for southern areas (Chen et al. 2013). Most of the heat is co-generated by power plants with steam left over from electricity generation. We test the policy's effects on power plants using the regression discontinuity (RD) design of Ebenstein et al. (2017). Figure A2 shows the changes in coal efficiency, coal consumption, output, and operating hours based on the distance of the plant from the Huai-River-Qinling boundary. We find no visible changes at the boundary for the four outcome variables. Robust point estimators with mean-squared-error optimal bandwidth, as proposed by Calonico et al. (2014) are reported in Table A4; they are statistically insignificant. That is, there is no evidence that the winter heating policy affected electricity production of the northern power plants during this period.

Two-Control-Zones. We should mention another well-known policy, the Two-Control-Zones (TCZ) policy for acid rain and SO_2 (e.g., Hering and Poncet 2014, Tanaka 2015, Cai et al. 2016, and Chen et al. 2018). This policy targeted more than 170 cities and required them to reach a national SO_2 emission standard by 2000 and curb their SO_2 emissions in 2010 to below their levels in 2000. However, particulate matter pollution became the major air pollutant in China, outweighing SO_2 and acid rain, and the TCZ policy was terminated in 2010.[1] This policy is therefore unlikely to drive the results in Table 2 because it ended before the ETS began and we thus do not consider it in our tests for confounding factors.

A.3 Robustness checks with alternative specifications and data

Within-province variation. The main results compare ETS treated plants with unregulated plants in non-pilot provinces. The between-province comparison allows us to obtain a more comparable control group at the plant level, but it is susceptible to parallel policies even after controlling time-varying regional trends and interactive fixed effects for common shocks. For further robustness checks, we compare the ETS treated plants with unregulated coal-fired power plants in the same pilot provinces by controlling province-year fixed effects. However, the selection of plants into the ETS is non-random, and Table 1 shows that unregulated plants in pilot provinces are much smaller in scale than regulated plants. DiD estimators are therefore likely to be biased by the selection. The matched DiD estimators are not applicable because almost all plants with large coal consumption and emissions in pilot provinces are covered by the ETS pilots. Therefore, we use generalized synthetic control (GSC) to construct counterfactuals for treated plants and estimate average treatment effects on them using within-province variation from the entire sample of all coal-fired power plants in the pilot provinces (including the non-regulated plants) by controlling province-year fixed effects. Table A5 reports the estimation results. The coefficient on coal intensity becomes negative but is not statistically significant. Consistent with the main results, we also find significant reductions in coal consumption and output in the ETS-treated plants.

Regression discontinuity. The plants in pilot provinces that are to be included in the ETS pilots are selected based on cutoffs in past coal consumption and CO_2 emissions. This special

[1] Ministry of Ecology and Environment (Jan 7, 2019), "Consideration of whether the two-control zones regulations are still valid." http://www.mee.gov.cn/hdjl/hfhz/201901/t20190107_688656.shtml.

design allows us to conduct an alternative within-province analysis with regression discontinuity. In most pilot provinces, the official cutoff to determine ETS participation is 10,000 tons of annual coal consumption. This cutoff is used for all sectors and is too low for power plants in our dataset. Figure A3 shows that nearly all plants had coal consumption exceeding this level in 2012 (marked by the left vertical dashed line). We follow Porter and Yu (2015) to use a data-driven method to find a suitable cutoff for our dataset by maximizing the estimated jump in treatment propensity in the first stage of fuzzy regression discontinuity estimation.[2] The chosen cutoff is 0.54 million tons of coal, and Figure A3 shows that the coal consumption of most non-regulated plants is below this cutoff. After obtaining this cutoff, we use coal consumption in 2012 as the running variable for the RD estimation, with local linear regression and mean-squared-error optimal bandwidth (Calonico et al. 2014). Table A6 reports the estimation results for pilot provinces, columns (1)-(4) for the years after 2013 and columns (5)-(8) for the years before. The coefficients for coal intensity are not statistically significant in both periods, while the coefficients for coal consumption and electricity generation after 2013 are significantly negative. We plot the outcome variables against the coal consumption in 2012 in Figure A4 and this shows significant drops in coal consumption and output at the cutoff. We also examine the balance of city-level covariates around the cutoff in Table A7 and find that none of them has a statistically significant discontinuity.

Triple-difference estimators. Another available source of variation is at the industry level, since the ETS pilots mainly cover several high-polluting industrial sectors such as steel and cement. We follow Cui et al. (2018, 2020) to use triple differences to compare coal consumption changes after the ETS in the electricity sector with the changes in non-regulated sectors, and between pilot and non-pilot provinces. To do so, we use the firm-level STA-MOF dataset. An additional benefit of using this dataset is that the information of coal consumption is less likely to be misreported because firm-level environmental performance is not a concern of the STA or MOF. We estimate the following equation:

$$y_{kipt} = \beta Electricity_i \times PilotProvince_p \times TP_t + \gamma_{pt} + \eta_{it} + \mu_k + \epsilon_{kipt}$$

where y_{kipt} is the outcome variable for firm k from industry i in province p at year t, $Electricity_i$

[2]To avoid over-estimation and report the most conservative estimates for the effects of the ETS, we choose to maximize the probability change of receiving the treatment instead of maximizing the sum of probability change and the change in the outcome variable.

is a dummy indicating whether the firm is in the electricity sector, $PilotProvince_p$ denotes the pilot provinces, TP_t represents the periods when ETS pilots are in operation, γ_{pt}, η_{it}, and μ_k represent province-year-level, industry-year-level, and firm-level fixed effects, respectively, and ϵ_{kipt} is the error term.

