Evaluating Power Sector Emissions under China's Regional Carbon ETS Pilots: A View from Space

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Abstract

Tradable performance standard (TPS) is an important policy instrument for mitigating carbon dioxide (CO_2) emissions in developing countries, who play an essential role in achieving drastic global carbon emissions reduction. However, whether a TPS system effectively reduces firm-level emissions in a developing country context remains unknown. This paper answers this question based on a policy experiment in China. Since 2013, China has introduced carbon emissions trading systems based on TPS in eight regions (ETS pilots). This study provides a timely ex-post evaluation of these ETS pilots' effects on sulfur dioxide (SO_2) emissions from coal-fired thermal power generation facilities using staggered and dynamic difference-in-differences models. This study uses a novel data from NASA's Aura satellite to measure SO_2 emissions at the facility level. Contrary to the common belief, results show that although SO_2 emissions of all facilities declined steadily from 2010 to 2019, SO_2 emissions of facilities covered by the ETS pilots (ETS facilities) increased by about 5-7% relative to those of non-ETS facilities. Moreover, the relative increase in SO_2 emissions of ETS facilities grew over time. A model is developed to show that the implicit output subsidy from the TPS design could increase the output of cleaner facilities, leading to more SO2 emissions.

Keywords: China ETS, Carbon Market, Air Pollution Regulations, Thermal Power Generation, Impact Evaluation
JEL Codes: H23, Q48, Q53, Q58

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1 Introduction

Sustaining economic growth, reducing poverty, and achieving ambitious climate change mitigation goals is arguably the main challenge of this century. At the center of this challenge lies the energy sectors of fast-growing developing economies like China, which has historically relied on burning coal to meet the ever-increasing energy demand of a rapidly expanding economy and a more affluent population. To achieve environmental goals in the power generation sector, China has traditionally relied on command-and-control style policies. However, in 2011 China announced the plan to experiment with regional pilot programs of carbon emission trading systems (ETS pilots) to reduce its carbon emissions.

The ETS pilots in China have generated broad interest from policymakers and scholars from across the world. This interest is not only motivated by the combined scale of the ETS pilots as the world's second-largest carbon market at the time of their launch (following the EU ETS), but also by their unusual rate-based design based on Tradable Performance Standards (TPS). Because TPS systems reduce carbon emission intensity rather than total carbon emission, they are less restrictive on output growth and could be more suitable for developing countries, where economic growth is usually given high policy priorities. The ETS pilots in China could thus generate valuable insights regarding the effectiveness of a TPS system in the developing country context.

Despite the prominence of China's ETS pilots in policy and academic discussions, questions remain about their actual performance, especially when they operate alongside other command-and-control environmental regulations. An undesirable feature of a TPS system is that it can amount to implicit output subsidies for a portion of the covered emitters (Fischer, 2001; Goulder et al., 2022), thus reducing its efficiency compared to a more traditional Cap and Trade (C&T) system. This feature raises an important empirical question of whether the ETS pilots in China have effectively reduced emissions from large emitters in the short- and mid-run. This paper answers this question by providing a timely *ex post* evaluation of the causal effects of the ETS pilots on SO_2 emissions from coal-fired power plants during the 2010-2019 period.

The analysis adopts staggered and dynamic difference-in-differences (DID) frameworks: comparing changes in SO_2 emissions from coal-fired power plants covered by the ETS pilots (treated facilities) versus power plants not covered by the ETS pilots (untreated facilities) before and after the launch of the ETS pilots. To disentangle the causal effect of the ETS pilots from confounding factors of co-existing environmental regulations, identification exploits the variations in the temporal and spatial coverage of the ETS pilots compared to those of two major sets of air pollution and power sector regulations. To overcome the problem of limited data availability and concerns over data quality in the Chinese context, I estimate monthly and quarterly SO_2 emissions at the power plant level using a novel NASA satellite data product.

Contrary to the belief that ETS pilots could reduce emissions of co-pollutants (Li et al., 2018; Zhang and Zhang, 2020; Cai et al., 2016), the baseline results show that although SO_2 emissions have declined for all coal-fired power generation facilities in the sample, SO_2 emissions of the treated facilities have increased by about 5% vis-á-vis untreated facilities since the ETS pilots began. Moreover, after conditioning on the stringency of two sets of overlapping air pollution and power sector regulations, the relative increase in SO_2 emissions by the treated facilities climbs to 5.9% and 6.7%, respectively.

Results of the event study models show no significant divergence in the pre-trends of SO_2 emissions between the treated and untreated facilities, lending credence to the baseline results. Furthermore, the event study models reveal that the relative increase in SO_2 emissions from the treated facilities becomes statistically significant one year after the launch of the ETS pilots and grows over the post-treatment period. These results stand a battery of robustness checks, including controlling for potential spillover effects to power plants in the neighboring provinces within the same regional power grid, using different functional form assumptions and data frequencies, and using alternative sample selection criteria for large and isolated coal-fired power plants. The results also pass placebo tests.

This paper contributes to three strands of literature. A large empirical literature examines the effectiveness of market instruments in regulating pollution, such as the lead trading program (Kerr and Newell, 2003; Nichols, 1997; Hahn and Hester, 1989), the SO_2 allowance trading program (Chan et al., 2018; Schmalensee and Stavins, 2013; Busse and Keohane, 2007; Carlson et al., 2000; Ellerman et al., 2000; Joskow, Schmalensee, and Bailey, 1998), the NOx Budget Program (Curtis, 2018; Deschenes, Greenstone, and Shapiro, 2017; Fowlie, 2010; Linn, 2010, 2008), and the RECLAIM program (Fowlie, Holland, and Mansur, 2012; Fowlie and Perloff, 2013). In contrast, fewer empirical studies have examined the effectiveness of market instruments adopted by developing countries, which generally have lower institutional and technological capability and fewer financial and human resources. This study adds to this strand of literature, by providing rigorous evaluation of the causal effects of an important market mechanism in a developing country context.

Second, this study contributes to the burgeoning literature on the effects of carbon trading schemes. Due to the prominence of the EU ETS, numerous empirical studies have shed light on its effects on innovation (Calel, 2020; Calel and Dechezleprêtre, 2016), firms' carbon emissions, employment, and productivity (Calel, 2020; Dechezleprêtre, Nachtigall, and Venmans, 2018; Marin, Marino, and Pellegrin, 2018; Martin, De Preux, and Wagner, 2014; Jaraite-Kažukauske and Di Maria, 2016), and the power generation sector (Zaklan, 2021; Fabra and Reguant, 2014). In comparison, rigorous *ex post* evaluation of the performance of the ETS pilots in China has only a few entries (Cui et al., 2021; Cao et al., 2021) and needs further development.[1] By leveraging recent advancements in remote-sensing technologies and utilizing publicly available satellite data, this paper provides much-need evidence of the short- to mid-run *ex post* effects of the ETS pilots on emissions of a co-pollutant, SO_2. By focusing on the thermal power generation sector, the only sector covered by the national ETS that launched in July 2021, the study provides valuable policy-relevant insights for the regulators of the national ETS.

Last but not least, this study also adds to the literature on tradable performance standards (TPS) systems. Previous studies on TPS systems have examined their performance in the context of the U.S. transportation sector (Yeh et al., 2021; Ito and Sallee, 2018; Klier and Linn, 2016; Jacobsen, 2013; Anderson et al., 2011; Anderson and Sallee, 2011) and the U.S. electricity sector (Chen, Tanaka, and Siddiqui, 2018; Zhang, Chen, and Tanaka, 2018; Fischer, Mao, and Shawhan, 2018; Burtraw et al., 2014; Linn, Mastrangelo, and Burtraw, 2014). This study contributes to this literature by documenting the effects of TPS systems in the power generation sector of a large and fast-growing developing economy.

2 Policy Background

To achieve the ambitious greenhouse gasses (GHG) emission reduction goals pledged in the 2015 United Nations Climate Change Conference in Paris (COP21)[2], China implemented

[1]Numerous studies focus on the market design issues of China's ETS pilots and National ETS. (Karplus, 2021; Stavins and Stowe, 2020; Goulder et al., 2017; Karplus and Zhang, 2017; Duan, 2017, 2015; Pang and Duan, 2016). Due to data availability and data quality issues, previous *ex post* evaluations of China's ETS pilots examined their effects on firms' innovation and low-carbon investments (Tian, 2020; Zhu et al., 2019; Cui, Zhang, and Zheng, 2018; Mo et al., 2016), co-pollutants (Kou et al., 2021; Huang et al., 2021; Yan et al., 2020), and health co-benefits (Chang et al., 2020; Li et al., 2018; Cai et al., 2016). In addition, Goulder et al. (2022) provides an excellent *ex ante* evaluation of the National ETS in China.

[2]China's pledged goals, termed Nationally Determined Contributions (NDCs), include reducing carbon intensity by 60-65% relative to 2005 levels by 2030; increasing the share of non-fossil fuels in primary energy

a series of policies during the 12th Five Year Plan (FYP) period (2011-2015) and the 13th FYP (2016-2020) period. A milestone policy is the establishment of regional carbon emissions trading system (ETS) pilots in eight municipalities and provinces, which have helped China accumulate the institutional and technical know-how of carbon markets and paved the way for the national ETS launched in July 2021.

2.1 A Brief History of ETS Pilots in China

The National Development and Reform Commission (NDRC)[3] approved and announced seven regional ETS pilots in October 2011, with an initial trial-run period of 2013-2015. These pilots cover five municipalities, Beijing, Tianjin, Shanghai, Chongqing, and Shenzhen, and two provinces, Hubei and Guangdong. An eighth ETS pilot was established in Fujian Province in 2016, after the conclusion of the trial-run period of the first seven ETS pilots.

The ETS pilots cover direct and indirect CO_2 emissions[4] from large emitters in various industrial, transportation, and service sectors. In the covered sectors, participation is mandatory for large emitters, selected based on their historical annual CO_2 emissions.[5]The thermal power generation sector is covered by all ETS pilots due to its lion's share in local carbon emissions.[6] The ETS pilots cover 40-60% of local carbon emissions (ICAP, 2020). In total, the eight pilots cover approximately 650 megatons of carbon emissions – roughly a

consumption to 20% by 2030; and increasing its forest stock by 4.5 billion cubic meters. In 2014, China also pledged to peak its total CO_2 emissions by 2030 as a part of the US-China Joint Announcement on Climate Change. In the Climate Ambition Summit 2020, China upgraded its climate change mitigation goals and announced its plan to reach carbon neutrality by 2060.

[3]The NDRC is a ministry-level agency under the State Council (the central government of China). It is in charge of drafting and coordinating the implementation of socio-economic development strategies, mid- to long-term development plans, and annual development goals.

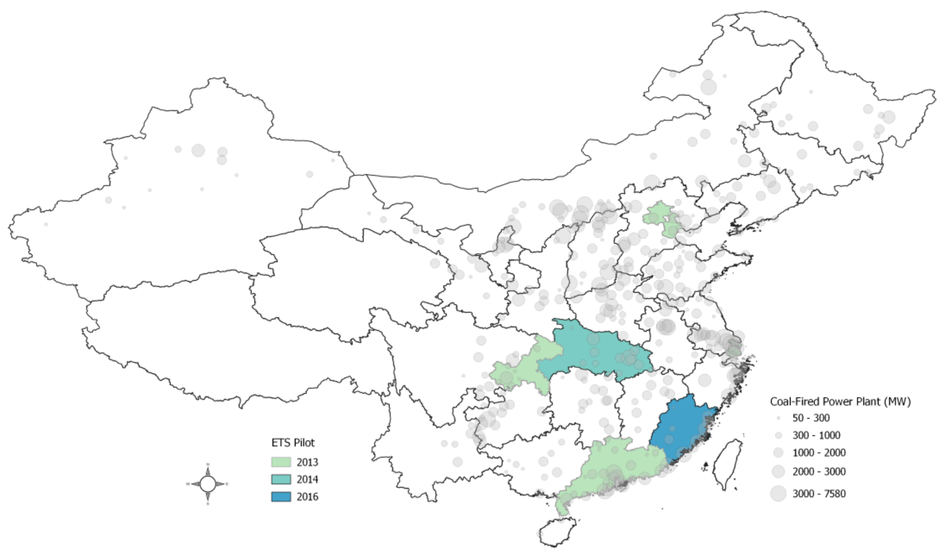
[4]Pang and Duan (2016) discuss three reasons for the ETS pilots to cover indirect carbon emissions. First, there is no binding cap on total carbon emissions in the ETS pilots. Second, electricity price is regulated by the provincial Development and Reform Commission (DRC), which prevents the cost of carbon emissions to be passed through to electricity consumers, thus nullifying incentives for energy saving behaviours. Third, the ETS pilot regions import a fraction of their electricity from other regions. So, indirect emissions (mainly through electricity consumption) are covered to prevent carbon leakage.

[5]Details on the industries covered by each ETS pilot and the thresholds of historical carbon emissions are provided in Table A7. Except for Chongqing, all ETS pilots only cover CO_2 emissions. The Chongqing ETS also covers five other GHG, including methane (CH4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulfur hexafluoride (SF_6).

[6]In 2021, following the start of the national ETS, thermal power generation facilities covered by the regional ETS pilots began transferring into the national ETS. The national ETS currently only covers the thermal power generation sector, although its planned expansion will cover more sectors in the future.

third of the size of the EU ETS.[7]

Figure 1: Regional Emission Trading System Pilots by Launch Year



Notes: From north to south and east to west, the light green areas cover the following six ETS pilots: Beijing, Tianjin, Shanghai, Chongqing, Guangdong, and Shenzhen. These six ETS pilots started their first compliance period (CP) on January 1, 2013. The darker green area is the Hubei ETS that began its first CP on January 1, 2014. The blue area covers the Fujian ETS that began its first CP on January 1, 2016. Light grey bubbles represent 346 large and relatively isolated coal-fired power generation facilities, selected based on criterion detailed in Section 4. The size of the bubbles represents the capacity of the facilities in 2012. *Source:* Author's compilation based on Global Energy Monitor - Global Coal Plant Tracker.

The staggered rollout of the ETS pilots occurred between 2013 and 2016 in three episodes. The first group of six ETS pilots, including Beijing, Tianjin, Shanghai, Chongqing, Guangdong, and Shenzhen, started their first compliance period (CP) on January 1, 2013. Due to delays in preparation, the Hubei ETS began its first CP on January 1, 2014. Lastly, the first CP for the Fujian ETS started on January 1, 2016. The location and rollout timing of all eight ETS pilots are shown in Figure 1.

The defining feature of the ETS pilots is their rate-based design, called Tradable Performance Standards (TPS). In TPS systems, emitters must meet certain CO_2 emission intensity standards (or performance standards) set by regulators. However, their total CO_2 emissions are not capped – as in a mass-based Cap and Trade (C&T) system – because they can freely adjust output in response to market demand. Due to this rate-based design, the ETS pilots can amount to an implicit output subsidy for cleaner emitters, whose carbon emission inten-

[7]The World Bank. "Carbon Pricing Dashboard." Accessed on September 5, 2021. `https://carbonpricingdashboard.worldbank.org/`

sities are already below the mandated standards or whose costs of meeting such standards are sufficiently low (Goulder et al., 2022; Fischer, 2001).

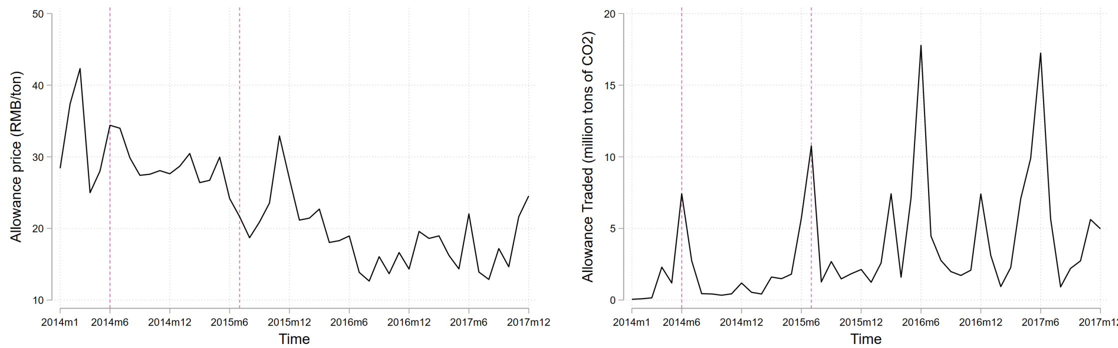
Thermal power generation facilities under the ETS pilots can meet the mandated carbon emission intensity standards by reducing their emission intensities (abatement) or purchasing emission credits from the carbon market. Abatement is mainly achieved by reducing coal consumption per unit of electricity production, which typically requires capital-intensive investment to retrofit existing boiler units with cleaner technologies or to replace inefficient units. In the short-run, it is also possible for a covered facility to reduce carbon emission intensities by cutting back electricity production, if, for example, it is able to switch electricity production from less to more efficient units. In the long-run, however, covered facilities will likely retire or replace inefficient boiler units, since idle or standby units still require constant maintenance.[8]

The cost of carbon emission credits across the ETS pilots is low, with the trading-volume-weighted average carbon price ranging between 20 and 40 RMB/ton during the 2013-2015 trial-run period and an average spot price of about 28 RMB/ton (approximately $4.5/ton). For reference, the U.S. EPA's Social Cost of Carbon (SCC) in 2025 is 46$/ton.[9] By the end of 2015, the cumulative trading volume across all ETS pilots has amounted to 50.3 million tons of CO_2 (Ministry of Ecology and Environment, PRC, 2016). Figure 2 shows the trends of trading-volume-weighted average carbon price and trading volume between 2014 and 2017. Trading activities in the ETS pilots mostly occur around the annual deadlines for submitting carbon emission credits, as Panel (b) of Figure 2 shows. In addition, Figures A4 and A5 in the Appendix show the heterogeneity in local carbon prices and trading volumes across the ETS pilots.

[8]In theory, facilities can also remove carbon emissions by installing carbon capture, utilization, and storage (CCUS) technologies. However, in practice, the CCUS technologies are still in the early stage of adoption in China and are not yet a cost-efficient option. Finally, switching to coal with higher heating ratings may also be an abatement option. However, as Yang et al. (2018) show, coal-switching is also not cost-efficient in the Chinese context.

[9]EPA's Social Cost of Carbon (SSC) ranges between 12$/ton to 138$/ton. The SSC in the year 2025, based on a 3% discount rate, is 46$/ton. Source: U.S. EPA. "Social Cost of Carbon Fact Sheet." `https://www.epa.gov/sites/default/files/2016-12/documents/social_cost_of_carbon_fact_sheet.pdf`.