Since we focus on the electricity sector, our sample includes all treated electricity plants in pilot provinces (excluding the non-regulated plants in the pilot areas), all electricity plants in the non-pilot provinces, and all firms in the non-electricity sectors (mostly manufacturing) in all provinces except for the sectors that are covered by the ETS in the pilot provinces. This allows us to use the sector-province-year variations to examine outcome variable changes with triple differences - the differences between ETS treated power plants and firms in non-regulated sectors, the differences between pilot provinces and other provinces, and the differences between periods before and after the start of the ETS pilots.

Table A8 reports the triple-differences estimation results. Consistent with the main results, we find an insignificant change in coal efficiency, but statistically significant reductions in coal consumption and output. Furthermore, the reductions in coal consumption and output are close to, but slightly larger than, the main results in Table 2, indicating that the reductions in coal use and output are even greater when comparing with firms in non-regulated sectors.

CO_2 emissions. Since the CO_2 emission intensity in the electricity sector is relatively stable over time, the observed decline in coal consumption should imply a significant decrease in CO_2 emissions. To examine this, we use a dataset that contains data on CO_2 emissions and output of power plants. In addition, there are concerns about misreporting in the official industrial data, whereas Zhang et al. (2019) find no evidence of deliberate misreporting on firms' reported CO_2 emissions. Therefore, using this dataset can alleviate the concerns over misreporting. The dataset covers 868 generator units from 420 large coal-fired power plants in 28 provinces from 2013 to 2015, including 181 units covered by the ETS pilots. We regard the year 2013 as the pre-treatment period and estimate the effects of ETS participation with DiD and matched DiD estimators. We match the ETS treated plants with the power plants that have the most similar CO_2 emissions in 2013 from non-pilot provinces. Columns (1)-(3) of Table A9 present the DiD estimation results on CO_2 emission intensity, total CO_2 emissions, and output. The coefficients on CO_2 emissions and output are significantly negative, while the estimators on CO_2 intensity is close to zero and statistically insignificant. Columns (4)-(6) report the matched DiD estimators, which also have significant coefficients on emissions and output though the significance levels fall slightly. Overall, this dataset suggests reductions in CO_2 emissions and output of more than 10%. The effects are somewhat smaller than the main results, possibly due to the considerably shorter sample period. The results also confirm that there is no statistically significant change in CO_2 intensity associated with the ETS pilots.

B Air quality benefits

In section 4.7 we discussed the reduction in CO_2 emissions due to a fall in coal combustion. The lower coal combustion would also lower emissions of conventional air pollutants such as sulfur dioxide and nitrogen oxides. We use pollution concentrations from satellite data as described in section 3.2 and put them on the left-hand side of regressions. Table B1 reports the estimation results. We find that the coefficients on $ETS_i \times TP_t$ for SO_2 concentrations are significantly negative for all three estimators. The absolute magnitudes are quite large, implying a reduction in SO_2 of more than 20% in the areas around ETS treated plants. Meanwhile, most coefficients on NO_2 and $PM_{2.5}$ concentrations are significantly negative, but with much smaller magnitudes. The results suggest that the coal consumption decline in the ETS treated plants is associated with substantial reductions in SO_2, and moderate reductions in NO_2 and $PM_{2.5}$ concentrations.

One particular concern regarding the air quality improvement is that the anti-pollution campaign parallel with the ETS pilots may lead to the observed air quality improvement reported in Table B1. More specifically, China implemented new emission standards for thermal power plants in 2014 that imposed stricter regulations on 47 cities, located in both ETS pilot and non-pilot provinces (Karplus et al. 2018).[3] To examine whether the fall in air pollution is caused by the stricter emission standards in the 47 cities, we separately estimate the coefficients on $ETS_i \times TP_t$ for power plants in the 47 cities and power plants in other regions.

For the 47 cities with stricter standards, Panel A of Table B2 shows that the coefficients remain significant except for the matched DiD estimator on NO_2 and $PM_{2.5}$. This suggests that even among the subsample of cities that implemented the stricter emission standard, air pollutant concentrations near ETS treated plants fell more than the concentrations near other coal-fired power plants. Meanwhile, for the GSC estimator the magnitude of the coefficient on SO_2 concentrations becomes much smaller (-0.136). The GSC estimator can capture heterogeneous impacts

[3]The emission concentrations of smoke, sulfur dioxide, and nitrogen oxides are required to be no greater than 20, 50, and 100 mg/m^3 for coal-fired power plants in the 47 cities, while the upper limits in other regions are 30, 400, and 200 mg/m^3.

of common shocks. This allows for heterogeneous effects of the same emission standard. The results suggest that absorbing those variations renders a smaller, but still statistically significant, effect of the ETS pilots on SO_2 concentrations. To further understand the effects of the emission standards on air pollution, Table B3 reports the estimation results by regressing air pollutant concentrations on $HighStandard_c \times TH_t$, where $HighStandard_c$ is a dummy denoting cities with the stricter emission standard, and TH_t is a dummy denoting the years when the new emission standards are in operation.[4] The coefficients on the interaction term are significantly negative for all pollutants, confirming significant improvement in air quality associated with the stricter emission standard.