Figure 2: Spot Price and Trading Volume of Carbon Emission Credits (2014-2017)



(a) Price (b) Volume

Notes: Carbon emission credit price shown in Panel (a) are trading-volume-weighted monthly average spot price and is in nominal RMB. Trading volumes are denoted in million tons of CO_2. The first dashed vertical lines in both panels roughly mark the first carbon emission credit submission deadlines for Beijing, Tianjin, Shanghai, Shenzhen, and Guangdong. The second dashed vertical lines in both panels roughly mark the first carbon emission credit submission deadlines for Hubei and Chongqing and the second carbon credit submission deadlines for the other five ETS pilots. (Actual submission deadlines varied between May and July.) *Source:* Author's calculation based on Zhang et al. (2020).

2.2 Overlapping Environmental Regulations

Since the start of the 12th Five Year Plan (2011-2015), China has taken a comprehensive approach to combat environmental problems, introducing stricter environmental laws and new emissions standards, incorporating pollution reduction targets into socioeconomic planning and local government officials' evaluations, and creating a mixture of new regulatory tools.[10] Due to the prominence of the thermal power generation sector in governmental efforts to reduce carbon emission and air pollution, a series of new environmental regulations have targeted this sector. A summary of two sets of air pollution and power sector regulations, most likely to contaminate the effects of the ETS pilots on coal-fired power generation facilities' emissions, are provided below.

Ultra-Low Emissions Standard The most prominent air pollution regulation in the thermal power generation sector is the "Emission Standards for Atmospheric Pollutants for Thermal Power Generation" (GB13223-2011) released in 2011. Compared with the outgoing standard, the new standard requires thermal power generation facilities to significantly reduce their emission rates of sulfur dioxide (SO2), nitrogen oxides (NOx), particulates (PM), mercury, and other pollutants by 50% or more. Due to its stringency, this new standard is

[10]Karplus, Zhang, and Zhao 2021 provides an excellent comprehensive review of the environmental policy landscape in China

widely known as the ultra-low emissions (ULE) standard. This new standard went into effect on July 1st, 2014 for all existing thermal power generation facilities.[11] An essential feature of the ULE standard is its tiered structure: the ULE standard sets lower (more stringent) emission rates of air pollutants for facilities located in 47 prefecture cities, designated as the "Key Zones of Atmospheric Pollutants Prevention and Control" (APPC key zones), and higher (less stringent) rates for facilities in Chongqing, Guangxi, Sichuan, and Guizhou. (A map of APPC zones in relation to the ETS pilots are shown in Figure A1.)

Energy Efficiency and Pollution Control Besides the ULE standard, China also promulgated two plans to induce thermal power generation facilities to retire small and inefficient boiler units and to invest in energy efficiency and pollution control technologies. They are the "Action Plan for Atmospheric Pollutant Prevention and Control" (2013-2017, known as the "Air Ten") and the "Work Plan for the Comprehensive Implementation of Ultra-Low Emissions and Energy Efficiency Upgrades of Coal-Fired Power Generation Facilities" (2014-2020, hereafter, the "Work Plan"). The "Work Plan" includes performance standards on energy efficiency for boiler units of different sizes and technologies and provides financial incentives for facilities that adopt the recommended energy efficiency and pollution control technologies[12]. Moreover, the "Work Plan" sets different regional deadlines for thermal power generation facilities to meet the energy efficiency standards. The deadline for facilities located in 11 eastern and eight central provinces to complete their upgrades and meet the standards are 2017 and 2018, respectively, and the deadline for facilities elsewhere in China is 2020. (A map of Eastern and Central provinces is shown in Figure A2.)

3 Research Design

As discussed above, the key to estimating the effects of ETS pilots on power generation facilities' SO_2 emissions is to disentangle them from potential contamination effects from overlapping air pollution and energy efficiency regulations in the power sector. Therefore, to identify the causal effect of the ETS pilots on the covered facilities' SO_2 emissions, the DID research design exploits the differences in temporal and spatial coverage of the ETS pilots

[11] The ULE standards came into effect for newly constructed thermal power generation units on January 1, 2012, and then for all existing units on July 1, 2014.

[12] Thermal power generation facilities that meet the energy efficiency improvement and emission reduction targets on time are awarded a 0.001 RMB/kwh increase in electricity price, an additional 200 guaranteed hours per year, and a 50% discount on pollution charges.

relative to that of the overlapping regulations. The baseline two-way fixed effect (TWFE) model is shown below.

$$Y_{ijt} = \gamma_i + \lambda_t + \lambda_t \alpha_k + \delta D_{it} + X_{ijt}^{'} \beta + \varepsilon_{ijt} \tag{1}$$

The dependent variable of interest, Y_{ijt}, is log SO_2 emissions of thermal power generation facility i in prefecture city j in period t. Since SO_2 emissions is the product of output (q_{it}) and emission rates (μ_{it}^s), $Y_{ijt} = q_{it} \times \mu_{ijt}^s$, a logarithmic transformation of SO_2 emissions thus additively decompose them into two terms, $ln(Y_{ijt}) = ln(\mu_{ijt}^s) + ln(q_{it})$. The first term, μ_{ijt}^s, is affected by the ETS pilots, as treated facilities are incentivize to reduce their coal consumption per unit of electricity output. This term is also regulated by the ULE standard and the "Work Plan".[13]

D_{it} is a binary treatment indicator that equals 1 for treated facilities in post-treatment periods and 0 otherwise. $\hat{\delta}$ is the estimator for the Average Treatment Effect on the Treated (ATT) of the ETS pilots on SO_2 emissions, the parameter of interest.

γ_i are facility fixed effects that control for time-invariant unobserved characteristics of thermal power generation facilities that determine the dynamics of their SO_2 emissions or treatment status. For instance, facilities' historical carbon emission intensities or average annual carbon emissions prior to the start of ETS pilots are captured by these facility fixed effects. This term also captures any time-invariant technological attributes of facilities' boiler units. Moreover, the stringency of local environmental regulations may also differ based on facilities' fixed locations. For example, facilities located nearer to city centers or in the upwind direction of large cities may be subject to more frequent and strict monitoring by local government officials. This type of policy stringency variation is also captured by these facility fixed effects.

λ_t are time fixed effects that capture macroeconomic or environmental policy shocks that

[13]Similarly, log CO_2 emissions can also be decomposed into an output component and an intensity component, $ln(Z_{ijt}) = ln(q_{it}) + ln(\mu_{ijt}^c)$, where $ln(Z_{ijt})$ and $ln(\mu_{ijt}^c)$ are facilities' CO_2 emissions and CO_2 emission intensities in logs, respectively. Substituting this equation into the log decomposition of SO_2 emissions yields the following expression: $ln(Y_{ijt}) = ln(Z_{ijt}) + [ln(\mu_{ijt}^s) - ln(\mu_{ijt}^c)]$. This equation characterizes the relationship between SO_2 and CO_2 emissions. When the second term on the right-hand side, $ln(\mu_{ijt}^s) - ln(\mu_{ijt}^c) = ln(\mu_{ijt}^s / \mu_{ijt}^c)$, is held constant, changes in SO_2 emissions equal changes in CO_2 emissions. When facilities' SO_2 emission intensities μ_{ijt}^s decrease faster than their CO_2 emission intensities μ_{ijt}^c, the $ln(\mu_{ijt}^s / \mu_{ijt}^c)$ term is increasingly negative, in which case the increases in SO_2 emissions $ln(Y_{ijt})$ provide lower bound estimates for increases in CO_2 emissions $ln(Z_{ijt})$.

affect all thermal power generation facilities. The interaction term, $\lambda_t \alpha_k$, is key to separating the effect of ETS pilots from that of overlapping regulations such as the ULE standard and the "Work Plan". α_k are dummy variables that categorize facilities' locations based on the above-mentioned regulations. This interaction term allows facilities subject to different air pollutant emissions or energy efficiency standards to experience different technological progress in each period that could change their SO_2 and CO_2 emissions intensities. Take the ULE standard as an example, by controlling for differential effects of the ULE standard in this flexible manner, the model only compares treated facilities with untreated facilities within the same type of APPC zones (key vs. non-key) and thus netting out the potential contamination effects of the ULE standard.

X_{ijt} is a vector of control variables in logs, such as facility capacity; province-level energy supply and demand variables like electricity demand, electricity price, and the fraction of power generated by thermal sources (coal, oil, and natural gas); and local weather variables such as cooling degree days (CDD) and heating degree days (HDD).[14]

The key identification assumption in the DID framework is the parallel trend assumption. To provide indirect support for this assumption and examine the dynamic effect of ETS pilots on SO_2 emissions from large isolated coal-fired power plants, I estimate the following event study (or dynamic DID) model.

$$Y_{ipt} = \gamma_i + \lambda_t + \lambda_t \alpha_k + \sum_{j=2}^{J} \theta_j D_i \mathbb{1}[t^* - t = j] + \sum_{\tau=0}^{T} \phi_\tau D_i \mathbb{1}[t - t^* = \tau] + X'_{ijt}\beta + \varepsilon_{ipt}p \quad (2)$$

A notable difference in this event study specification is the addition of leads and lags. As equation (2) shows, J leads and T lags have been added. D_i is a binary treatment dummy that equals 1 for treated facilities and 0 for untreated facilities. $\mathbb{1}[t^* - t = j]$ is an indicator function that yields 1 when the time of observation t is j periods before the occurrence of treatment t^*. Similarly, the $\mathbb{1}[t - t^* = \tau]$ terms equal 1 when the time of observation is τ periods after the treatment. Figure

[14] Cooling and heating degree days measure how hot and cold the daily temperatures are during a certain period. These two measures are typically used in energy studies to control for the influence of weather on energy demand for the cooling and heating of buildings and homes. They measure how far daily temperatures are from a given threshold temperature. Consider the example of CDD using 24° Celsius as the threshold temperature. A day with a mean temperature of 30° Celsius counts as 6 CDD as the temperature is 6 degrees hotter than the threshold temperature, and a day with a mean temperature of 20° Celsius counts as 0 CDD as it is not hotter than the threshold temperature.

The θ_j describe the changes in SO_2 emission of eventually treated facilities net of the changes in untreated facilities before the launch of ETS pilots. A joint statistical test on these terms provides evidence for the parallel trend assumption. The ϕ_τ trace out how the sample average treatment effect on the treated (ATT) evolves through time. Y_{ijt}, γ_i, λ_t, $\lambda_t\alpha_k$ and X_{ijt} are defined as before.

4 Data

Coal-Fired Power Plants Characteristics Data on coal-fired power generation facilities are obtained from the Global Coal Plant Tracker (GCPT).[15] The GCPT database contains information on 2,990 boiler units of 1,087 operating facilities in China. For each power plant, GCPT reports their longitude and latitude, ownership, and additional background information. Additionally, GCPT provides detailed boiler-unit-level information such as capacity, combustion technology, operational status, commission year, and, if applicable, retirement year. Units that have retired before 2010 or are still under construction in 2019 are dropped, leaving me with a sample of 2,680 boiler units, belonging to 838 coal-fired power generation facilities.[16]

SO_2 Emissions of Coal-Fired Power Plants SO_2 emissions of thermal power generation facilities are derived from a NASA Ozone Monitoring Instrument (OMI) satellite product.[17] This data provides daily SO_2 concentrations with global coverage at a maximum spatial resolution of 0.25 by 0.25 degrees. The high spatial resolution of OMI SO_2 products makes them ideal for studying the SO_2 emissions of large stationary sources such as thermal power generation facilities. The accuracy and credibility of OMI SO_2 products in estimating thermal power generation facilities' emissions have been demonstrated by numerous studies (Karplus, Zhang, and Almond, 2018; Fioletov et al., 2011, 2015; Mclinden et al., 2016; Liu et al., 2015; Lu et al., 2013; Li et al., 2010).

[15] Global Coal Plant Tracker, Global Energy Monitor, July 2022, `https://globalenergymonitor.org/projects/global-coal-plant-tracker/`

[16] Some coal-fired power generation facilities have moved to a new site during the study period 2010-2019. I treat the new and the old sites of a facility as separate facilities. If the old site shut down before 2010, it is dropped from the sample.

[17] OMI/Aura Sulfur Dioxide (SO2) Total Column L3 1 day Best Pixel in 0.25 degree x 0.25 degree V3 (OMSO2e). `https://disc.gsfc.nasa.gov/datacollection/OMSO2e_003.html`. This data product is developed and made public by a team of scientists (Li et al., 2020) at the Goddard Earth Sciences Data and Information Services Center (GES DISC).

Table 1: Summary Statistics on Large and Isolated Coal-Fired Power Generation Facilities

	ETS			Non-ETS		
	obs	mean	sd	obs	mean	sd
Capacity in 2012	67	1797.224	1370.928	279	1551.405	1345.239
Number of units	67	4.047	2.060	279	3.443	1.649
Share of outdated capacity	67	0.216	0.408	279	0.139	0.308
Share of capacity built between 2009-2019	67	0.450	0.609	279	0.444	0.787
Share of capacity built between 2014-2019	67	0.084	0.224	279	0.116	0.628
Share of capacity retired between 2009-2019	67	0.110	0.276	279	0.036	0.153
Share of capacity retired between 2014-2019	67	0.087	0.254	279	0.035	0.151
Subcritical (dummy)	67	0.588	0.424	279	0.617	0.437
Supercritical (dummy)	67	0.174	0.315	279	0.167	0.326
Ultra-supercritical (dummy)	67	0.164	0.307	279	0.119	0.288
CFB (dummy)	67	0.020	0.128	279	0.003	0.034

Notes: This table presents summary statistics of 346 large and isolated coal-fired power generation facilities. Large and isolated coal-fired power generation facilities are defined in Section 4. Capacity shown in the first row is in megawatt (MW). Outdated capacity is defined as subcritical units with 200 MW or less capacity, based on the "Action Plan for Energy Efficiency and Pollution Reduction Upgrade in the Coal-Fired Power Generation Sector" (2014-2020). Percentages of outdated, new, and retired capacity, shown in the second to the seventh row, are in decimal points and are calculated by dividing capacity that match each category against facilities' total capacity in 2012. Four dummy variables in rows 8-11 indicate shares of facilities capacity with each specific combustion technology. CFB stands for circulating fluidized bed. For a given capacity, boiler units' carbon emission intensity decreases from subcritical, to super-critical and ultra-supercritical technologies. Although CFB technology reduces emissions of co-pollutants such as SO2, the CFB technologies adopted in China tend to have higher CO_2 emission intensities than the subcritical boiler units (see Table 1 in Goulder et al. 2022).
Source: Author's calculation based on Global Energy Monitor - Global Coal Plant Tracker.

Since the Aura/OMI SO_2 product only produces accurate and credible estimates of SO_2 emissions for large facilities, I follow the methods of Lu et al. (2013) and Karplus, Zhang, and Almond (2018) and select a subset of large and relatively isolated facilities. A facility is considered as large and relatively isolated if its operating capacity in 2012 exceeds 1,700 megawatts[18] or 50% of the total operating capacity of all facilities within a 35 km radius.[19] This process yields a sample of 346 facilities, consisting of 67 treated facilities[20] and 279 untreated facilities. As table 1 shows, the treated and untreated facilities have similar observable characteristics.

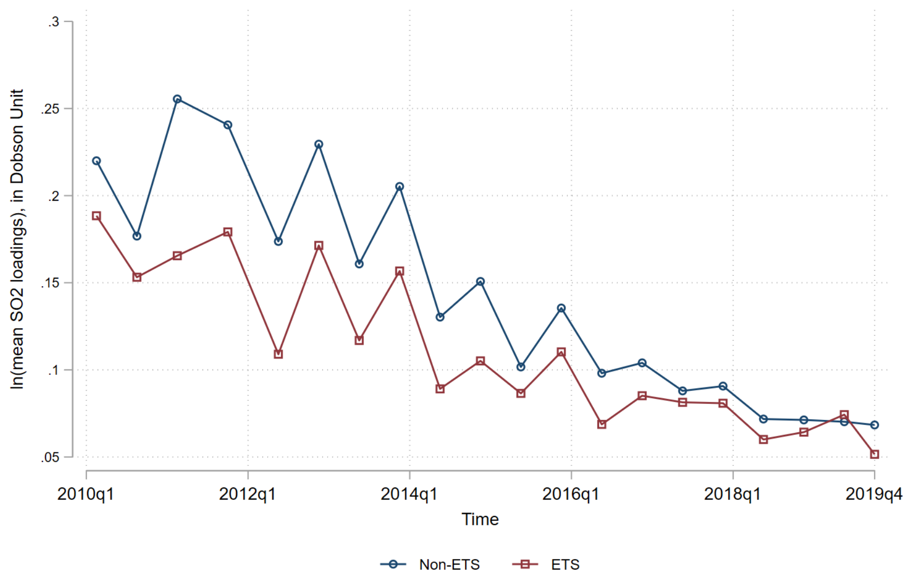
[18] 1700 megawatts is the 75th percentile of the size distribution of all Chinese coal-fired power plants in the GCPT database.

[19] A detailed description of the data processing procedure is provided in Appendix C.

[20] The 67 facilities covered by the ETS pilots include 1 facility in Beijing, 3 in Tianjin, 4 in Shanghai, 1 in Shenzhen and 23 in the rest of Guangdong, 11 in Hubei, 7 in Chongqing, 10 in Fujian, and 7 in two cities in Inner Mongolian that have voluntarily joined the Beijing ETS in 2015.

Figure 3 below provides descriptive evidence on the effects of the ETS pilots on SO_2 emissions. It shows that SO_2 emissions of both the treated and untreated facilities have declined rapidly between 2012 and 2019. However, the decline is more pronounced for the untreated facilities than the treated facilities (about 16% versus 12% from 2012 to 2019). Furthermore, SO_2 emissions show high degrees of co-movement during the pre-ETS period, particularly between 2012 and 2014. This pattern provides visual evidence in support of the parallel trend assumption of the DID research design. Importantly, an apparent break in the co-movement of SO2 emissions is also visible after 2014, with the trend of SO_2 emissions of treated facilities flattened relative to that of the untreated facilities. This pattern is also robust when directly comparing the level of emissions (see Figure A6 in the Appendix).

Figure 3: SO2 Emissions of Coal-Fired Power Generation Facilities (2010-2019)



Notes: Quarterly group average SO2 emissions in logs are plotted above. The ETS line is plotted using quarterly averages of SO2 emissions from 50 large and isolated coal-fired power generation facilities covered by the ETS pilots, excluding ten facilities in Fujian and seven facilities in Inner Mongolia. The Non-ETS line is plotted using quarterly averages of 278 facilities located outside the ETS pilots. *Source:* Author's calculation based on NASA Aura/OMI OMSO2e.