On the other hand, for regions with the less strict emission standard, Panel B of Table B2 shows that most coefficients are not statistically significant, and the only significant result is the coefficient on $PM_{2.5}$ for the GSC estimator. This could be due to the ETS treated plants in those regions with less strict standards are mainly located in Hubei[5], while Table A4 finds no significant effects of the Hubei ETS on coal consumption. Moreover, only 17% of the treated plants are located in those regions; this small number of the ETS treated plants may also contribute to the lack of statistical power and the large coefficients of the GSC estimators.

References

[1] D. Arkhangelsky, S. Athey, D. A. Hirshberg, G. W. Imbens, and S. Wager, "Synthetic difference in differences," *arXiv. org*, 2020.

[2] X. Cai, Y. Lu, M. Wu, and L. Yu, "Does environmental regulation drive away inbound foreign direct investment? evidence from a quasi-natural experiment in China," *Journal of Development Economics*, vol. 123, pp. 73 – 85, 2016.

[3] S. Calonico, M. D. Cattaneo, and R. Titiunik, "Robust nonparametric confidence intervals for regression-discontinuity designs," *Econometrica*, vol. 82, no. 6, pp. 2295–2326, 2014.

[4] The matched DiD estimators are constructed by matching plants in the cities with the stricter emission standard with 10 coal-fired power plants that have the most similar coal consumption in 2014 from the other regions.

[5] The four municipalities, nine cities in Guangdong, and one city in Hubei belong to the regions with the stricter emission standard.

[4] Y. Chen, A. Ebenstein, M. Greenstone, and H. Li, "Evidence on the impact of sustained exposure to air pollution on life expectancy from china's huai river policy," *Proceedings of the National Academy of Sciences*, vol. 110, no. 32, pp. 12 936–12 941, 2013.

[5] Y. J. Chen, P. Li, and Y. Lu, "Career concerns and multitasking local bureaucrats: Evidence of a target-based performance evaluation system in china," *Journal of Development Economics*, vol. 133, pp. 84–101, 2018.

[6] S. Cicala, "When does regulation distort costs? lessons from fuel procurement in us electricity generation," *American Economic Review*, vol. 105, no. 1, pp. 411–44, 2015.

[7] J. Cui, J. Zhang, and Y. Zheng, "Carbon pricing induces innovation: Evidence from China's regional carbon market pilots," *AEA Papers and Proceedings*, vol. 108, pp. 453–57, 2018.

[8] ——, "Effects of carbon market on firm's competitiveness: evidence from the regional experiments of China," *Working paper*, 2020.

[9] A. Ebenstein, M. Fan, M. Greenstone, G. He, and M. Zhou, "New evidence on the impact of sustained exposure to air pollution on life expectancy from china's huai river policy," *Proceedings of the National Academy of Sciences*, vol. 114, no. 39, pp. 10 384–10 389, 2017.

[10] L. Hering and S. Poncet, "Environmental policy and exports: Evidence from chinese cities," *Journal of Environmental Economics and Management*, vol. 68, no. 2, pp. 296–318, 2014.

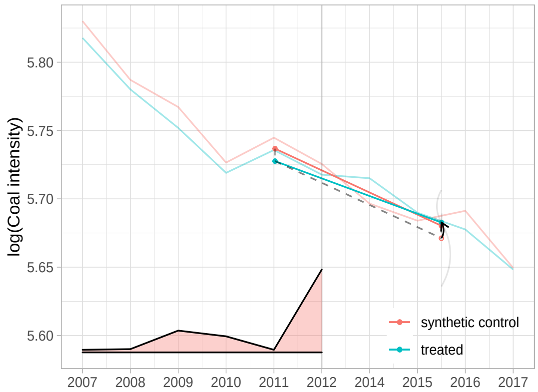
[11] V. J. Karplus, S. Zhang, and D. Almond, "Quantifying coal power plant responses to tighter SO_2 emissions standards in China," *Proceedings of the National Academy of Sciences*, vol. 115, no. 27, pp. 7004–7009, 2018.

[12] J. Porter and P. Yu, "Regression discontinuity designs with unknown discontinuity points: Testing and estimation," *Journal of Econometrics*, vol. 189, no. 1, pp. 132 – 147, 2015.

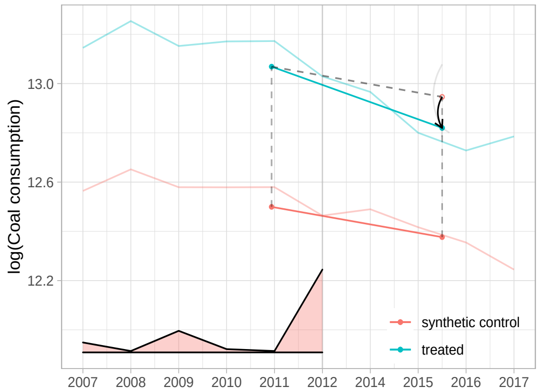
[13] S. Tanaka, "Environmental regulations on air pollution in china and their impact on infant mortality," *Journal of Health Economics*, vol. 42, pp. 90–103, 2015.