Socioeconomic Characteristics Province-level socioeconomic variables are collected from CEIC data[21]. Energy demand and supply variables are gathered from EPS China Statistics. All energy sector variables are annually updated official statistics at the province level, except for the industrial-use electricity price, which is reported at monthly frequency.

[21]CEIC Data is a data service that compiles various social, economic, and financial data from official statistical agencies. In the case of China, most socioeconomic statistics come from the National Bureau of Statistics

Lastly, to measure provincial private and public investments in environmental protection, I collected annual investments in industrial waste gas control and annual public environmental protection expenditures from CEIC data. Lastly, I collected heating degree days (HDD) and cooling degree days (CDD) data from the International Energy Agency (IEA) to control for the impact of local weather on energy demand.

As is shown in Table 2, the pilot ETS regions have higher GDP, more service-oriented local economies, and higher population densities and growth rates than the non-ETS regions. Moreover, the ETS regions also consume less electricity, have lower energy intensity, and experience slower growth rate in electricity consumption compared with the non-ETS regions.

Table 2: Macroeconomic, Energy, and Weather Characteristics of ETS vs. Non-ETS Regions

	Non-ETS Provinces			ETS Provinces		
	obs	mean	sd	obs	mean	sd
Panel A. Macroeconomy						
GDP (bn. 2015 RMB)	230	2035.208	1696.862	70	2939.505	2042.295
Real GDP, growth rate	207	0.072	0.036	63	0.078	0.026
Primary industry (% GDP)	230	0.117	0.046	70	0.046	0.037
Secondary industry (% GDP)	230	0.426	0.071	70	0.398	0.105
Tertiary industry (% GDP)	230	0.458	0.056	70	0.556	0.133
Population (mn. ppl)	230	46.488	26.187	70	42.210	30.450
Population, growth rate	230	0.005	0.008	70	0.012	0.013
Population density (thn. ppl/km2)	230	0.263	0.206	70	1.136	1.160
Panel B. Energy Sector						
Electricity price, industry (2015 RMB/kwh)	230	0.731	0.121	70	0.824	0.090
Electricity consumption (bn. kwh)	230	1523.186	910.841	70	1330.195	767.390
Electricity consumption, growth rate	207	0.034	0.052	63	0.019	0.046
Electricity generation, thermal (%)	230	0.735	0.249	70	0.767	0.211
Panel C. Environment & Climate						
Industrial wastegas control investment (mn. 2015 RMB)	220	1537.558	1777.099	70	949.830	767.358
Public environmental protection expenditure (% GDP)	176	0.015	0.007	56	0.012	0.007
CDD26	230	111.464	109.693	70	196.648	78.574
HDD14	230	1903.300	1324.311	70	1006.231	737.135

Note: The selection of ETS pilot regions is not random. The ETS pilot regions are more economically developed. Moreover, their local economies are also less energy-intense. Except for industrial electricity price, cooling degree days (CDD), and heating degree days (HDD), all variables are province-level yearly variables. Industrial electricity price, CDD, and HDD are province-level monthly variables. *Source:* CEIC Data, EPS China Statistics, and IEA.

5 Results

Regression results from the two-way-fixed effects and dynamic difference-in-differences models show participation in ETS pilots has led to statistically significant increases in SO2 emissions of about 5-7% from the ETS-treated facilities vis-á-vis the untreated facilities. Furthermore, the event study model suggests that this relative increase in SO_2 emissions is mainly driven by outcomes one year after the rollout of the ETS pilots and grows over time. Further analysis reveals that the estimated sample average treatment effect on the treated (ATT) is mainly driven by the 2013 cohort.

5.1 Effects of ETS Pilots on Treated Facilities' SO_2 Emission

Table 3 shows the regression results from the baseline two-way-fixed effects (TWFE) model shown in equation (1). On average, participation in the ETS pilots has led to a 5-7% increase in SO_2 emissions from the treated facilities compared to the counterfactuals. In other words, SO_2 emissions of the treated facilities have increased relative to those of untreated facilities by about 5-7% since the launch of the ETS pilots. This result is consistent with the post-ETS trends of SO_2 emissions shown in Figure 3.

Column (1) of Table 3 reports the regression results without controlling for the potential contaminating effects of the overlapping regulations. The coefficient of interest, $Treat \times Post$, is the DID estimator of the ATT of ETS pilots. This coefficient suggests that, on average, the ETS pilots have led to a relative increase in SO_2 emissions by about 5.4%.

Robust standard errors are reported in column (1) of Table 3, and cluster robust standard errors are reported in columns (2)-(5). Following Bertrand, Duflo, and Mullainathan (2004), standard errors in columns (2)-(5) are clustered at the prefecture city level, because environmental policies are typically implemented at this administrative level. A comparison of column (1) and (2) suggests that clustering standard errors at the prefecture city level does not change the significance of the point estimates.

Column (3) of Table 3 controls for seasonal changes in SO_2 emissions due to winter heating, by adding an interaction term between quarter fixed effects and a winter heating dummy. The winter heating dummy equals 1 if a prefecture city supplies a central heating during winter months and 0 otherwise. Generally speaking, cities to the north of the Huai River have central heating and cities to the south do not, as is discussed in Chen et al.

Table 3: Relationship between ETS Pilots and Treated Facilities' SO_2 Emissions

	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	0.054***	0.054***	0.053***	0.059***	0.067***	0.069***
	(0.013)	(0.018)	(0.018)	(0.019)	(0.021)	(0.022)
Ln(capacity)	-0.00014	-0.00014	-0.00014	-0.00023	-0.00066	-0.00067
	(0.0019)	(0.0021)	(0.0021)	(0.0020)	(0.0022)	(0.0022)
Ln(electricity price)	0.26***	0.26***	0.25***	0.24***	0.25***	0.25***
	(0.043)	(0.061)	(0.063)	(0.062)	(0.056)	(0.057)
Ln(power consumption)	0.10***	0.10**	0.10**	0.12***	0.12**	0.13**
	(0.036)	(0.045)	(0.044)	(0.042)	(0.054)	(0.052)
% Power generation, thermal	-0.012**	-0.012*	-0.012*	-0.012*	-0.018**	-0.019**
	(0.0056)	(0.0065)	(0.0065)	(0.0064)	(0.0075)	(0.0079)
Ln(HDD14)	0.0072***	0.0072***	0.0074***	0.0063***	0.0053**	0.0057**
	(0.0018)	(0.0020)	(0.0019)	(0.0020)	(0.0024)	(0.0025)
Ln(CDD26)	-0.0025	-0.0025	-0.00019	-0.0012	0.00091	0.0015
	(0.0016)	(0.0020)	(0.0024)	(0.0020)	(0.0020)	(0.0020)
Constant	-0.40	-0.40	-0.41	-0.51*	-0.48	-0.52
	(0.26)	(0.32)	(0.32)	(0.30)	(0.38)	(0.36)
N	11759	11759	11759	11759	11759	11759
R-Square	0.3011	0.3011	0.3039	0.3120	0.3240	0.3374
Plant FE	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Central Heating Dummy × Quarter FE			✓			
APPC Key Zone Dummy × Year-Quarter FE				✓		
Region Dummies × Year-Quarter FE					✓	
APPC Key Zone × Region × Year-Quarter FE						✓

Notes: Standard errors are reported in parentheses. Robust standard errors are reported in column (1), and cluster-robust standard errors are reported in columns (2)-(5). The clustering is by prefecture cities, because environmental regulations are typically enforced at the city level (Bertrand, Duflo, and Mullainathan, 2004). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Model in column (3) controls for differences in seasonal changes in SO_2 emissions due to winter heating. The central heating dummy equals 1 if a city provides centralized heating to residents and businesses and 0 otherwise. Model in column (4) controls for the effects of the ultra-low emissions (ULE) standard (see Section 2.2 for details), by adding interaction terms between the Air Pollution Prevention and Control (APPC) Key Zone dummy and year-quarter fixed effects. Model in column (5) controls for the effects of several power sector regulations (see Section 2.2) that more aggressively promote energy efficiency improvements in thermal power plants in eastern and central provinces in China. Model in column (6) simultaneously controls for the effects of the ULE standard and power sector regulations that affect facilities' energy efficiencies, by adding a triple interaction term between APPC Key Zone dummy, region dummies, and year-quarter fixed effects.

Seven facilities in two Inner Mongolia cities were dropped, because they were reported to have voluntarily joined the Beijing ETS in 2015 but no further information can be found on whether they remained in it since then. Ten facilities in Fujian Province were dropped from the treated group due to violation of the parallel trend assumption (see Panel (c) of Figure 5).

(2013). The addition of this interaction term only results in minor changes the estimated treatment effect.

Column (4) of Table 3 presents the regression coefficients of the baseline DID model shown in equation (1) in Section 3. As discussed, this model flexibly controls for the effects of the ULE standard on SO_2 emission intensities. To the extent that differences in local stringency of the ULE standard fully account for the variation in facility-level SO_2 emission intensities, changes in SO_2 emissions have a one-to-one correspondence with changes in output. A comparison of columns (2) with (4) shows that controlling for effects of ULE standards increases the estimated treatment effect by about half a percentage point.

To control for the effects of power sector policies that improve facilities' energy efficiency (the "Work Plan"), column (5) adds an interaction term between dummy variables for eastern and central provinces and year-quarter fixed effects. As discussed in Section 2.2, these regulations could affect facilities' coal consumption intensity. The results suggest that conditioning on this source of variation in facility-level SO_2 emission intensities increases the estimated treatment effect to 6.7%.

Finally, the model in column (6) simultaneously controls for the effects of the ULE standard and the "Work Plan" by adding triple interaction terms between APPC Key Zone dummy, region dummies, and year-quarter fixed effects. The results are virtually unchanged compared the those of the model in column (5).

Across all model specifications shown in Table 3, the coefficients on industrial-use electricity price and electricity consumption at the province level are significant and positive. These two energy supply- and demand-side variables are arguably exogenous to individual facilities. Moreover, local electricity consumption is a function of economic activities, energy intensity, population, and other factors that affect energy demand. Under the assumption that SO_2 emissions is a linear function of output, the coefficients on log electricity price can be interpreted as the price elasticity of electricity supply. Consistent with the fact that price and output are regulated in the power sector in China (Goulder et al., 2022), the estimated price elasticity of supply is inelastic in all columns of Table 3.

The coefficient on the fraction of power generation from thermal sources (coal, natural gas, and oil) is significant and negative in all columns of Table 3. This variable captures local dependence on fossil fuels. Since recent air pollution regulations more heavily impact regions with more thermal power generation facilities, high shares of fossil fuel facilities could be a proxy for higher levels of impact from air pollution regulations or higher levels of local environmental enforcement efforts. Lastly, the coefficient on heating degree days (HDD) is statistically significant and positive, suggesting that colder climate is correlated with higher energy demand for heating, and thus, responsible for higher SO_2 emissions.

5.2 Robustness of the Baseline Results

To evaluate the robustness of the baseline results, I test whether the estimated coefficients are sensitive to alternative definitions of treatment timing, potential spillover effects, and using different sub-samples. Results from the robustness tests are presented in Table A2.

Alternative Treatment Timing As mentioned in Section 2.1, the start of the first compliance period is defined as the time of treatment to avoid anticipation effects in the study. As Duan (2015, 2017) discuss, firms were in the consultation process leading up to the launch of ETS pilots, which implies that they could have formed expectations of how the pilots were to be implemented and could have planned their responses accordingly. Nevertheless, column (2) of Table A2 tests the robustness of TWFE model results to using the opening dates of carbon markets as the timing of treatment. In comparison with column (1), which uses the beginning of the first compliance period as the time of treatment, as in the baseline models, the estimated treatment effect of the ETS pilots does not change at all.

Spillover Effects An implicit assumption for the causal interpretation of the estimated ATT is the stable unit treatment value (SUTVA) assumption embedded in the Neyman-Rubin Causal Model. SUTVA requires the potential outcome of a given facility to be unaffected by the treatment status of any other facility. For this assumption to hold, SO_2 emissions of untreated facilities must not be affected by the effect of ETS pilots on the treated facilities. In other words, there must be no spillover effects. A potential violation of this assumption is the shifting of electricity production from the treated to untreated facilities. To the extent that this type of spillover has occurred, the estimated ATT will be downward biased and, thus, provides a lower bound of the true effect.

Under the hypothesis that the shifting of electricity production is more likely to occur within a regional power grid, I expect to find a smaller treatment effect when comparing treated facilities only to untreated facilities in the same regional power grid. As column (3) of Table A2 shows, the estimated treatment effect increases rather than decreases, after adding interaction terms between regional power grid dummies and year-quarter fixed effects. However, I acknowledge that this test does not rule out potential violation of SUTVA, especially in the long run. This is because untreated facilities are more likely to be affected via general equilibrium effects in the long run.

Alternative Samples Selection Criteria Next, I provide evidence that the results are robust to changes to the sample. In column (4) of Table A2, I show that results of the baseline model are robust to dropping ten facilities that have completely retired since the start of the ETS pilots. Furthermore, I show in column (5) that the results of the baseline model are also robust to dropping ten facilities in Fujian. As Goodman-Bacon (2021) discusses, the traditional TWFE estimator may be biased when it assigns large weights to comparisons between late-treated and early-treated facilities. To assess the magnitude of this potential bias, facilities in Fujian are dropped because they are treated three years after the rest of the treated facilities. As column (5) shows, the results do not change significantly, indicating that such bias, if exists, is minimal. To further investigate components within the TWFE estimator, I perform the decomposition described in Goodman-Bacon (2021). As Figure A11 in Appendix D suggests, the weights assigned to the late versus early comparison are too small to affect the TWFE estimator.

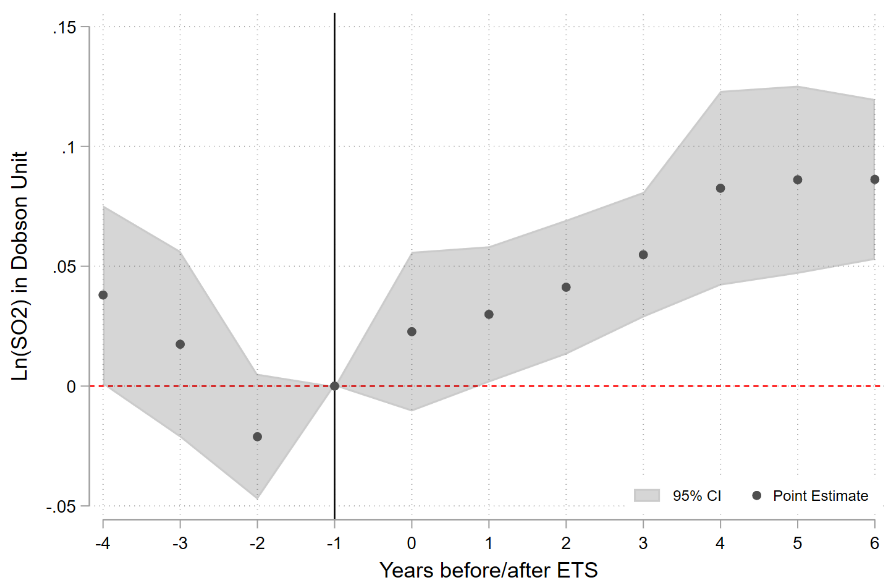
Lastly, I show in column (6) of Table A2 that the results of the TWFE model are also robust to using a smaller sample of much larger thermal power generation facilities, selected using more strict criterion. This sample contains isolated large facilities, whose capacities are at least 2,600 megawatts or account for 75% of all coal-fired power generation capacity within a 35 km radius (see Appendix C for details).

5.3 Assessing the Parallel Trend Assumptions using Dynamic Difference in Differences

To provide indirect support for the parallel trend assumption and to shed light on the dynamic effect of ETS pilots on large power plants' SO_2 emissions, I estimate the event study (or dynamic DID) model shown in equation (2) in Section 3. Figure 4 provides evidence that, conditional on a vector of covariates, the differences between the average annual SO_2 emissions of the treated and untreated facilities are not statistically different from zero prior to the rollout of ETS pilots.

Furthermore, Figure 4 shows that the effects of the ETS pilots on treated facilities' SO_2 emissions become significantly one year after the launch of ETS pilots. This timing coincides with the completion of the first compliance period (2013-2014) in Beijing, Tianjin, Shanghai, Shenzhen, Guangdong, and Chongqing. This delayed effect is also consistent with the hypothesis that learning takes time. As the covered facilities complete the first compliance period, they accumulate knowledge, develop capacity, and adjust their production and investment plans based on their experience with the ETS pilots. Moreover, the estimated treatment effect of the ETS pilots increases over time, which is consistent with the hypothesis that capital-intensive abatement technologies take time to build.

Figure 4: Dynamic Effects of ETS Pilots on Treated Facilities' SO2 Emissions

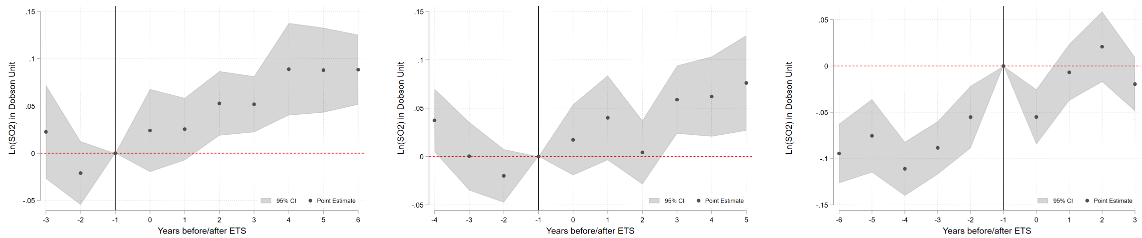


Notes: Estimated causal effects of ETS pilots on treated facilities' SO2 emissions based on the event study model (see Equation (2) in Section 3) are plotted above. The dependent variable is log SO2 emissions, and the control variables include province-level energy market and weather variables such as log electricity price, log electricity consumption, percentage of electricity generated from thermal sources, log investment in industrial waste gas control, HDD (14°C), CDD (26°C), and interaction terms between dummies for air pollutant prevention and control key zones and year-fixed effects.

Next, I estimate the heterogeneous treatment effects of ETS pilots on each treatment cohort and report the results in Figure 5. A treatment cohort or a timing group (to borrow the language of Sun and Abraham (2020) and Callaway and Sant'Anna (2020)) consists of facilities whose treatment began in the same period. Using the start of the first compliance period as the timing of treatment, I group facilities into three cohorts. The 2013 cohort consists of 39 facilities located in Beijing, Tianjin, Shanghai, Shenzhen, Guangdong, and Chongqing. The 2014 cohort consists of 11 facilities located in Hubei province, and the 2016 cohort includes ten facilities covered by the Fujian ETS.

Figure 5 yields two important takeaways. First, the pre-trends in SO_2 emissions of the 2013 and 2014 cohorts, conditional on the control variables, are not statistically different

Figure 5: Heterogeneity in Dynamic Effects of Pilot ETS on Treated Facilities' SO2 Emissions



(a) ETS (2013) (b) Hubei (c) Fujian

Notes: ETS pilots are grouped by the timing of treatment, defined as the start of the first compliance period. The 2013 cohort includes facilities in Beijing, Tianjin, Shanghai, Shenzhen, Guangdong, Chongqing. The 2014 cohort includes 11 facilities in the Hubei ETS. The 2016 cohort consists of 10 facilities in Fujian. The control group in all three event study models above is the untreated facilities. The dependent variable is log SO2 emissions, and the control variables include province-level energy market and weather variables such as log electricity price, log electricity consumption, percentage of electricity generated from thermal sources, log investment in industrial waste gas control, HDD (14°C), CDD (26°C), and interaction terms between dummies for air pollutant prevention and control key zones and year-fixed effects.

from those of the untreated facilities. However, the parallel trend assumption is violated for the facilities in Fujian. As a result, the main event study results shown above in Figure 4 are produced without the ten facilities in Fujian. Second, the treatment effects are mainly driven by the 2013 cohort, especially two to three years after treatment. The lag in treatment effects is more pronounced for the 11 facilities in Hubei.

5.4 Falsification Tests

To further assess the validity of my baseline results, I perform placebo tests by randomly assigning ETS treatment to untreated facilities. The 278 untreated facilities in the non-ETS regions are randomly split into two groups. One group is assigned the placebo ETS treatment (placebo group), and the other acts as the control group. Since the rollout of ETS did not occur simultaneously, the random assignment of treatment timing is carried out in two ways. First, all facilities in the placebo group are assigned the treatment timing of the first quarter of 2013, when the first compliance period began for all ETS pilots except for Hubei and Fujian. Second, three treatment timings that match the launch of carbon exchanges, the second quarter of 2013 (Shenzhen), the fourth quarter of 2013 (Beijing, Tianjin, Shanghai, Guangdong), and the second quarter of 2014 (Hubei and Chongqing) were randomly assigned to facilities in the placebo group.

Table 4 presents the results of the placebo tests. In columns (1) and (2), the timing of treatment of the placebo group is the first quarter of 2013. In columns (3) and (4), three treatment timings are randomly assigned to facilities in the placebo group. In addition, models in columns (2) and (4) include an interaction term between the dummy variable for APPC key zones and year-quarter fixed effects to control for effects of the ULE standards. The estimated placebo effects are not statistically different from zero, which lends credence to the main results of this study.

Table 4: Placebo Treatment Effects of ETS Pilots on SO2 emissions

	(1)	(2)	(3)	(4)
Placebo × Post	0.0076	0.0069	0.0073	0.0070
	(0.010)	(0.010)	(0.011)	(0.011)
Ln(capacity)	0.0011	0.00052	0.0011	0.00050
	(0.0019)	(0.0018)	(0.0019)	(0.0018)
Ln(electricity price)	0.27***	0.27***	0.27***	0.27***
	(0.063)	(0.070)	(0.063)	(0.070)
Ln(power consumption)	0.089**	0.10**	0.089**	0.10**
	(0.044)	(0.040)	(0.044)	(0.040)
% Power generation, thermal	-0.012*	-0.024***	-0.012*	-0.024***
	(0.0073)	(0.0067)	(0.0073)	(0.0067)
Ln(HDD14)	0.0097***	0.011***	0.0097***	0.011***
	(0.0026)	(0.0029)	(0.0026)	(0.0029)
Ln(CDD26)	-0.0046**	-0.0030	-0.0046**	-0.0030
	(0.0023)	(0.0023)	(0.0023)	(0.0023)
Constant	-0.32	-0.34	-0.32	-0.34
	(0.31)	(0.28)	(0.31)	(0.28)
N	11119	11119	11119	11119
R-Square	0.3146	0.3435	0.3147	0.3435
Plant FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
APES Zones × Year-Quarter		✓		✓

Notes: The 278 untreated facilities in the non-ETS regions are randomly split into two groups. One group is assigned the placebo ETS treatment (placebo group), and the other acts as the control group. Since the rollout of ETS did not occur at the same time, the random assignment of treatment timing is carried out in two ways. First, all facilities in the placebo group are assigned the treatment timing of the 2013q1, when the first compliance period began for all ETS pilots except for Hubei and Fujian. Second, three treatment timings that match the launch of carbon exchanges, 2013q2 (Shenzhen), 2013q4 (Beijing, Tianjin, Shanghai, Guangdong), and 2014q2 (Hubei and Chongqing) were randomly assigned facilities in the placebo group.

5.5 An Economic Explanation for the Relationship between ETS and Power Plants' SO2 Emissions

To explain the main empirical findings of the TWFE and event study models, I present a stylized model adapted from Goulder et al. (2022). This model explicitly examines the interactions between ETS pilots that regulate CO_2 emission intensities and overlapping environmental regulations that regulate SO_2 emission intensities. I argue that the implicit output subsidy from the ETS pilots could explain the relative increase in SO_2 emissions by the ETS-treated facilities compared with the untreated facilities. In addition, as ETS facilities become cleaner and more fuel-efficient due to capital-intensive investments in abatement technologies, the positive effects of ETS pilots on output are further strengthened.

Why Do SO2 Emissions of Treated Facilities Increase Relative to the Untreated?

To see how the implicit output subsidy of ETS pilots affects thermal power generation facilities' output, I begin by defining the profit maximization problem of a representative facility (shown below). Assume that this facility is a price-taker in both the electricity market and the carbon market.

$$\max_{q_i, c_i, s_i} \pi_i = \bar{p}\bar{q_i} + p(q_i - \bar{q_i}) - C_0 - C(q_i, c_i, s_i) - \tau(c_i - \bar{\mu_c} q_i) \tag{3}$$

$$s.t. \quad \frac{s_i}{q_i} \leqq \bar{\mu_s} \tag{4}$$

$\bar{p}$ and $\bar{q_i}$ are government-guaranteed electricity price and output, and p is market price for electricity. As Goulder et al. (2022) describe, China has a three-tiered electricity pricing scheme. In the first two tiers, power generators face fixed electricity prices ("guaranteed price") for output up to certain thresholds ("guaranteed hours"), which government regulators set. When power generators' output exceeds the thresholds, they can sell the excess electricity at market price (the third tier). Given that the guaranteed prices are typically higher than market prices, the guaranteed hours are typically exhausted, so I assume that $q_i > \bar{q_i}$ in what follows.

C_0 is a fixed cost that captures any lump sum capital investments. The variable cost is a function of output q_i, carbon emissions c_i, and SO_2 emissions s_i. The cost function is assumed to be increasing in output and decreasing in emissions over the relevant range, so $C_q > 0$,

$C_c < 0$, and $C_s < 0$, where subscripts denote the partial derivatives of the cost function. Furthermore, assume the cost function is convex in output, $C_{qq} > 0$ and that the marginal cost of output increases as more CO_2 and SO_2 emissions are abated, $C_{qc} < 0$, $C_{qs} < 0$. For simplicity, assume that the marginal cost of abating CO_2 emissions and SO_2 emissions are independent of each other, $C_{cs} = C_{sc} = 0$. Note that the average abatement cost is decreasing in output due to upfront fixed-cost investments required to upgrade, retrofit, or replace existing boiler units and pollution control technologies, or in the form of overhead cost of improving management and production processes to run the existing facilities more efficiently.

τ is the price of carbon, determined by supply and demand of carbon emission credits in the ETS pilots. $\bar{\mu_c}$ is the mandated carbon emission intensity, and each thermal power generation facility's actual carbon emission intensity is given by c_i/q_i. Facilities can sell carbon credits for profit if $c_i - \bar{\mu_c} q_i < 0$, but will need to purchase credits if the opposite is true. $\bar{\mu_s}$ is the command-and-control style SO_2 emission intensity standard that applies to all facilities.

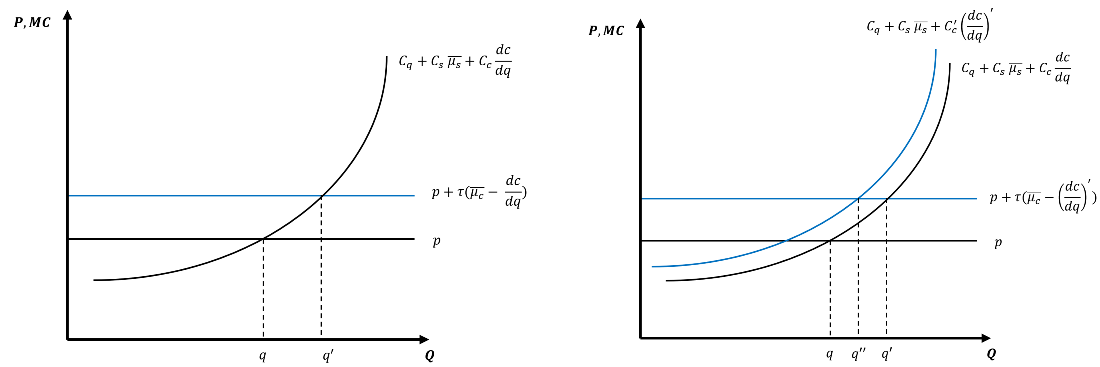
Under the assumption that $C_s < 0$, firms will always choose to emit as much SO_2 as regulation permits, so $\frac{s_i^*}{q_i^*} = \bar{\mu_s}$ for optimal SO_2 emission level and output. I can therefore replace s_i in equation (3) with $\bar{\mu_s} q_i$. To determine the optimal output for specific values of $\bar{\mu_c}$ and $\bar{\mu_s}$, I then take the total derivative of the profit function and set $\frac{d\pi}{dq} = 0$ (see Appendix D: Mechanism for details), this yields:

$$p + \tau(\bar{\mu_c} - \frac{dc}{dq}) = C_q + C_e \bar{\mu_s} + C_c \frac{dc}{dq} \tag{5}$$

The facility subscript i is suppressed in equation (5) for brevity. The left-hand side is the marginal revenue from producing an additional unit of output. It consists of two parts, the market price of electricity and an extra term $\tau(\bar{\mu_c} - \frac{dc}{dq})$ that represents a *net* implicit output subsidy when $\bar{\mu_c} - \frac{dc}{dq} > 0$ and a *net* carbon tax otherwise. The right-hand side is the marginal cost of producing an additional unit of output. It is made up of three terms. The second and third terms capture the marginal cost of reducing SO2 and CO2 emissions.

Under the assumptions that $C_{qq} > 0$ and $C_{qc} < 0$, $C_{qs} < 0$, the marginal cost curve (the right-hand side of equation (5)) is upward sloping in output. The slope of the marginal benefit curve (the left-hand side of equation (5)) depends on the relationship between marginal emission intensity $\frac{dc}{dq}$ and output. For simplicity, assume that $\frac{dc}{dq}$ is constant so that marginal emission intensity equals average emission intensity. This assumption is plausibly realistic because emission rates are primarily determined by the type of technology that facilities use, for example, the combustion technology of boilers.

Figure 6: Predicted Effects of ETS on Treated Facilities' Output



(a) Non-binding

(b) Binding

As Figure 6 shows, the effects of ETS pilots on facilities' output depend on their carbon emission intensities. Panel (a) depicts one of two possible corner solutions when carbon emission intensity is not binding[22]. In this case, the representative facility's initial carbon emission intensity is already lower than the mandated intensity, $\frac{dc}{dq} < \bar{\mu_c}$. Therefore, the TPS amounts to an implicit output subsidy and raises the marginal revenue curve, which leads to an increase in output from q to q'.

It is worth noting that SO_2 emission intensity standards are held constant in the analysis above. As Figure A9 in the Appendix shows, ceteris paribus, more stringent SO_2 emission standards reduce facilities' output. This prediction is supported by Table A6 in the Appendix, which shows that the ULE standard has led to a reduction in SO_2 emissions from facilities located in the APPC Key Zones vis-á-vis facilities located elsewhere. Therefore, the correct interpretation of the result above in light of co-existing SO_2 emission standards is that ETS pilots increase the output of the treated facilities relative to the untreated facilities subject to the same SO_2 emission standards, if their carbon emission intensities are below the mandated level.

[22]The other corner solution is when the marginal abatement cost the first unit of CO_2 emissions of a facility is higher than the equilibrium carbon price, which means it is cheaper for the facility to not abate any CO_2 emissions but rely on purchasing carbon emission credits to meet the mandated emission intensity. In this case, TPS amounts to a carbon tax and reduces output.

Panel (b) of Figure 6 shows one of two possible interior solutions when the mandated carbon emission intensity is binding. In this case, the TPS induces a covered facility to reduce its carbon emission intensity below the mandated level. This has two effects. First, it provides an implicit output subsidy and shifts the marginal benefit curve up. Second, it shifts the marginal cost curve up as a result of the increased marginal cost of abating CO_2 emissions because $C_{qc} < 0$. When the increase in marginal benefit is greater than that of the marginal cost, the facility's output increases from q to q'', although the increase is not as large as in the previous case. However, a second possible interior solution exists. A facility's marginal cost of abating CO_2 emissions could be high enough that it does not reduce its emission intensity below the mandated intensity. In this scenario, the TPS reduces marginal benefit by placing a carbon tax and/or increases marginal cost due to carbon emission abatement. As a result, output decreases.

To sum up, I show that the ETS pilots could increase the output of two types of treated facilities relative to the untreated. And for a given SO_2 emission intensity standard, increases in output lead to increases in SO_2 emissions. On average, this increase in SO_2 emissions may be observed in data if the selected facilities are more likely to have relatively low carbon emission intensities or marginal abatement cost of carbon emissions. To provide some suggestive evidence, I show in Table A1 in the Appendix that the treated facilities in my sample have about twice the capacity, more boiler units and more fuel-efficient units (i.e., units with supercritical and ultra-supercritical combustion technologies), and lower shares of outdated and retired capacity compared with other facilities inside or outside the ETS pilot regions.

Why Do the SO2 Emissions of Treated Facilities Increase over Time vis-á-vis the Untreated?

As mentioned in Section 2, although thermal power generation facilities can reduce CO_2 emission intensities in the short run by switching electricity production from inefficient boiler units to more efficient ones, abatement of CO_2 emissions in the long run likely requires capital-intensive investments. For example, thermal power generation facilities can increase fuel efficiency by retrofitting and upgrading existing boiler units with better technologies. They can also retire inefficient units and build new ones.

Since building new equipment takes time due to governmental approval and construction processes, it takes time for their effects to manifest. As the new equipment is gradually commissioned, a facility' carbon emission intensity decreases relative to the mandated level, further increasing its marginal benefit via the implicit output subsidy provided by the TPS system. Furthermore, the government provides financial incentives to thermal power generation facilities that have installed new equipment with high fuel efficiency and low emission intensity[23]. The incentives include a 0.001 RMB/kwh increase in guaranteed electricity price, an additional 200 guaranteed hours per year, and a 50% discount on pollution charges. These financial incentives could further encourage facilities to increase output. Last but not least, Fowlie (2010) shows that co-existing command and control policies could further strengthen the investment incentives of ETS (a cap and trade system on NOx called RECLAIM in her context) and encourage power plant managers to take more capital-intensive abatement options.

6 Conclusion

This study provides a timely *ex post* evaluation of the ETS pilots in China, not long after the launch of the national ETS in July 2021. By exploiting differences in the temporal and spatial coverage of the ETS pilots vis-á-vis the ULE standards and other power sector regulations, I causally estimate the sample average treatment effect on the treated (ATT) of the ETS pilots on SO_2 emissions of large and relatively isolated thermal power generation facilities, using staggered and dynamic difference-in-differences (DID) frameworks.

Contrary to the belief that the ETS pilots can reduce the emissions of co-pollutants (Li et al., 2018; Zhang and Zhang, 2020; Cai et al., 2016), I document three important empirical findings. First, although SO_2 emissions declined significantly for all facilities during the study period (2010-2019), SO_2 emissions of treated facilities increased by about 5% relative to those of untreated facilities as a result of their participation in the ETS pilots. Second, the estimated ATT of the ETS pilots on SO_2 emissions increases to about 6-7% upon controlling for the influence of ULE standards and other power sector regulations on facilities' SO_2 emission rates. Third, the relative increase in SO_2 emissions of treated facilities grows over time.

To provide an economic explanation of the empirical findings, I present a stylized model based on Goulder et al. (2022). The model shows that the ETS pilots based on TPS could

[23] Ministry of Ecology and Environment. 2015. "Work Plan for the Comprehensive Implementation of Ultra-Low Emissions and Energy Efficiency Upgrades of Coal-Fired Power Generation Facilities" (in Chinese). Accessed Sept 15, 2021. https://www.mee.gov.cn/gkml/hbb/bwj/201512/t20151215_319170.htm

encourage facilities with relatively low initial carbon emission intensities or marginal abatement cost to increase output and thus emit more SO_2 relative to a counterfactual world in which the ETS pilots had not been established. Furthermore, based on the findings of Fowlie (2010), I postulate that capital-intensive investments in carbon emission abatement technologies explain the continued relative increase in SO_2 emissions over time and that overlapping command-and-control regulations could have strengthened the incentives for the treated facilities to invest in abatement technologies.

The observed relative increase in SO_2 emissions from the ETS-treated facilities points to a low-hanging fruit for policymakers in China. Introducing policy measures to offset the TPS system's incentives to increase output and thus SO_2 emissions could bring co-benefits in terms of public health and improved environmental quality (Kou et al., 2021; Almond and Zhang, 2021; Li et al., 2018; Dong et al., 2015). SO_2 emissions are widely known to harm human respiratory systems, particularly for people with pre-existing respiratory conditions, such as asthma (Sims, Leggett, and Myla, 2020; Smargiassi et al., 2009). In addition, SO_2 can form acid rain that damages sensitive ecosystems (Powe and Willis 2004; U.S. EPA[24]). Therefore, reducing SO_2 emissions from the ETS-covered facilities with relatively low carbon emission intensities or marginal abatement costs could reap health and environmental benefits.