[14] D. Zhang, Q. Zhang, S. Qi, J. Huang, V. J. Karplus, and X. Zhang, "Integrity of firms' emissions reporting in China's early carbon markets," *Nature Climate Change*, vol. 9, no. 2, pp. 164–169, 2019.

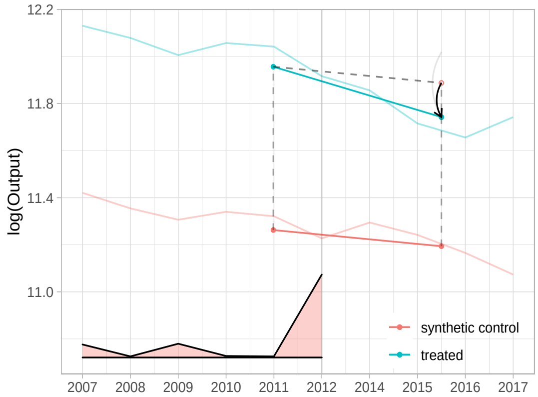
Figures and Tables for Online Appendix



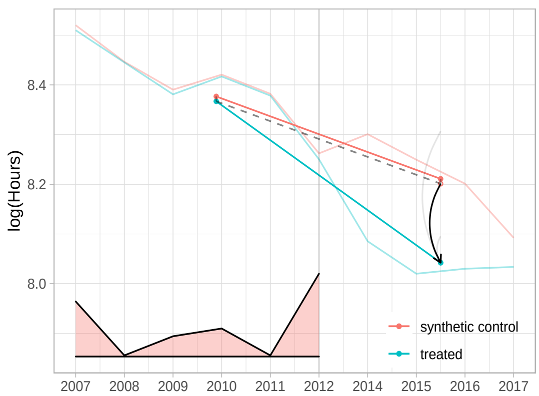
(a) Coal intensity



(b) Coal consumption



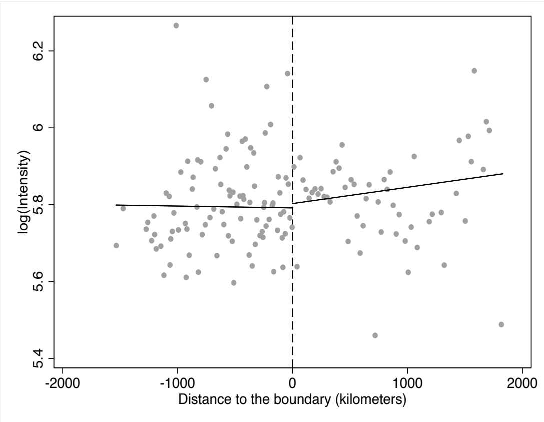
(c) Output



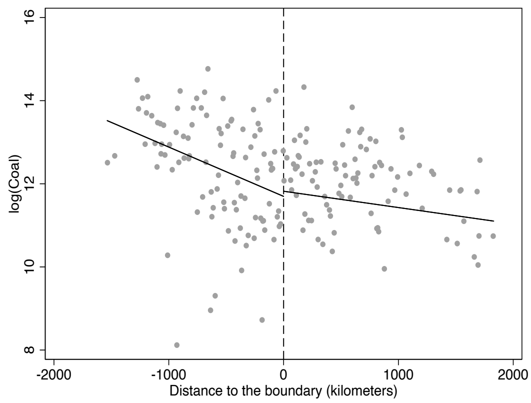
(d) Hours

Figure A1: Time trends for the treated plants and the synthetic group imputed by SDID

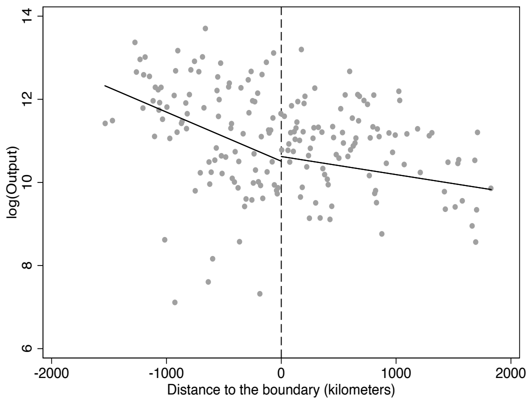
Note: The weights used to average pre-treatment periods are at the bottom of each graph. The estimated effects are indicated by arrows.



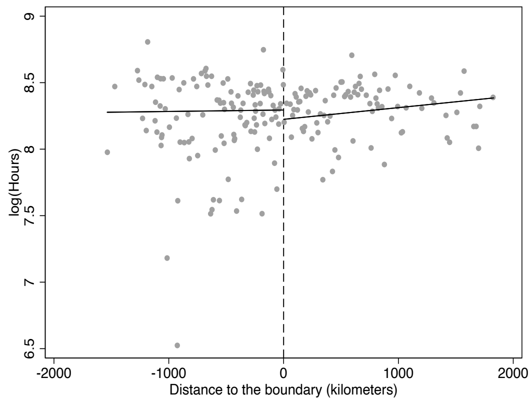
(a) Coal intensity



(b) Coal consumption



(c) Output



(d) Hours

Figure A2: Effects of the winter heating policy based on distance to the policy boundary

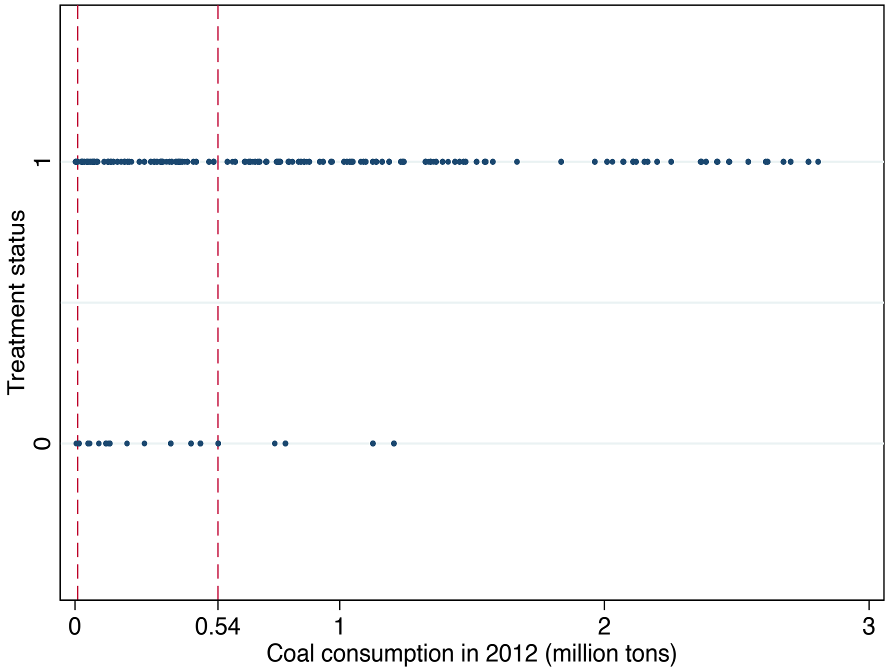
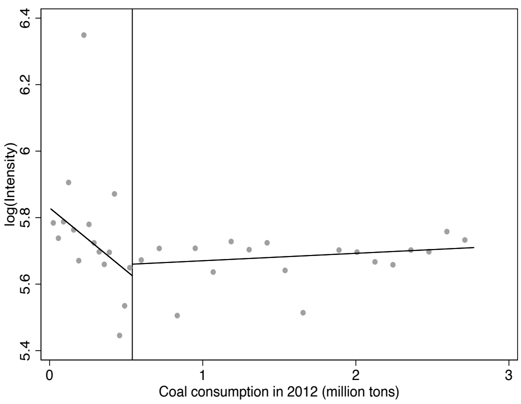
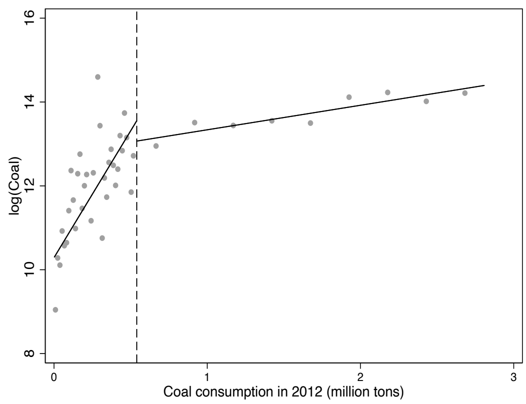


Figure A3: ETS participation and coal consumption in 2012

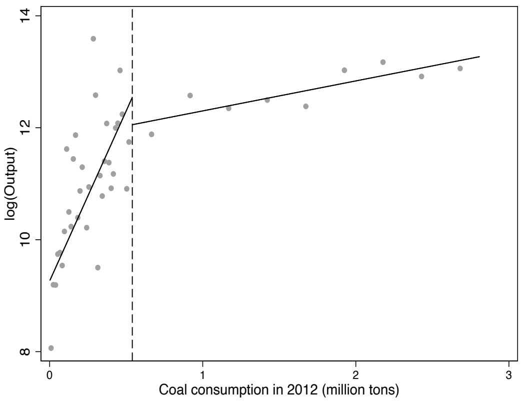
Note: The official cutoff for ETS participation is 0.01 million tons of coal in most pilot provinces. The chosen cutoff by maximizing the treatment probability jump is 0.54 million tons.