Furthermore, the focus of this study on the thermal power generation sector makes the empirical findings informative for the national ETS that covers the same sector. Thermal power generation facilities in the coastal regions in Eastern China are generally more technologically advanced (Pang and Duan, 2016), they are therefore more likely to have relatively low carbon emission intensities or marginal abatement costs compared to facilities in the central and western parts of China. Therefore, a national ETS based on TPS could increase electricity output and emissions of co-pollutants such as SO_2 in the more densely populated eastern provinces vis-á-vis other regions. In this context, the empirical findings of this study call for measures to alleviate this potential issue. One possible policy response is designing separate emission intensity standards for different regions or power generation facilities using different combustion and cooling technologies. Another potential policy response could be to restrict the trading of carbon emission credits between facilities located in different regions.

Lastly, due to the lack of high-quality publicly available facility-level data on emissions and operation, this study relies on SO_2 emission estimates derived from a NASA Aura/OMI satellite SO_2 data product. Although OMI satellite data products provide good alternatives to ground-based pollutant emission measures, they also have one major limitation: accurate

[24]`https://www.epa.gov/so2-pollution/sulfur-dioxide-basics`

and credible estimates of SO_2 emissions can only be obtained for large and relatively isolated stationary sources such as thermal power generation facilities, which means that the empirical results of this study may not extend to smaller facilities. Future empirical work can extend the analyses in this study when new and credible facility-level air pollutant emissions data becomes available. Moreover, future work that examines the ETS pilots' effects on firms' performance, abatement actions, and adoption of cleaner technologies is also needed to shed light on the mechanisms through which carbon markets impact firm behaviours.

References

Almond, Douglas and Shuang Zhang. 2021. "Carbon-Trading Pilot Programs in China and Local Air Quality." In *AEA Papers and Proceedings*, vol. 111. 391–95.

Anderson, Soren T, Ian WH Parry, James M Sallee, and Carolyn Fischer. 2011. "Automobile fuel economy standards: Impacts, efficiency, and alternatives." *Review of Environmental Economics and Policy* 5 (1):89–108.

Anderson, Soren T and James M Sallee. 2011. "Using loopholes to reveal the marginal cost of regulation: The case of fuel-economy standards." *American Economic Review* 101 (4):1375–1409.

Athey, Susan and Guido W Imbens. 2021. "Design-based analysis in difference-in-differences settings with staggered adoption." *Journal of Econometrics* .

Bailey, Martha J and Andrew Goodman-Bacon. 2015. "The War on Poverty's experiment in public medicine: Community health centers and the mortality of older Americans." *American Economic Review* 105 (3):1067–1104.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2004. "How Much Should We Trust Differences-in-Differences Estimates?" *Quarterly Journal of Economics* 119 (1).

Borysyak, K and X Jaravel. 2017. "Revisiting event study designs, with an application to the estimation of the marginal propensity to consume." Tech. rep.

Burtraw, Dallas, Josh Linn, Karen Palmer, and Anthony Paul. 2014. "The costs and consequences of clean air act regulation of CO2 from power plants." *American Economic Review* 104 (5):557–62.

Busse, Meghan R and Nathaniel O Keohane. 2007. "Market effects of environmental regulation: coal, railroads, and the 1990 Clean Air Act." *The RAND Journal of Economics* 38 (4):1159–1179.

Cai, Bofeng, Xin Bo, Lixiao Zhang, James K Boyce, Yanshen Zhang, and Yu Lei. 2016. "Gearing carbon trading towards environmental co-benefits in China: Measurement model and policy implications." *Global Environmental Change* 39:275–284.

Calel, Raphael. 2020. "Adopt or innovate: Understanding technological responses to cap-and-trade." *American Economic Journal: Economic Policy* 12 (3):170–201.

Calel, Raphael and Antoine Dechezleprêtre. 2016. "Environmental policy and directed technological change: evidence from the European carbon market." *Review of economics and statistics* 98 (1):173–191.

Callaway, Brantly and Pedro H.C. Sant'Anna. 2020. "Difference-in-Differences with Multiple Time Periods." *Journal of Econometrics* (xxxx):1–31. URL `https://doi.org/10.1016/`

j.jeconom.2020.12.001.

Cao, Jing, Mun S Ho, Rong Ma, and Fei Teng. 2021. "When carbon emission trading meets a regulated industry: Evidence from the electricity sector of China." *Journal of Public Economics* 200:104470.

Carlson, Curtis, Dallas Burtraw, Maureen Cropper, and Karen L Palmer. 2000. "Sulfur dioxide control by electric utilities: What are the gains from trade?" *Journal of political Economy* 108 (6):1292–1326.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. 2019. "The Effect of Miminum Wages on Low-Wage Jobs." *Quarterly Journal of Economics* 134 (3):1405–1454.

Chan, H Ron, B Andrew Chupp, Maureen L Cropper, and Nicholas Z Muller. 2018. "The impact of trading on the costs and benefits of the Acid Rain Program." *Journal of Environmental Economics and Management* 88:180–209.

Chang, Shiyan, Xi Yang, Haotian Zheng, Shuxiao Wang, and Xiliang Zhang. 2020. "Air quality and health co-benefits of China's national emission trading system." *Applied Energy* 261:114226.

Chen, Yihsu, Makoto Tanaka, and Afzal S Siddiqui. 2018. "Market power with tradable performance-based CO2 emission standards in the electricity sector." *The Energy Journal* 39 (6).

Chen, Yuyu, Avraham Ebenstein, Michael Greenstone, and Hongbin Li. 2013. "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* 110 (32):12936–12941.

Cui, Jingbo, Chunhua Wang, Junjie Zhang, and Yang Zheng. 2021. "The effectiveness of China's regional carbon market pilots in reducing firm emissions." *Proceedings of the National Academy of Sciences* 118 (52):e2109912118.

Cui, Jingbo, Junjie Zhang, and Yang Zheng. 2018. "Carbon pricing induces innovation: evidence from China's regional carbon market pilots." In *AEA Papers and Proceedings*, vol. 108. 453–57.

Curtis, E Mark. 2018. "Who loses under cap-and-trade programs? the labor market effects of the nox budget trading program." *Review of Economics and Statistics* 100 (1):151–166.

de Chaisemartin, Clément and Xavier D'Haultfœuille. 2020. "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects." *American Economic Review* 110 (9):2964–2996.

Dechezleprêtre, Antoine, Daniel Nachtigall, and Frank Venmans. 2018. "The joint impact of the European Union emissions trading system on carbon emissions and economic performance." .

Deschenes, Olivier, Michael Greenstone, and Joseph S Shapiro. 2017. “Defensive investments and the demand for air quality: Evidence from the NOx budget program.” *American Economic Review* 107 (10):2958–89.

Dong, Huijuan, Hancheng Dai, Liang Dong, Tsuyoshi Fujita, Yong Geng, Zbigniew Klimont, Tsuyoshi Inoue, Shintaro Bunya, Minoru Fujii, and Toshihiko Masui. 2015. “Pursuing air pollutant co-benefits of CO2 mitigation in China: A provincial leveled analysis.” *Applied Energy* 144:165–174.

Duan, Maosheng. 2015. “From Carbon Emissions Trading Pilots to National System: The Road Map for China.” *Carbon & Climate Law Review* 9 (3):231–242.

———. 2017. “Key Issues in Designing China’s National Carbon Emissions Trading System.” *Economics of Energy and Environmental Policy* 6 (2):55–72.

Ellerman, A Denny, Paul L Joskow, Richard Schmalensee, Juan-Pablo Montero, and Elizabeth M Bailey. 2000. *Markets for clean air: The US acid rain program.* Cambridge University Press.

Fabra, Natalia and Mar Reguant. 2014. “Pass-through of emissions costs in electricity markets.” *American Economic Review* 104 (9):2872–99.

Fioletov, V. E., C. A. McLinden, N. Krotkov, and C. Li. 2015. “Lifetimes and Emissions of SO2 from Point Sources Estimated from OMI.” *Geophysical Research Letters* 42:1969–1976.

Fioletov, V. E., C. A. McLinden, N. Krotkov, M. D. Moran, and K. Yang. 2011. “Estimation of SO2 Emissions Using OMI Retrievals.” *Geophysical Research Letters* 38 (21):1–5.

Fischer, Carolyn. 2001. “Rebating Environmental Policy Revenues: Output-Based Allocations and Tradable Performance Standards.” *Resources for the Future Discussion Paper* (July 2001):1–22. URL `http://www.rff.org/Documents/RFF-DP-01-22.pdf`.

Fischer, Carolyn, Biao Mao, and Daniel Shawhan. 2018. “Trade between mass-and rate-based regulatory regimes: Bad for emissions?” *Energy Economics* 73:326–336.

Fowlie, Meredith. 2010. “Emissions Trading , Electricity Restructing, and Investment in Pollution Abatement.” *American Econmic Review* 100 (June):837–869.

Fowlie, Meredith, Stephen P. Holland, and Erin T. Mansur. 2012. “What Do Emissions Markets Deliver and to Whom? Evidence from Southern California’s NOX Trading Program.” *American Economic Review* 102 (2):965–993.

Fowlie, Meredith and Jeffrey M Perloff. 2013. “Distributing pollution rights in cap-and-trade programs: are outcomes independent of allocation?” *Review of Economics and Statistics* 95 (5):1640–1652.

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics* 225 (2):254–277.

Goulder, Lawrence H, Xianling Long, Jieyi Lu, and Richard D Morgenstern. 2022. "China's unconventional nationwide CO2 emissions trading system: Cost-effectiveness and distributional impacts." *Journal of Environmental Economics and Management* 111:102561.

Goulder, Lawrence H., Richard D. Morgenstern, Clayton Munnings, and Jeremy Schreifels. 2017. "China's national carbon dioxide emission trading system: An introduction." *Economics of Energy and Environmental Policy* 6 (2):1–18.

Hahn, Robert W and Gordon L Hester. 1989. "Marketable permits: lessons for theory and practice." *Ecology Law Quarterly* 16 (2):361–406.

Huang, Jingru, Jie Shen, Lu Miao, and Weikun Zhang. 2021. "The effects of emission trading scheme on industrial output and air pollution emissions under city heterogeneity in China." *Journal of Cleaner Production* 315:128260.

ICAP. 2020. "Emissions Trading Worldwide: Status Report 2020." Tech. rep., International Carbon Action Partnership.

Ito, Koichiro and James M Sallee. 2018. "The economics of attribute-based regulation: Theory and evidence from fuel economy standards." *Review of Economics and Statistics* 100 (2):319–336.

Jacobsen, Mark R. 2013. "Evaluating US fuel economy standards in a model with producer and household heterogeneity." *American Economic Journal: Economic Policy* 5 (2):148–87.

Jaraite-Kažukauske, Jurate and Corrado Di Maria. 2016. "Did the EU ETS make a difference? An empirical assessment using Lithuanian firm-level data." *The Energy Journal* 37 (1).

Joskow, Paul L, Richard Schmalensee, and Elizabeth M Bailey. 1998. "The market for sulfur dioxide emissions." *American Economic Review* :669–685.

Karplus, Valerie J. 2021. "China's CO2 Emissions Trading System: History, Status, and Outlook." Tech. Rep. June.

Karplus, Valerie J., Junjie Zhang, and Jinhua Zhao. 2021. "Navigating and Evaluating the Labyrinth of Environmental Regulation in China." *Review of Environmental Economics and Policy* 15 (2):300–322.

Karplus, Valerie J., Shuang Zhang, and Douglas Almond. 2018. "Quantifying coal power plant responses to tighter SO2 emissions standards in China." *Proceedings of the National Academy of Sciences* 115 (27):7004–7009.

Karplus, Valerie J and Xiliang Zhang. 2017. "Incentivizing firm compliance with China's national emissions trading system." *Economics of Energy & Environmental Policy* 6 (2):73–86.

Kerr, Suzi and Richard G Newell. 2003. "Policy-induced technology adoption: Evidence from the US lead phasedown." *The Journal of Industrial Economics* 51 (3):317–343.

Klier, Thomas and Joshua Linn. 2016. "The effect of vehicle fuel economy standards on technology adoption." *Journal of Public Economics* 133:41–63.

Kou, Po, Ying Han, Xiaoyuan Qi, and Yuanxian Li. 2021. "Does China's policy of carbon emission trading deliver sulfur dioxide reduction co-benefits?" *Environment, Development and Sustainability* :1–22.

Li, Can, Nickolay A. Krotkov, Peter J.T. Leonard, Simon Carn, Joanna Joiner, Robert J.D. Spurr, and Alexander Vasilkov. 2020. "Version 2 Ozone Monitoring Instrument SO2 product (OMSO2 V2): New anthropogenic SO2 vertical column density dataset." *Atmospheric Measurement Techniques* 13 (11):6175–6191.

Li, Can, Qiang Zhang, Nickolay A. Krotkov, David G. Streets, Kebin He, Si Chee Tsay, and James F. Gleason. 2010. "Recent large reduction in sulfur dioxide emissions from Chinese power plants observed by the Ozone Monitoring Instrument." *Geophysical Research Letters* 37 (8):1–6.

Li, Mingwei, Da Zhang, Chiao-Ting Li, Kathleen M Mulvaney, Noelle E Selin, and Valerie J Karplus. 2018. "Air quality co-benefits of carbon pricing in China." *Nature Climate Change* 8 (5):398–403.

Linn, Joshua. 2008. "Technological modifications in the nitrogen oxides tradable permit program." *The Energy Journal* 29 (3).

———. 2010. "The effect of cap-and-trade programs on firms' profits: Evidence from the Nitrogen Oxides Budget Trading Program." *Journal of Environmental Economics and management* 59 (1):1–14.

Linn, Joshua, Erin Mastrangelo, and Dallas Burtraw. 2014. "Regulating greenhouse gases from coal power plants under the clean air act." *Journal of the Association of Environmental and Resource Economists* 1 (1/2):97–134.

Liu, F., Q. Zhang, D. Tong, B. Zheng, M. Li, H. Huo, and K. B. He. 2015. "High-resolution inventory of technologies, activities, and emissions of coal-fired power plants in China from 1990 to 2010." *Atmospheric Chemistry and Physics* 15 (23):13299–13317.

Lu, Zifeng, David G. Streets, Benjamin De Foy, and Nickolay A. Krotkov. 2013. "Ozone monitoring instrument observations of interannual increases in SO2 emissions from Indian coal-fired power plants during 2005-2012." *Environmental Science and Technology*

47 (24):13993–14000.

Marin, Giovanni, Marianna Marino, and Claudia Pellegrin. 2018. "The impact of the European Emission Trading Scheme on multiple measures of economic performance." *Environmental and Resource Economics* 71 (2):551–582.

Martin, Ralf, Laure B De Preux, and Ulrich J Wagner. 2014. "The impact of a carbon tax on manufacturing: Evidence from microdata." *Journal of Public Economics* 117:1–14.

Mclinden, Chris A, Vitali Fioletov, Mark W Shephard, Nick Krotkov, Can Li, Randall V Martin, Michael D Moran, and Joanna Joiner. 2016. "Space-based detection of missing sulfur dioxide sources of global air pollution." *Nature Geoscience* 9 (May).

Ministry of Ecology and Environment, PRC. 2016. "The First Biannual Report on Climate Change of the People's Republic of China." Tech. rep.

Mo, Jian Lei, Paolo Agnolucci, Mao Rong Jiang, and Ying Fan. 2016. "The impact of Chinese carbon emission trading scheme (ETS) on low carbon energy (LCE) investment." *Energy Policy* 89 (2016):271–283. URL `http://dx.doi.org/10.1016/j.enpol.2015.12.002`.

Nichols, Albert L. 1997. "Lead in gasoline." *Economic Analyses at EPA: Assessing Regulatory Impact* 49.

Pang, Tao and Maosheng Duan. 2016. "Cap setting and allowance allocation in China's emissions trading pilot programmes: special issues and innovative solutions." *Climate Policy* 16 (7):815–835. URL `https://doi.org/10.1080/14693062.2015.1052956`.

Powe, Neil A and Kenneth G Willis. 2004. "Mortality and morbidity benefits of air pollution (SO2 and PM10) absorption attributable to woodland in Britain." *Journal of environmental management* 70 (2):119–128.

Schmalensee, Richard and Robert N Stavins. 2013. "The SO2 allowance trading system: the ironic history of a grand policy experiment." *Journal of Economic Perspectives* 27 (1):103–22.

Sims, Jennifer N, Sophia S Leggett, and Anitha Myla. 2020. "Industrial Emissions and Asthma Prevalence." *European Journal of Environment and Public Health* 4 (2):em0046.

Smargiassi, Audrey, Tom Kosatsky, John Hicks, Céline Plante, Ben Armstrong, Paul J Villeneuve, and Sophie Goudreau. 2009. "Risk of asthmatic episodes in children exposed to sulfur dioxide stack emissions from a refinery point source in Montreal, Canada." *Environmental Health Perspectives* 117 (4):653–659.

Stavins, Robert N. and Robert C. Stowe, editors. 2020. *Subnational Climate Change Policy in China*. Cambridge, Massachusetts: Harvard Project on Climate Agreements.

Sun, Liyang and Sarah Abraham. 2020. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics* .

Tian, Ruijie. 2020. "Emissions Trading Schemes and Directed Technological Change: Evidence from China." Tech. rep.

Yan, Yaxue, Xiaoling Zhang, Jihong Zhang, and Kai Li. 2020. "Emissions trading system (ETS) implementation and its collaborative governance effects on air pollution: the China story." *Energy Policy* 138:111282.

Yang, Hang, Yongxin Zhang, Chenghang Zheng, Xuecheng Wu, Linghong Chen, Joshua S Fu, and Xiang Gao. 2018. "Cost estimate of the multi-pollutant abatement in coal-fired power sector in China." *Energy* 161:523–535.

Yeh, Sonia, Dallas Burtraw, Thomas Sterner, and David Greene. 2021. "Tradable performance standards in the transportation sector." *Energy Economics* 102:105490.

Zaklan, Aleksandar. 2021. "Coase and Cap-and-Trade: Evidence on the Independence Property from the European Carbon Market." .

Zhang, Duan, Yihsu Chen, and Makoto Tanaka. 2018. "On the effectiveness of tradable performance-based standards." *Energy Economics* 74:456–469.