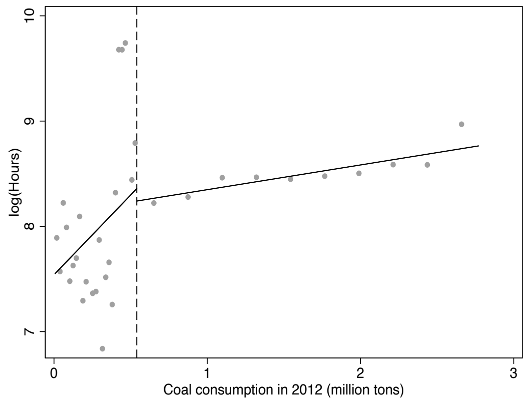
(a) Coal intensity



(b) Coal consumption



(c) Output



(d) Hours

Figure A4: Discontinuity in the outcome variables

Table A1: Robustness: alternative matched DiD estimators

	(1) log(Intensity)	(2) log(Coal)	(3) log(Output)	(4) log(Hours)
Panel A: 1-to-5 matching				
ETS×TP	-0.005	-0.228***	-0.224***	-0.100*
	(0.022)	(0.078)	(0.077)	(0.054)
#Plants	387	387	387	387
#ETS plants	177	177	177	177
Observations	3,386	3,386	3,386	3,361
R-squared	0.603	0.908	0.917	0.684
Panel B: 1-to-3 matching				
ETS×TP	-0.010	-0.222***	-0.214***	-0.138**
	(0.020)	(0.078)	(0.079)	(0.054)
#Plants	330	330	330	330
#ETS plants	177	177	177	177
Observations	2,810	2,810	2,810	2,788
R-squared	0.567	0.897	0.908	0.679
Panel C: matching with plants that exist for at least 5 years				
ETS×TP	-0.003	-0.297***	-0.294***	-0.082
	(0.017)	(0.078)	(0.078)	(0.055)
#Plants	606	606	606	606
#ETS plants	177	177	177	177
Observations	5,086	5,086	5,086	5,050
R-squared	0.648	0.905	0.914	0.617
Panel D: matching with plants that exist for at least 3 years				
ETS×TP	-0.007	-0.331***	-0.324***	-0.103*
	(0.017)	(0.079)	(0.078)	(0.055)
#Plants	612	612	612	612
#ETS plants	177	177	177	177
Observations	5,038	5,038	5,038	5,004
R-squared	0.642	0.905	0.914	0.619
Panel E: matching by average coal consumption from 2010 to 2012				
ETS×TP	0.000	-0.248***	-0.249***	-0.086
	(0.019)	(0.073)	(0.073)	(0.058)
#Plants	488	488	488	488
#ETS plants	160	160	160	160
Observations	4,402	4,402	4,402	4,369
R-squared	0.612	0.920	0.929	0.647

Note: The dependent variables in Columns (1)-(4) are the logarithms of coal intensity, coal consumption, output, and operating hours. ETS_i and TP_t are defined in Table 2. Fixed effects are at the plant level and the region-year level. Control variables are the same as those in Table 2 and confounding policies including the ULES, NSMF, and green dispatch pilots. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A2: Balance checks for the matched sample

	ETS plants			Matched non-ETS plants			Mean
	Mean	Std	N	Mean	Std	N	difference
Panel A: the year before treatment (2012)							
log(Intensity)	5.693	0.153	177	5.757	0.274	312	-0.064
log(Coal)	13.258	1.296	177	13.020	1.430	312	0.238
log(Output)	12.176	1.307	177	11.856	1.492	312	0.320
log(Hours)	8.351	0.582	177	8.415	0.495	312	-0.063
Panel B: five years before treatment (from 2008 to 2012)							
log(Intensity)	5.720	0.164	776	5.770	0.256	1535	-0.050
log(Coal)	13.153	1.351	776	13.040	1.489	1535	0.113
log(Output)	12.047	1.360	776	11.855	1.545	1535	0.192
log(Hours)	8.383	0.590	771	8.420	0.567	1522	-0.037

Note: The variables log(Intensity), log(Coal), log(Output), and log(Hours) represent the logarithms of coal intensity, coal consumption, output, and operating hours. The treated plants are matched with 10 coal-fired untreated power plants with the closest coal consumption in 2012. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Robustness: synthetic difference-in-differences estimators

	(1) log(Intensity)	(2) log(Coal)	(3) log(Output)	(4) log(Hours)
ETS×TP	0.012	-0.126*	-0.145**	-0.159**
	(0.019)	(0.072)	(0.072)	(0.066)
#Plants	265	265	265	265
#ETS plants	41	41	41	41
Observations	2,650	2,650	2,650	2,650

Note: The dependent variables in Columns (1)-(4) are the logarithms of coal intensity, coal consumption, output, and operating hours. ETS_i and TP_t are defined in Table 2. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A4: Potential confounder: Winter heating policy

	(1) log(Intensity)	(2) log(Coal)	(3) log(Output)	(4) log(Hours)
Estimator	-0.005	-0.099	-0.121	-0.096
	(0.060)	(0.522)	(0.536)	(0.090)
Left Mean	5.779	11.859	10.686	8.274
Right Mean	5.838	11.824	10.592	8.286
#Northern plants	2,170	2,170	2,170	2,155
#Southern plants	1,584	1,584	1,584	1,581
Observations	17,405	17,405	17,405	17,284

Note: The dependent variables in Columns (1)-(4) are the logarithms of coal intensity, coal consumption, output, and operating hours. Robust RD estimators and inferences proposed by Calonico et al. (2014), and mean square error optimal bandwidths are used. Covariates are the same as those in Table 2. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A5: Robustness: within-province GSC estimators

	(1) log(Intensity)	(2) log(Coal)	(3) log(Output)	(4) log(Hours)
ETS×TP	-0.010	-0.250***	-0.211***	-0.143
	(0.038)	(0.083)	(0.076)	(0.091)
#Plants	1,179	1,179	1,179	1,179
#ETS plants	117	117	117	117
Observations	10,549	10,549	10,549	10,484

Note: The dependent variables in Columns (1)-(4) are the logarithms of coal intensity, coal consumption, output, and operating hours. ETS_i and TP_t are defined in Table 2. Fixed effects are at the plant level and the province-year level. Control variables are the same as those in Table 2 and confounding policies including the ULES, NSMF, and green dispatch pilots. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A6: Robustness: effects of the ETS pilots by regression discontinuity

	After 2013				Before 2013			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(Intensity)	log(Coal)	log(Output)	log(Hours)	log(Intensity)	log(Coal)	log(Output)	log(Hours)
Estimator	0.045	-0.181***	-0.184***	0.028	-0.044	-0.041	-0.040	-0.027
	(0.027)	(0.061)	(0.067)	(0.044)	(0.044)	(0.088)	(0.111)	(0.037)
Left Mean	5.917	11.113	9.801	8.029	5.740	11.342	10.207	8.025
Right Mean	5.734	13.839	12.710	8.566	5.674	13.677	12.608	8.304
#Left plants	70	70	70	70	111	111	111	110
#Right plants	91	91	91	90	236	236	236	235
Observations	561	561	561	557	1,677	1,677	1,677	1,661

Note: The dependent variables in Columns (1)-(4) and Columns (5)-(8) are the logarithms of coal intensity, coal consumption, output, and operating hours. Robust RD estimators and inferences proposed by Calonico et al. (2014) are used, including their mean square error optimal bandwidths. Covariates are the same as those in Table 2. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A7: Robustness: effects of the ETS pilots on covariates by regression discontinuity

	(1) ElecDemand	(2) GDP	(3) POP	(4) Output	(5) Firmnum	(6) IndustryRatio	(7) ServiceRatio	(8) RegStringency
Estimator	-0.297	0.636	-0.184	-0.779	0.333	0.788	-1.493	0.010
	(0.689)	(3.484)	(1.111)	(3.452)	(0.300)	(1.421)	(1.587)	(0.008)
Left Mean	15.732	9.528	6.925	19.047	8.479	39.916	56.947	0.035
Right Mean	15.368	9.193	6.441	18.726	8.261	40.881	55.486	0.031
#Left plants	97	97	97	97	97	97	97	96
#Right plants	110	110	110	110	110	110	110	110
Observations	588	588	588	588	588	588	588	580

Note: The dependent variables in Columns (1)-(8) are the logarithms of city-year level electricity consumption, GDP, population, industrial outputs, number of industrial firms, value added to GDP ratios for the secondary and tertiary sectors, and environment-related text proportion in cities' annual government work reports. Robust RD estimators and inferences proposed by Calonico et al. (2014) are used, including their mean square error optimal bandwidths. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A8: Robustness: triple-difference estimations using the MOF-STA dataset

	(1) log(Intensity)	(2) log(Coal)	(3) log(Output)
Electricity×PilotProvince×TP	0.062	-0.249***	-0.272***
	(0.081)	(0.091)	(0.081)
Province×Year	Yes	Yes	Yes
Industry×Year	Yes	Yes	Yes
Plant	Yes	Yes	Yes
#Plants	118,654	126,263	118,667
#ETS plants	162	162	162
Observations	534,985	581,842	535,234
R-squared	0.690	0.754	0.836

Note: The dependent variables in Columns (1)-(3) are the logarithms of coal intensity, coal consumption, and output. $Electricity_i$ is a dummy for the electricity sector, $PilotProvince_p$ represents the pilot provinces, TP_t represents the years when the ETS pilots are in operation. Fixed effects are at the province-year level, the industry-year level, and the plant level. Control variables are the same as Table 2. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A9: Robustness: effects of the ETS pilots on CO_2 emissions

	DiD estimators			Matched DiD estimators			GSC estimators		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	log(CO_2 intensity)	log(CO_2)	log(Output)	log(CO_2 intensity)	log(CO_2)	log(Output)	log(CO_2 intensity)	log(CO_2)	log(Output)
ETS×TP	0.009	-0.122**	-0.133**	0.001	-0.145*	-0.146*	-0.000	-0.146*	-0.091*
	(0.006)	(0.059)	(0.059)	(0.011)	(0.080)	(0.081)	(0.013)	(0.075)	(0.052)
#Plants	827	858	825	327	327	327	788	817	783
#ETS plants	174	174	174	171	171	171	171	171	171
Observations	2,077	2,082	2,153	909	909	909	1,875	1,879	2,035
R-squared	0.986	0.885	0.936	0.991	0.949	0.934	-	-	-