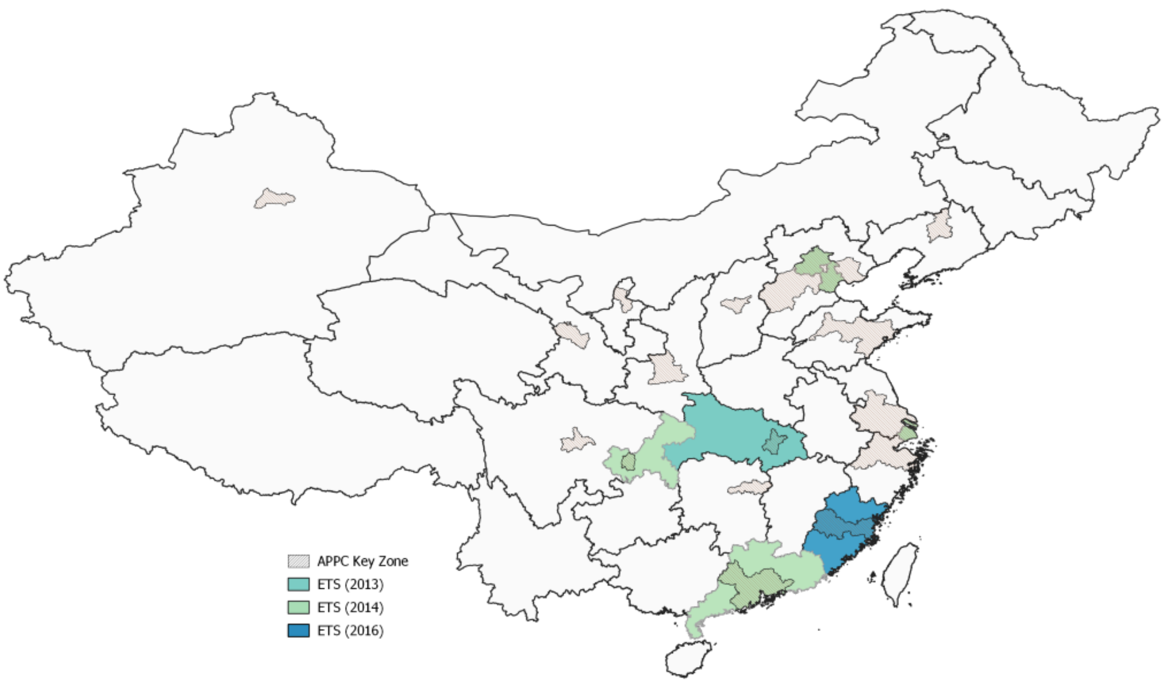
Zhang, Hui and Bing Zhang. 2020. "The Unintended Impact of Carbon Trading of China's Power Sector." *Energy Policy* 147:111876.

Zhang, Qianyun, Jin Li, Zhang Yao, Zhao Dong, and Chen Liu. 2020. "A dataset for trade information during 2014-2017 of seven pilot carbon markets in China." *China Science Data* .

Zhu, Junming, Yichun Fan, Xinghua Deng, and Lan Xue. 2019. "Low-carbon innovation induced by emissions trading in China." *Nature Communications* 10 (1):1–8. URL `http://dx.doi.org/10.1038/s41467-019-12213-6`.

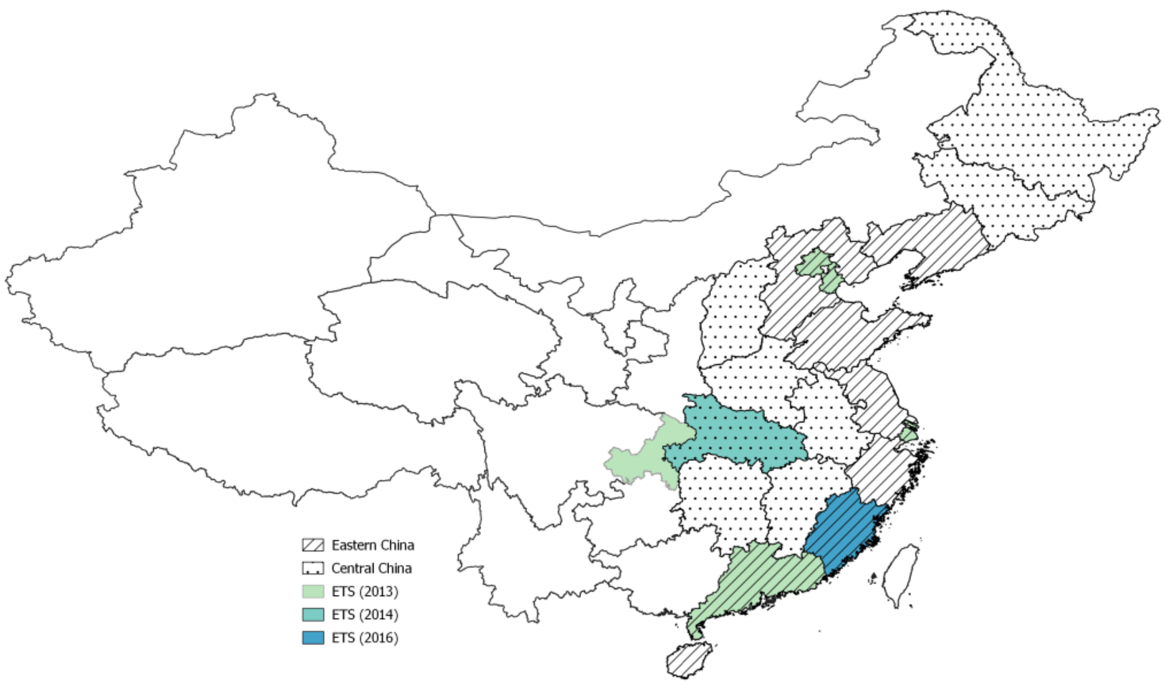
Appendix A: Additional Tables and Figures

Figure A1: Geographic Overlap between ETS Pilots and APPC Key Zones



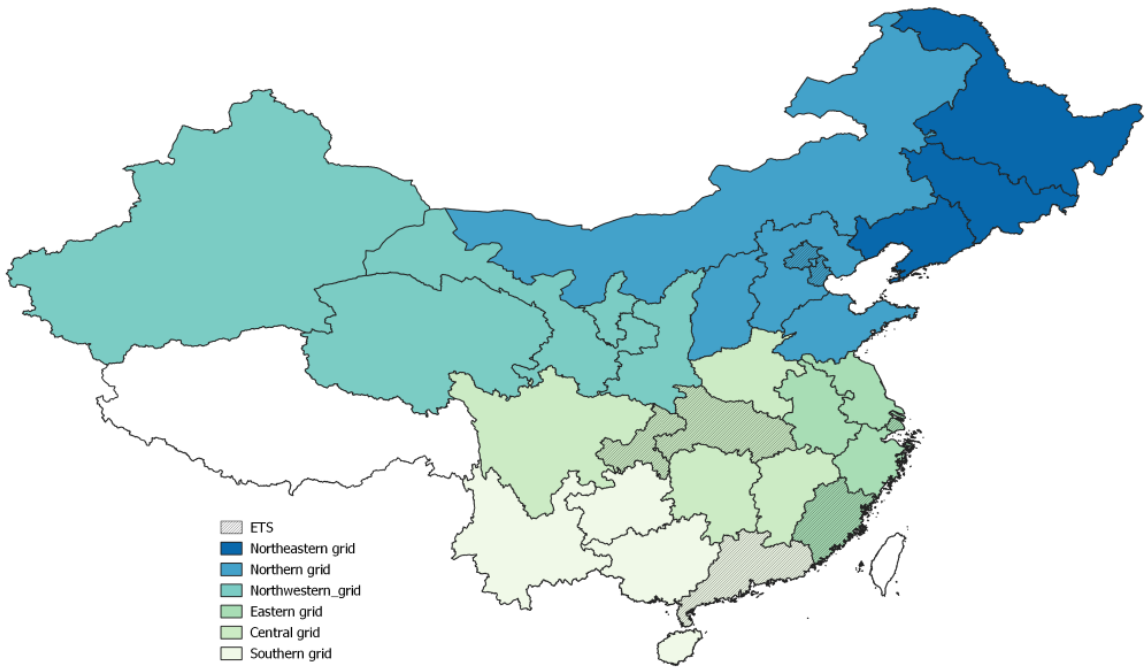
Notes: 47 prefecture cities were designated as the Atmospheric Pollutant Prevention and Control (APPC) Key Zones in the "12th Five-Year Plan for Atmospheric Pollution Prevention and Control in Key Zones". As discussed in Section 2.2, thermal power generation facilities in APPC Key Zones are subject to more stringent air pollutants emissions standards.

Figure A2: Geographic Overlap between ETS Pilots and Eastern, Central, and Western Provinces in China



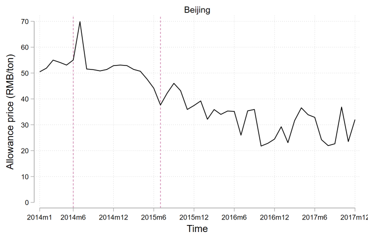
Notes: Eleven eastern Provinces include Beijing, Tianjin, Hebei, Liaoning, Shandong, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, and Hainan. Eight central Provinces include Heilongjiang, Jilin, Shanxi, Anhui, Hubei, Hunan, Henan, and Jiangxi. As discussed in Section 2.2, the "Work Plan" sets different regional deadlines for thermal power generation facilities to meet the energy efficiency standards. The deadline for facilities located in 11 eastern and eight central provinces to complete their upgrades and meet the standards are 2017 and 2018, respectively, and the deadline for facilities elsewhere in China is 2020.

Figure A3: Location of ETS Pilots in Relation to Regional Power Grids

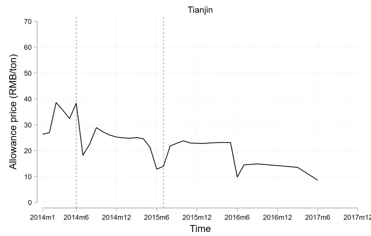


Notes: In 2002, the national power grid in China was broken into 6 regional grids (as shown above) in an effort to introduce competition into electricity transmission and distribution. Of the 8 ETS pilots, Beijing and Tianjin belong to the Northern China Grid, Shanghai and Fujian to the Eastern China Grid, Shenzhen and the rest of Guangdong to the Southern China Grid, and Chongqing and Hubei to the Western China Grid.

Figure A4: Carbon Emission Credit Price by ETS Pilots, 2014-2017

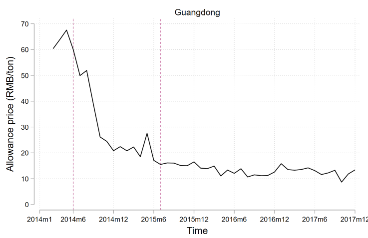


(a) Beijing

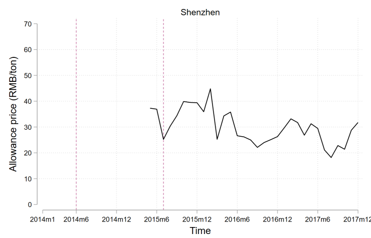


(b) Tianjin

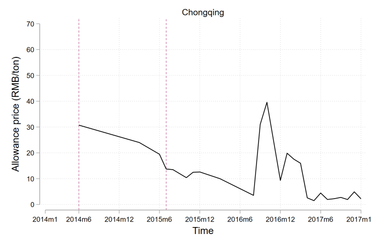
(c) Shanghai



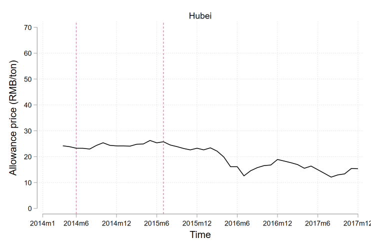
(d) Guangdong



(e) Shenzhen



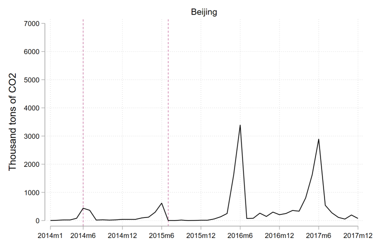
(f) Chongqing



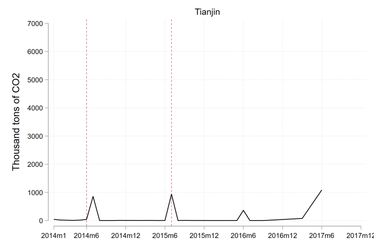
(g) Hubei

Notes: Volume-weighted monthly average nominal spot carbon credit prices are shown in figures above. The first dashed vertical line in each panel marks the first carbon emission credit submission deadlines for Beijing, Tianjin, Shanghai, Shenzhen, and Guangdong. Actual submission deadlines varied between May and July. The second dashed vertical line in each panel marks the first carbon emission credit submission deadlines for Hubei and Chongqing and the second carbon credit submission deadlines for the other five ETS pilots. *Source:* Author's calculation based on Zhang et al. (2020)

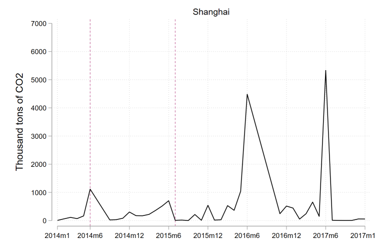
Figure A5: Carbon Emission Credit Trading Volumes by ETS Pilots, 2014-2017



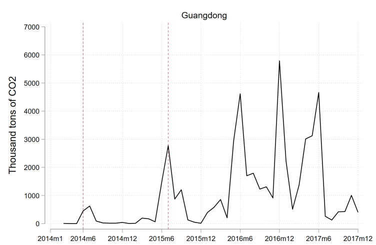
(a) Beijing



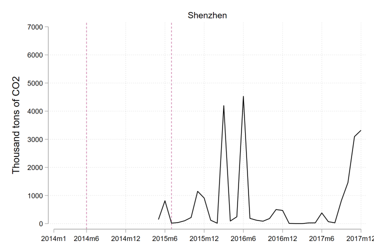
(b) Tianjin



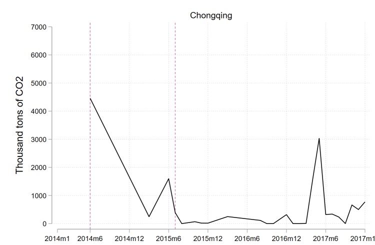
(c) Shanghai



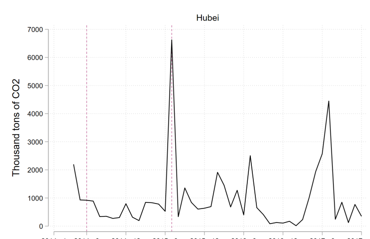
(d) Guangdong



(e) Shenzhen



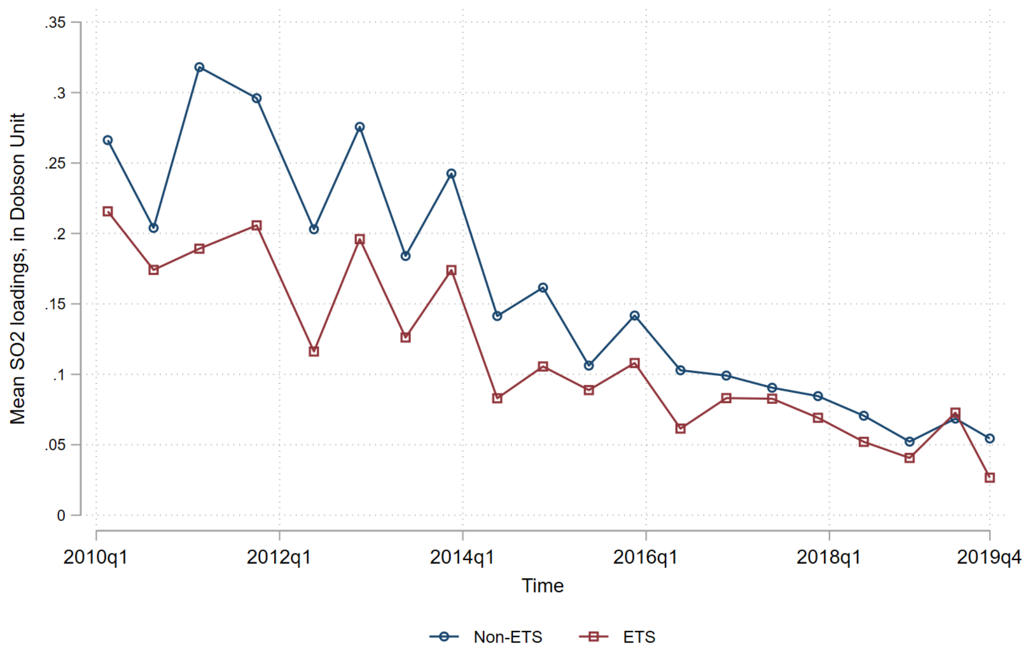
(f) Chongqing



(g) Hubei

Notes: Allowance traded are in thousand tons of CO_2. The first dashed vertical line in each panel marks the first carbon emission credit submission deadlines for Beijing, Tianjin, Shanghai, Shenzhen, and Guangdong. Actual submission deadlines varied between May and July. The second dashed vertical line in each panel marks the first carbon emission credit submission deadlines for Hubei and Chongqing and the second carbon credit submission deadlines for the other five ETS pilots. *Source:* Author's calculation based on Zhang et al. (2020)

Figure A6: Reduction in SO2 Emissions from Coal-Fired Power Generation Facilities



Notes: Quarterly group average SO2 emissions are plotted above. The ETS line is plotted using quarterly averages of SO2 emissions from 50 large and isolated coal-fired power generation facilities covered by the ETS pilots, excluding ten facilities in Fujian and seven facilities in Inner Mongolia. The Non-ETS line is plotted using quarterly averages of 278 facilities located outside the ETS pilots. *Source:* Author's calculation based on NASA Aura/OMI OMSO2e.