Note: The dependent variables in Columns (1)-(3) and (4)-(6) are the logarithms of CO_2 intensity (the ratio of CO_2 emissions to output), CO_2 emissions, and output. ETS_i and TP_t are defined in Table 2. Fixed effects are at the plant level and the region-year level. Control variables are the same as Table 2. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table B1: Effects of the ETS pilots on air pollution

	DiD estimators			Matched DiD estimators			GSC estimators		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SO_2	NO_2	$PM_{2.5}$	SO_2	NO_2	$PM_{2.5}$	SO_2	NO_2	$PM_{2.5}$
ETS×TP	-0.204**	-0.017*	-0.034***	-0.373***	0.022	-0.025**	-0.220***	-0.093***	-0.062***
	(0.080)	(0.010)	(0.008)	(0.121)	(0.015)	(0.010)	(0.068)	(0.017)	(0.021)
#Plants	2,705	2,820	2,568	483	489	461	1,145	1,145	1,109
#ETS plants	208	209	198	176	177	166	117	117	111
Observations	15,462	16,635	14,500	4,207	4,414	3,795	8,267	8,215	7,857
R-squared	0.836	0.980	0.979	0.744	0.976	0.971	-	-	-

Note: The dependent variables in Columns (1), (4), and (7) are the logarithms of SO_2 concentrations, in Columns (2), (5), and (8) are the logarithms of NO_2 concentrations, and in Columns (3), (6), and (9) are the logarithms of $PM_{2.5}$ concentrations. ETS_i and TP_t are defined in Table 2. Fixed effects are at the plant level and the region-year level. Control variables are the same as those in Table 2 and confounding policies including the ULES, NSMF, and green dispatch pilots. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table B2: Heterogenous effects of the ETS pilots on air pollution by emission standards

	DiD estimators			Matched DiD estimators			GSC estimators		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SO_2	NO_2	$PM_{2.5}$	SO_2	NO_2	$PM_{2.5}$	SO_2	NO_2	$PM_{2.5}$
Panel A: High emission-standard regions									
ETS×TP	-0.287***	-0.035***	-0.042***	-0.211*	-0.013	-0.007	-0.136**	-0.031***	-0.025**
	(0.088)	(0.009)	(0.009)	(0.114)	(0.010)	(0.012)	(0.057)	(0.009)	(0.011)
#Plants	1,045	1,057	965	276	278	259	439	439	426
#ETS plants	171	172	162	147	148	140	96	96	90
Observations	6,198	6,410	5,545	2,295	2,404	2,043	3,519	3,630	3,196
R-squared	0.864	0.982	0.971	0.873	0.975	0.972	-	-	-
Panel B: Low emission-standard regions									
ETS×TP	-0.236	0.017	-0.022	-0.227	0.024	-0.007	-0.512	-0.072	-0.128**
	(0.243)	(0.019)	(0.019)	(0.262)	(0.016)	(0.024)	(0.403)	(1.030)	(0.046)
#Plants	1,660	1,763	1,602	208	211	201	702	702	683
#ETS plants	38	38	37	28	28	27	21	21	21
Observations	9,260	10,221	8,951	1,920	2,009	1,742	5,150	5,661	4,660
R-squared	0.830	0.979	0.980	0.832	0.988	0.971	-	-	-

Note: The dependent variables in Columns (1), (4), and (7) are the logarithms of SO_2 concentrations, in Columns (2), (5), and (8) are the logarithms of NO_2 concentrations, and in Columns (3), (6), and (9) are the logarithms of $PM_{2.5}$ concentrations. ETS_i and TP_t are defined in Table 2. Fixed effects are at the plant level and the region-year level. Control variables are the same as those in Table 2 and confounding policies including the ULES, NSMF, and green dispatch pilots. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table B3: Effects of high emission standards in 47 cities on air pollution

	DiD estimators			Matched DiD estimators			GSC estimators		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SO_2	NO_2	$PM_{2.5}$	SO_2	NO_2	$PM_{2.5}$	SO_2	NO_2	$PM_{2.5}$
HighStandard×TH	-0.169***	-0.037***	-0.062***	-0.210***	-0.017*	-0.038***	-0.163***	-0.096***	-0.076***
	(0.034)	(0.005)	(0.009)	(0.051)	(0.010)	(0.014)	(0.051)	(0.011)	(0.017)
#Plants	2,705	2,820	2,568	1,415	1,428	1,325	1,145	1,145	1,109
#Plants in HES regions	1,045	1,057	965	811	819	753	439	439	426
Observations	15,462	16,635	14,500	9,615	10,010	8,729	8,267	8,215	7,857
R-squared	0.836	0.980	0.979	0.842	0.977	0.974	-	-	-

Note: The dependent variables in Columns (1), (4), and (7) are the logarithms of SO_2 concentrations, in Columns (2), (5), and (8) are the logarithms of NO_2 concentrations, and in Columns (3), (6), and (9) are the logarithms of $PM_{2.5}$ concentrations. $HighStandard_c$ is a dummy variable that equals one if city c implements the high emission standard. TH_t is a dummy variable that equals one at the years when the new emission standards are in operation. Fixed effects are at the plant level and the region-year level. Control variables are the same as those in Table 2 and confounding policies including the ULES, NSMF, and green dispatch pilots. Standard errors are clustered at the plant level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.