Table A1: Summary Statistics of Coal-Fired Power Plants

	ETS			Non-ETS		
Panel A. All Facilities	obs	mean	sd	obs	mean	sd
Capacity in 2012	145	956.228	1095.227	693	764.209	796.413
Number of units	145	3.434	1.848	693	3.149	1.817
Share of outdated capacity	145	0.271	0.473	693	0.193	0.409
Share of capacity built between 2009-2019	145	0.454	0.602	693	0.535	0.706
Share of capacity built between 2014-2019	145	0.166	0.427	693	0.197	0.561
Share of capacity retired between 2009-2019	145	0.148	0.358	693	0.042	0.181
Share of capacity retired between 2014-2019	145	0.120	0.312	693	0.033	0.161
Subcritical (dummy)	145	0.624	0.452	693	0.583	0.479
Supercritical (dummy)	145	0.159	0.330	693	0.187	0.376
Ultra-supercritical (dummy)	145	0.118	0.285	693	0.111	0.299
CFB (dummy)	145	0.016	0.120	693	0.005	0.069
Panel B. Large and Isolated Facilities						
Capacity in 2012	67	1797.224	1370.928	279	1551.405	1345.239
Number of units	67	4.047	2.060	279	3.443	1.649
Share of outdated capacity	67	0.216	0.408	279	0.139	0.308
Share of capacity built between 2009-2019	67	0.450	0.609	279	0.444	0.787
Share of capacity built between 2014-2019	67	0.084	0.224	279	0.116	0.628
Share of capacity retired between 2009-2019	67	0.110	0.276	279	0.036	0.153
Share of capacity retired between 2014-2019	67	0.087	0.254	279	0.035	0.151
Subcritical (dummy)	67	0.588	0.424	279	0.617	0.437
Supercritical (dummy)	67	0.174	0.315	279	0.167	0.326
Ultra-supercritical (dummy)	67	0.164	0.307	279	0.119	0.288
CFB (dummy)	67	0.020	0.128	279	0.003	0.034

Notes: Panel A presents summary statistics of 838 coal-fired power generation facilities. Panel B is the same as Table 1 in Section 4. It presents summary statistics of 346 large and isolated coal-fired power generation facilities. Large and isolated coal-fired power generation facilities are defined in Section 4. Capacity shown in the first row of each panel is in megawatt (MW). Outdated capacity is defined as subcritical boiler units with 200 MW or less capacity, based on the "Action Plan for Energy Efficiency and Pollution Reduction Upgrade in the Coal-Fired Power Generation Sector" (2014-2020). Percentages of outdated, new, and retired capacity, shown in the second to the seventh row of each panel, are in decimal points and are calculated by dividing capacity of each category into facilities' total capacity in 2012. Four dummy variables in rows 8-11 of each panel indicate shares of facilities' capacity with each specific combustion technology. CFB stands for circulating fluidized bed. For a given capacity, boiler units' carbon emission intensity decreases from subcritical, to super-critical and ultra-supercritical technologies. Although CFB technology reduces emissions of co-pollutants such as SO2, the CFB technologies adopted in China tend to have higher CO2 emission intensities than the subcritical boiler units (see Table 1 in Goulder et al. 2022). *Source:* Author's calculation based on Global Energy Monitor - Global Coal Plant Tracker.

Table A2: Robustness of Relationship between ETS Pilots and Treated Facilities' SO_2 Emissions

	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	0.054***	0.054***	0.051***	0.055***	0.049***	0.052**
	(0.018)	(0.018)	(0.017)	(0.015)	(0.018)	(0.022)
Ln(capacity)	-0.00014	0.000042	0.00039	-0.00011	0.0055**	-0.00025
	(0.0021)	(0.0021)	(0.0018)	(0.0021)	(0.0022)	(0.0025)
Ln(electricity price)	0.26***	0.26***	0.21***	0.26***	0.26***	0.23***
	(0.061)	(0.061)	(0.066)	(0.060)	(0.062)	(0.055)
Ln(power consumption)	0.10**	0.100**	0.18***	0.11**	0.086*	0.11**
	(0.045)	(0.045)	(0.056)	(0.044)	(0.045)	(0.047)
% power generation, thermal	-0.012*	-0.013*	0.0068	-0.014**	-0.013*	-0.0038
	(0.0065)	(0.0065)	(0.0068)	(0.0054)	(0.0067)	(0.0080)
Ln(HDD14)	0.0072***	0.0073***	0.0094***	0.0070***	0.0071***	0.0080***
	(0.0020)	(0.0020)	(0.0031)	(0.0019)	(0.0021)	(0.0023)
Ln(CDD26)	-0.0025	-0.0024	-0.0017	-0.0021	-0.0030	-0.0011
	(0.0020)	(0.0020)	(0.0028)	(0.0020)	(0.0021)	(0.0021)
Constant	-0.40	-0.39	-1.22***	-0.42	-0.32	-0.55
	(0.32)	(0.32)	(0.41)	(0.32)	(0.32)	(0.33)
N	11759	11759	11759	12079	11359	8199
R-Square	0.3011	0.3016	0.3830	0.2973	0.3105	0.2715
Plant FE	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓		✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Grid × Year-Quarter			✓			

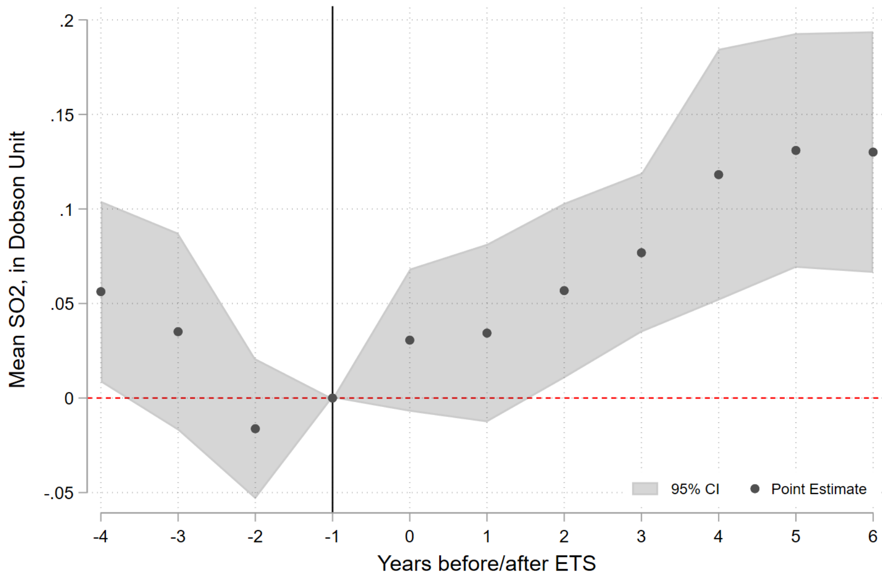
Notes:

Cluster-robust standard errors are reported in parentheses. The clustering is by prefecture cities, because environmental regulations are typically enforced at the city level (Bertrand, Duflo, and Mullainathan, 2004).

*** Significance at the 1% level; ** Significance at the 5% level; * Significance at the 10% level.

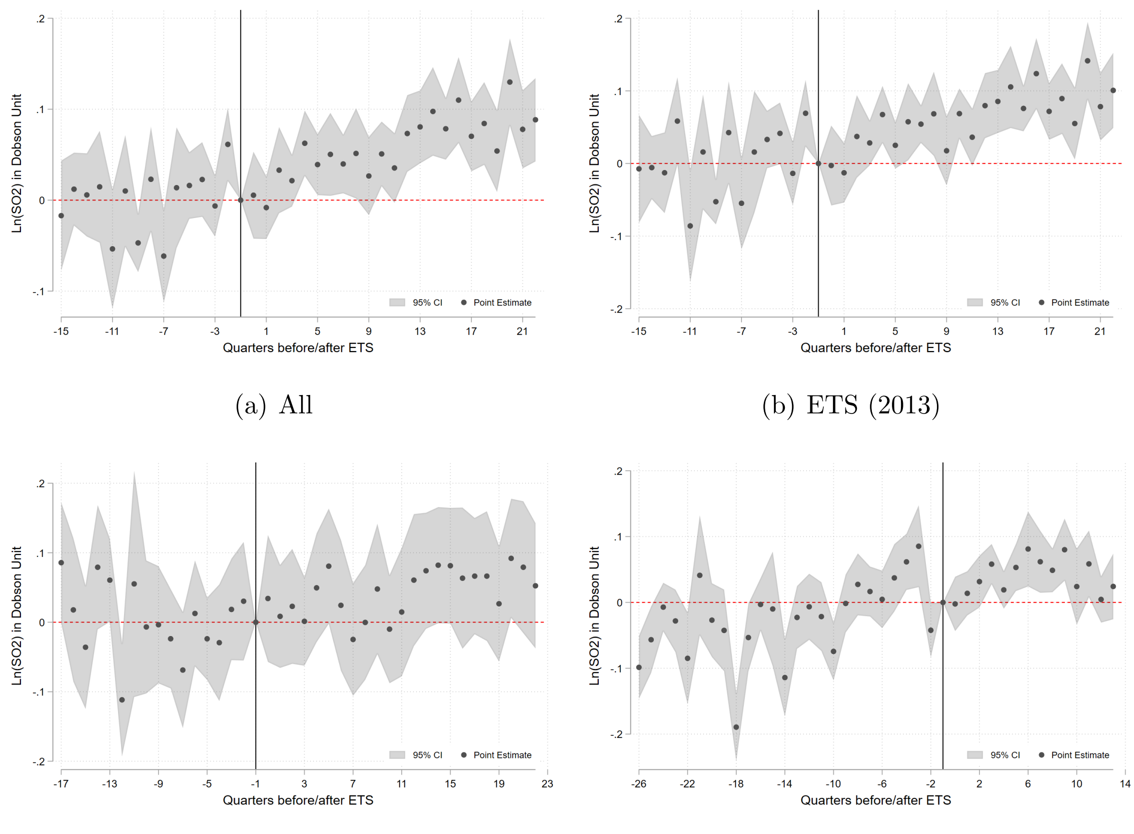
Column (1) reports the baseline results from the two-way fixed effect (TWFE) difference-in-differences (DID) model. Column (2) tests the robustness of the baseline results to an alternative definition of treatment timing. Instead of using the start of the first compliance period, treatment timing is defined as the quarter in which carbon exchanges opened in column (2). Column (3) tests the robustness of the baseline results to spatial spillover effects – the shifting of electricity production from the treated facilities to untreated facilities within the same regional power grid. Column (4) tests the robustness of the baseline results to the shutting down of facilities, by dropping facilities that have fully retired after 2013. Column (5) shows that the baseline results is virtually unchanged by dropping 10 facilities in Fujian, which provides evidence that the potential bias from comparing the late-treated group to the early-treated group (Goodman-Bacon, 2021) is minimal. Finally, column (6) shows that baseline results are robust to using a smaller sample of ultra-large facilities (see Section 4 for details).

Figure A7: Robustness of Dynamic Effects of ETS Pilots on SO2 Emissions by Coal-Fired Power Plants to Functional Form, Linear Model



Notes: Estimated causal effects of ETS pilots on treated facilities' SO2 emissions based on the event study model (see Equation (2) in Section 3) are plotted above. Unlike Figure 4, the dependent variable and control variables are in levels. Note that due to staggered rollout of the ETS pilots, the 4th lead term is estimated using the comparison of the 11 facilities in Hubei with the untreated facilities, and the last lag term is estimated using the 39 facilities in Beijing, Tianjin, Shanghai, Guangdong, Shenzhen, and Chongqing.

Figure A8: Dynamic Effects of ETS Pilots on Coal-Fired Power Plants, Quarterly Data



(a) All

(b) ETS (2013)

(c) Hubei

(d) Fujian

Notes: Estimated causal effects of ETS pilots on treated facilities' SO2 emissions based on the event study model (see Equation (2) in Section 3) are plotted above. The dependent variable is log SO2 emissions, and the control variables include province-level energy market and weather variables such as log electricity price, log electricity consumption, percentage of electricity generated from thermal sources, log investment in industrial waste gas control, HDD (14 °C), CDD (26 °C), and interaction terms between dummies for air pollutant prevention and control key zones and year-fixed effects.

The 2013 cohort consists of 39 facilities in Beijing, Tianjin, Shanghai, Guangdong, Shenzhen, and Chongqing. The 2014 cohort consists of 11 facilities in Hubei. The 2016 cohort consists of ten facilities in Fujian.

Unlike Figure 4, which pools four quarters into one period, the model above uses quarterly SO2 emissions. As Bailey and Goodman-Bacon (2015) mention, the point estimates from this specification are less precise. Nevertheless, the results shown above are consistent with those of the baseline event study model shown in Section 5.

Table A3: Sensitivity of TWFE Model Results to Covariates

	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	0.057***	0.054***	0.053***	0.043**	0.043**	0.043**
	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Ln(capacity)	-0.00052	-0.00014	-0.00011	-0.00052		
	(0.0023)	(0.0021)	(0.0021)	(0.0023)		
Ln(electricity price)	0.22***	0.26***	0.26***			
	(0.060)	(0.061)	(0.062)			
Ln(power consumption)	0.096**	0.10**	0.10**			
	(0.047)	(0.045)	(0.044)			
% Power generation, thermal	-0.013**	-0.012*	-0.012*			
	(0.0062)	(0.0065)	(0.0065)			
Ln(HDD14)	0.0054***	0.0072***				
	(0.0019)	(0.0020)				
Ln(CDD26)	-0.0012	-0.0025				
	(0.0022)	(0.0020)				
Ln(wastegas control investment)	-0.017***					
	(0.0043)					
Constant	-0.23	-0.40	-0.37	0.24***	0.24***	0.24***
	(0.34)	(0.32)	(0.32)	(0.016)	(0.0097)	(0.0097)
N	10919	11759	11759	11759	11759	11759
R-Square	0.3187	0.3011	0.2992	0.2823	0.2822	0.2822
Plant FE	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	
Year-Quarter FE	✓	✓	✓	✓	✓	✓

Notes: Standard errors are clustered at prefecture city level.

*** Significance at the 1% level; ** Significance at the 5% level; * Significance at the 10% level.

Table A4: Robustness of TWFE Model Results to Functional Form Assumption, Linear Model

	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	0.081***	0.081***	0.080***	0.086***	0.10***	0.10***
	(0.020)	(0.028)	(0.028)	(0.029)	(0.035)	(0.035)
Capacity (MW)	-0.000012	-0.000012	-0.000012	-0.000010	-0.000011	-0.000011
	(0.000018)	(0.000018)	(0.000018)	(0.000017)	(0.000017)	(0.000016)
Electricity price (2015 RMB/kwh)	0.46***	0.46***	0.46***	0.43***	0.40***	0.41***
	(0.091)	(0.13)	(0.13)	(0.13)	(0.11)	(0.12)
Power consumption (GWh)	0.0000082	0.0000082	0.0000080	0.000026	0.000060	0.000062
	(0.000033)	(0.000039)	(0.000039)	(0.000039)	(0.000041)	(0.000042)
% Power generation, thermal	-0.019**	-0.019**	-0.019**	-0.019**	-0.026**	-0.028**
	(0.0081)	(0.0092)	(0.0092)	(0.0092)	(0.011)	(0.012)
HDD14	-0.0000064	-0.0000064	-0.0000024	-0.0000048	-0.000011	-0.000012
	(0.0000079)	(0.000010)	(0.000017)	(0.000010)	(0.0000099)	(0.0000097)
CDD26	-0.00018***	-0.00018***	-0.00013*	-0.00014***	-0.000050	-0.000030
	(0.000043)	(0.000056)	(0.000075)	(0.000055)	(0.000052)	(0.000053)
Constant	0.065	0.065	0.062	0.051	0.078	0.094
	(0.11)	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)
N	11759	11759	11759	11759	11759	11759
R-Square	0.2764	0.2764	0.2770	0.2861	0.3004	0.3140
Plant FE	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓		✓	✓	✓
Year-Quarter FE	✓	✓	✓			
APPC Key Zone × Year-Quarter FE				✓		
Region × Year-Quarter FE					✓	
Central Heating × Quarter FE			✓			
APPC Key Zone × Region × Year-Quarter FE						✓

Notes:

Standard errors are reported in parentheses. Robust standard errors reported in column (1) and cluster-robust standard errors are reported in columns (2)-(5). The clustering is by prefecture cities, because environmental regulations are typically enforced at the city level (Bertrand, Duflo, and Mullainathan, 2004).

*** Significance at the 1% level; ** Significance at the 5% level; * Significance at the 10% level.

Model in column (3) controls for differences in seasonal changes in SO_2 emissions due to winter heating. The central heating dummy equals 1 if a city provides centralized heating to local residents and businesses and 0 otherwise. Model in column (4) controls for the effects of the ultra-low emissions (ULE) standard (see Section 2 for details), by adding interaction terms between the Air Pollution Prevention and Control (APPC) Key Zone dummy and year-quarter fixed effects. Model in column (5) controls for the effects of several power sector regulations (see Section 2) that more aggressively promote energy efficiency improvements in thermal power plants in eastern and central provinces in China. Model in column (6) simultaneously controls for the effects of the ULE standard and power sector regulations that affect facilities' energy efficiencies, by adding a triple interaction term between APPC Key Zone dummy, region dummies, and year-quarter fixed effects. Seven facilities in two Inner Mongolia cities and ten facilities in Fujian Province were dropped from the treated group.

Table A5: Robustness of TWFE Model Results to Frequencies of SO2 Emissions Data

	(1)	(2)	(3)
Treat × Post	0.042***	0.058***	0.038**
	(0.016)	(0.021)	(0.016)
Ln(capacity)	-0.00069	-0.00033	-0.00083
	(0.0017)	(0.0022)	(0.0017)
Ln(electricity price)	0.24***	0.30***	0.33***
	(0.055)	(0.079)	(0.071)
Ln(power consumption)	0.12***	0.14**	0.14***
	(0.043)	(0.057)	(0.043)
% Power generation, thermal	-0.014***	-0.019***	-0.012**
	(0.0050)	(0.0068)	(0.0054)
Ln(HDD14)	0.0065***	0.00021	-0.032**
	(0.0020)	(0.0018)	(0.014)
Ln(CDD26)	-0.0018	-0.012***	0.020***
	(0.0019)	(0.0025)	(0.0054)
Constant	-0.52*	0.59	-0.53*
	(0.31)	(0.41)	(0.32)
N	13799	40727	3450
R-Square	0.2910	0.1895	0.4656
Plant FE	✓	✓	✓
Quarter FE	✓	✓	
Time FE	✓	✓	✓

Notes: All SE are clustered at prefecture city level. Column (1) runs the baseline TWFE specification on OMI SO2 data averaged to quarters, as in the baseline TWFE results shown in Table 3. Column (2) regresses the same TWFE model using monthly SO2 data. Column (3) uses yearly SO2 data and does not include quarter or month fixed effects.

Figure A9: Predicted Effects of Tightening SO2 Emission Standard on Power Generation Firms' Output

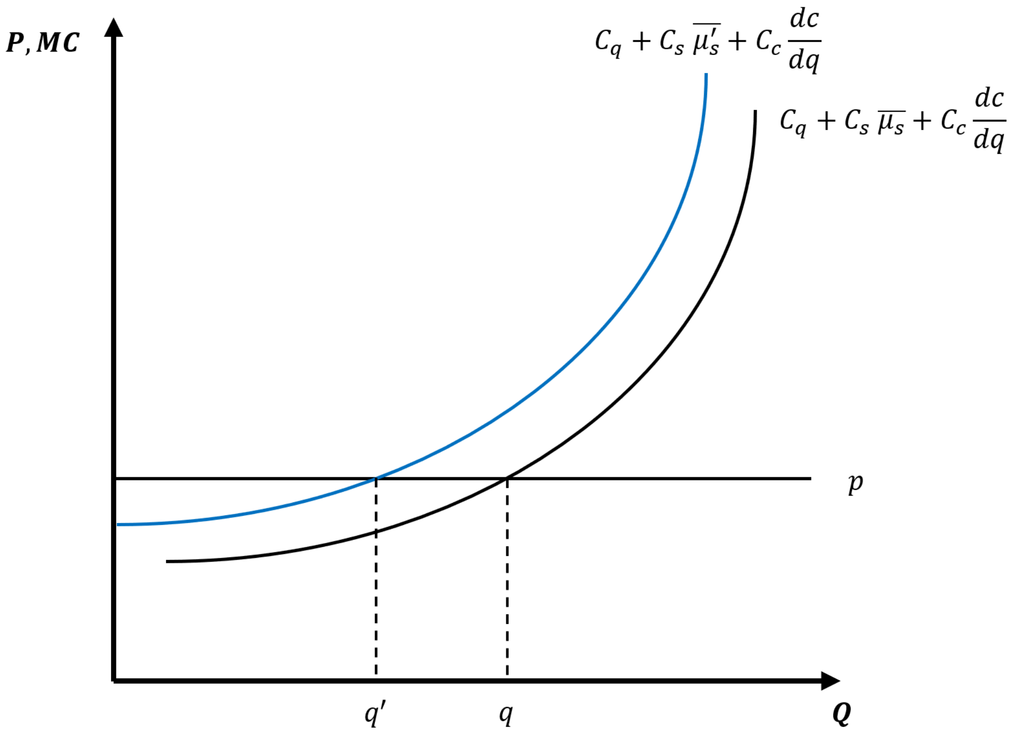


Table A6: Relationship between ULE Standards and Power Plants' SO2 Emission

	(1)	(2)	(3)	(4)
APPC Key Zones × Post ULE	-0.028*	-0.028*	-0.035**	-0.030*
	(0.016)	(0.016)	(0.016)	(0.016)
Ln(capacity)	-0.0016	-0.0016	-0.00077	-0.0011
	(0.0018)	(0.0018)	(0.0016)	(0.0016)
Ln(electricity price)	0.23***	0.23***	0.22***	0.19***
	(0.056)	(0.057)	(0.054)	(0.059)
Ln(power consumption)	0.12***	0.12***	0.13***	0.16***
	(0.038)	(0.038)	(0.041)	(0.049)
Pct. power generation, thermal	-0.010*	-0.010*	-0.015***	0.0064
	(0.0053)	(0.0053)	(0.0054)	(0.0057)
HDD14	0.0000043	0.000015	-0.0000019	-0.0000066
	(0.0000069)	(0.000011)	(0.0000073)	(0.000015)
CDD26	-0.00017***	-0.00012**	-0.00019***	-0.00014*
	(0.000040)	(0.000052)	(0.000041)	(0.000071)
Constant	-0.53*	-0.54*	-0.52*	-0.91**
	(0.27)	(0.28)	(0.29)	(0.36)
N	13799	13799	13799	13799
R-Square	0.2897	0.2911	0.3038	0.3633
Plant FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	No	No
Central Heating × Quarter	No	Yes	No	No
ETS × Year-Quarter	No	No	Yes	Yes
Grid × Quarter	No	No	No	Yes

Notes: Standard errors are clustered at prefecture city level. Column (2) adds controls for seasonality in average SO2 emission due to winter heating. Column (3) adds interaction term between ETS dummy and year-quarter FE. For further robustness, column (4) also includes regional power grid specific year-quarter FE.

Appendix B: Details of ETS Pilots

Table A7: ETS Pilots: Covered Sectors and Inclusion Thresholds for Firms

	Beijing	Tianjin	Shanghai	Shenzhen	Guangdong	Chongqing	Hubei	Fujian
Power and heat	✓	✓	✓	✓	✓	✓	✓	✓
Iron and steel		✓	✓	✓	✓	✓	✓	
Cement	✓		✓	✓	✓	✓	✓	
Petrochemicals	✓	✓	✓		✓		✓	✓
Chemicals		✓	✓				✓	✓
Manufacturing	✓			✓			✓	
Non-ferrous metals						✓	✓	✓
Textile			✓				✓	
Paper		✓	✓		✓		✓	✓
Other industries	✓	✓	✓			✓	✓	✓
Aviation		✓	✓		✓			✓
Shipping			✓	✓				
Other transportation	✓			✓				
Buildings			✓	✓				
Utilities			✓	✓			✓	
Services	✓		✓					
Inclusion thresholds	5,000	20,000	20,000 (10,000) 10,000 (5,000)	3000	20,000 10,000	20,000 10,000	10,000	10,000
Covered emissions	40%	55%	57%	40%	60%	50%	45%	60%

Notes: For inclusion thresholds, units are tons of CO2 (tCO2) per year for direct emissions and tons of carbon equivalent (tce) per year for indirect emissions; top numbers are for direct emissions, and bottom numbers indirect emissions. Only top numbers are shown for ETS pilots that adopt the same inclusion threshold for all industries and for direct and indirect emissions. Shanghai ETS sets different inclusion thresholds for different industries: numbers outside parenthesis are for power generation and industrial sectors, and numbers inside parenthesis are for aviation, ports, and buildings; inclusion thresholds for shipping is 100,000 tCO2/yr for direct emissions and 50,000 tce/yr for indirect emissions. *Source:* Duan (2015), ICAP (2020).

Table A8: Summary of ETS Pilots (Power Sector)

ETS	Launch Time	Cap ($MtCO_2e$)	Inclusion Thresholds ($tCO_2/yr.$)	Allocation	Flexibility	Price Stabilization	Enforcement
Beijing	Nov. 2013	~50 or 45%	5,000	Free allocation (benchmarking)	Banking is allowed, borrowing is not	Sell if avg. price $\geq$ 150 RMB for 10 days; buy if avg. price $\leq$ 20 RMB for 10 days	**False reporting**: max. fine 50k RMB; **Noncompliance**: max. fine = 5X the avg. price of past 6 months per missing allowance; other penalties such as restriction to bank loans and government subsidy programs
Chongqing	Jun. 2014	~100 or 50%	20,000	Free allocation (historic intensity, 2008-2012 peak levels)	Banking is allowed, borrowing is not	Entities must not sell more than 50% annual free allocation	**Noncompliance**: no financial penalty; non-financial penalties include public shaming, disqualification from subsidies and support, and record in SOE performance assessment system
Fujian	Sep. 2016	~200 or 60%	10,000	Free allocation (historic intensity)	Banking is allowed, borrowing is not	Buy or sell in cases of price fluctuations (i.e., cumulative price increase or decrease reach certain threshold for 10 days)	**False reporting**: 10-30k RMB in fines; **Noncompliance**: 1-3X avg. price of past 12 month per missing allowance (max.= 30k RMB); deduction of 2X the missing allowances from next year's free allocation; **Trading manipulation**: 10-30k RMB in fines
Guangdong	Dec. 2013	~465 or 60%	20,000	Free allocation (benchmarking)	Banking is allowed, borrowing is not	Price floors for auctioning of extra allowances	**False reporting**: 10-50k RMB in fines; **Noncompliance**: 50k RMB in fines; 2X missing allowances deducted from next year's free allocation; non-financial penalties include negative impacts on access to bank loans and government subsidies
Hubei	Apr. 2014	~258 or 45%	60,000 (2014); 10,000 (2017)	Free allocation (benchmarking)	Banking allowed (only for allowances that were traded at least once); borrowing not allowed	Buy or sell if price reaches a low or high point 6 times within a 20-day window; day-to-day price fluctuation limited to -10% and + 10%	**False reporting**: 10-30k RMB in fines; **Noncompliance**: 1-3X avg. price per missing allowances (max. = 150k RMB); 2X missing allowances deducted from next year's free allocation; **Trading manipulation**: up to 150k RMB in fines
Shanghai	Nov. 2013	~158 or 57%	20,000	Free allocation (benchmarking)	Banking allowed (compliant entities can use up to 1/3 of banked allowances from 2013-2015 per year in the post 2016 period); borrowing not allowed	Depending on transaction types, intervention if price volatility exceeding 10% or 30% in one day	**False reporting**: 10-50k RMB in fines; **Noncompliance**: 50-100k RMB in fines; submission of missing allowances; non-financial penalties include entry into credit record, public shaming, disqualification from subsidies and special funds
Shenzhen	Jun, 2013	~31.5 or 40%	3,000	Free allocation (benchmarking)	Banking is allowed, borrowing is not	Sell at fixed price when price fluctuates, buy back up to 10% annual total allocation	**False reporting**: 3X avg. price in fines for under-reported emissions; **Noncompliance**: 3X avg. price per missing allowance; missing allowances can be deducted from next year's allocation; non-financial penalties include entry into credit record and SOE performance assessment system, public shaming, and disqualification from subsidies and special funds; **Market manipulation**: max. fine = 100k RMB
Tianjin	Dec. 2013	~160-170 or 55%	20,000	Free allocation (historic intensity)	Banking is allowed, borrowing is not	Buy or sell in cases of price fluctuations	**Noncompliance**: disqualification from subsidies and other local preferential treatments for 3 yrs.

Source: ICAP Status Report 2020

Appendix C: Details on Data Cleaning and Processing

Data Processing

Coal-fired power plants tend to locate near cities. Due to high population and economic density in Eastern and Southern coastline areas in China, power plants may also locate near each other and even in clusters. This spatial feature poses a unique challenge in application of using remote-sensed SO_2 emission amount of power plants. OMI SO_2 data product, due to their high temporal and spatial resolutions, have been demonstrated to offer accurate estimates of SO_2 emissions of large stationary emission sources like coal-fired power plants when processed properly (Karplus, Zhang, and Almond, 2018; Fioletov et al., 2011, 2015; Mclinden et al., 2016; Liu et al., 2015; Lu et al., 2013; Li et al., 2010). So, extra care is given to the processing of power plants and OMSO2e data by following established procedures.

Clustering and Selection of Power Plants

Two techniques, the clustering and the selection of isolated large power plants, ensure that SO2 concentrations in pixels near a large stationary source can be mainly attributed to it. For power plants that collocate in close proximity to each other, a clustering procedure is performed. As is demonstrated in Lu et al. (2013) in the context of India, SO_2 concentrations of 23 clustered power plants regions derived from OMI SO_2 products closely match the readings of ground-based monitoring stations within those regions.

Clustering is performed using QGIS software with strict distance parameter (the "eps") of 13 kilometer (km) and a minimum number of members (the "minPts") of two. This low distance bound ensures that power plant clusters do not span a large geographic area and thus are more likely to cover other sources of SO2 emissions. 13 km is chosen because it is the minimum dimension of an OMI pixel, so clustered plants are likely to reside in the same pixel or in a neighboring pixel. The center of a cluster is computed as the capacity weighted centroid of member power plants. This procedure groups 349 power plants into 136 clusters, with an average cluster size of 3 plants and a median size of 2.

As the next step, only relatively isolated large power plants and clusters are selected into the analytical sample. The following selection criterion are adopted. Following Karplus, Zhang, and Almond (2018), a power plant or cluster is considered to be isolated if its installed capacity in 2012 accounts for at least 50% of the total capacity of all power plants/ clusters (including itself) that locate within 35 km radius. The 35 km distance cutoff is adopted in Karplus, Zhang, and Almond (2018) and can be justified on the basis of Fioletov et al. (2011). On average, the 35 km circle covers 6 OMI pixels, with a minimum of 4 pixels and a maximum of 9.

Additionally, power plants and clusters whose total capacity is equal to or greater than 1,700 megawatts (MW) are also selected into the analytical sample. 1,700 MW is the 75th percentile of the size distribution of all power plants in China in the GCPT database. In the top 25th percentile of the size distribution, the average capacity is 2915 MW, with a maximum capacity of 7500 MW. Power plants and clusters in this size class do not tend to locate near one another to avoid creating huge emission hot spots. Nevertheless, manual inspection was performed to ensure that they are not located near another large and isolated emission source defined above.

By applying the clustering and selection process described above, I obtain a sample of 349 large and isolated power plants and clusters, consisting of 251 power plants and 98 clusters. Power plants and clusters that pass this selection criterion (the "dominant facilities") can be considered as the most dominant source of emission within their own "circle of neighbors". The average capacity of power plants/ clusters in this selected sample is 1,165 MW, compared to the mean capacity of only 350 MW of the remaining power plants/ clusters in the full sample.

As a robustness check, the above-mentioned selection criteria were tightened to 75% of total capacity or 2,600 MW (90th percentile). Main results are not affected by this change (see Table A2).

Deriving coal power plants' SO2 emissions

The processing of NASA's OMISOe data product closely follow the methodology established by Karplus, Zhang, and Almond (2018), who performs pixel averaging with limited over-sampling. First, daily values of each pixel were average to month by using NASA's Giovanni application. This is done to over come the issue of having null pixels around a power plant and also to increase measurement precision. A pixel could contain null value if pixel quality is poor due to high cloud cover, high solar zenith angle, low air mass factor, etc. (see the linked READ-ME document[25] for more details). As Table A9 shows, the missing rate drops to 0.04 after averaging pixel values by month. As an additional step, pixel values were further averaged to the quarterly level to further increase measurement precision.

Second, a 35 kilometer circle is drawn around each isolated large power plant, and values of all pixels that fall within the 35 km radius are averaged to produce an estimate for the SO2 emission of the power plant. By assigning all SO2 concentrations near the dominant facilities as their emissions, an implicit assumption is made that the variations in atmospheric SO2 concentrations near the dominant facilities are driven by their emissions. In order words, it is assumed that the temporal variations in SO2 emissions by the dominant facilities drive changes in SO2 signals in OMI pixels.

As noted in Karplus, Zhang, and Almond (2018), the data retrieval algorithm used by NASA scientists (Li et al., 2020) produces some negative values in SO_2 column amounts. These values are the byproducts of the principal component analysis based algorithm and

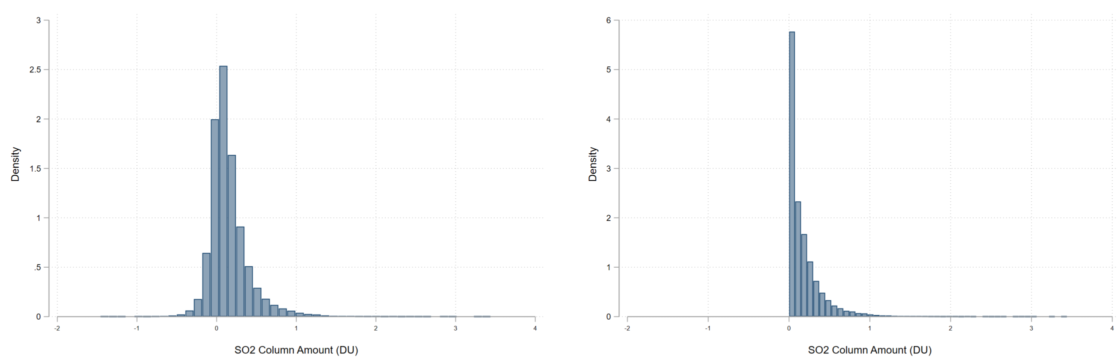
[25] https://cmr.earthdata.nasa.gov/search/concepts/C1266136112-GES_DISC.html

signify very small SO_2 concentrations. Following the approach taken in Karplus, Zhang, and Almond (2018), I set these values to zero. Figure A10 shows the histogram of power plants' SO_2 emissions before and after this change.

Table A9: Summary of OMI SO2 Data Quality

	obs	mean	std	min	max
Panel A. Monthly					
Number of pixels	41,880	6.006	0.996	4	9
Number of valid pixel	41,880	5.755	1.385	0	9
Number of null pixels	41,880	0.247	0.940	0	9
Missing ratio	41,880	0.043	0.162	0	1
Panel B. Quarterly					
Number of pixels	13,800	18.009	2.983	12	27
Number of valid pixel	13,800	17.266	3.616	0	27
Number of null pixels	13,800	0.743	1.940	0	19
Missing ratio	13,800	0.043	0.112	0	1

Figure A10: Distribution of SO2 Column Amounts from OMSO2e



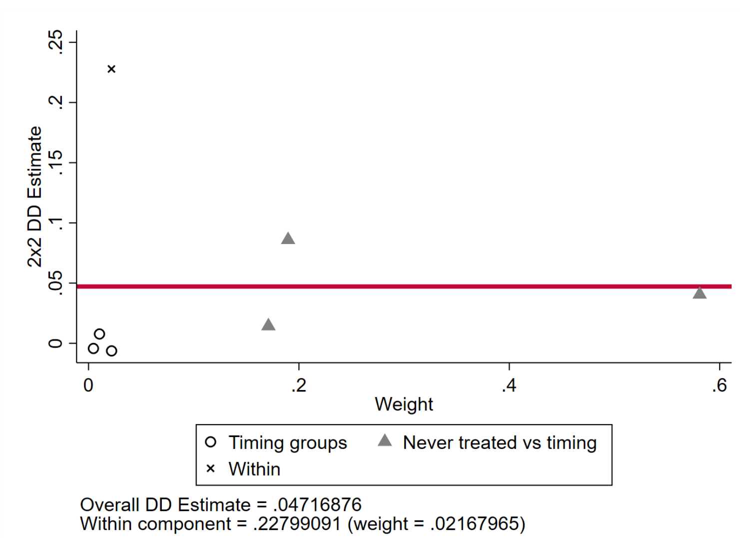
(a) Mean SO2 (b) Negative =0

Appendix D: Details on DID Research Design

The econometric literature on difference-in-differences (DID) research design has seen rapid new developments in recent years (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2020; Sun and Abraham, 2020; Athey and Imbens, 2021; de Chaisemartin and D'Haultfœuille, 2020; Borysyak and Jaravel, 2017; Cengiz et al., 2019). A key insight from these recent advancements in the DID literature is that the standard two-way fixed effect (TWFE) estimator, as shown in equation (1) of Section 3, can be biased, when there is heterogeneity in treatment effect across time. This bias arrives from comparing the late-treatment group with the early-treatment group.

To evaluate whether such bias is present in the context of this study, I perform the decomposition analysis recommended by Goodman-Bacon (2021). Figure A11 shows the results from this exercise. The red horizontal line marks the sample average treatment effect on the treated (ATT) estimated by the TWFE model (see Equation (1) in Section 4 of the paper). As is shown in Figure A11, although the estimated treatment effect from the pair-wise comparisons of the early and the late groups are close to zero, the weights assigned to these comparisons are also near zero. Therefore, even if the bias, described by Goodman-Bacon (2021), exists in the context of this study, it will have negligible effects on the ATT estimated from the TWFE models.

Figure A11: Bacon Decomposition of Baseline TWFE Model



Notes: The red horizontal line shows the sample average treatment effect on the treated (ATT) estimated by the TWFE model shown in Section 4 of the paper.