The Unintended Consequences of Coal-fired Power Plant Closures: Evidence from China

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This paper examines the impact of power plant closures on air quality and health outcomes in China by exploiting quasi-experimental variation from the closures. We collected information associated with more than 1,700 power plants across China, and combined with high resolution satellite data measuring monthly sulphur dioxide (SO2) levels. Our difference-in-difference (DID) estimates indicate that, while SO2 levels are 2.5% lower in areas surrounding closed power plants, areas surrounding power plants that remained opened suffer from 1.9% spike in SO2 levels. These results suggest that power plant closures lead to a displacement effect as plants that remained opened have to intensify their output to meet demands for electricity. We combine these localized reductions and displacement effects with granular information on population density to compute pollution exposure. Our results indicate that the displacement effects drastically undermine the effectiveness of plant closures. The net reduction in the exposure of SO2 levels from power plant closures is merely 11.6% of the localized reductions. It corroborates with the null effects associated with power plant closures on country-wide infant mortality rates, indicating that power plant closures have negligible benefits unless planners have cleaner alternative energy sources.

JEL: Q52, Q53, O13, Q42

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1 Introduction

Coal combustion from heavy manufacturing industries and power plants is a major source of air pollution in China, contributing around 79% of SO2, 35% of PM2.5, and 40% of PM10 of the national total emissions (Ma et al., 2017). Given the surmountable pollution externalities from burning coal to generate electricity, the Chinese government have taken numerous measures to clean up electricity production. This include enforcing stringent emission standards (Karplus et al., 2018), increasing pollution discharge fees (Gowrisankaran et al., 2020), conducting inspections (Karplus and Wu, 2023), increasing reliance on renewable energy and natural gas for electricity production, and retiring older, pollution inefficient coal-fired power plants.

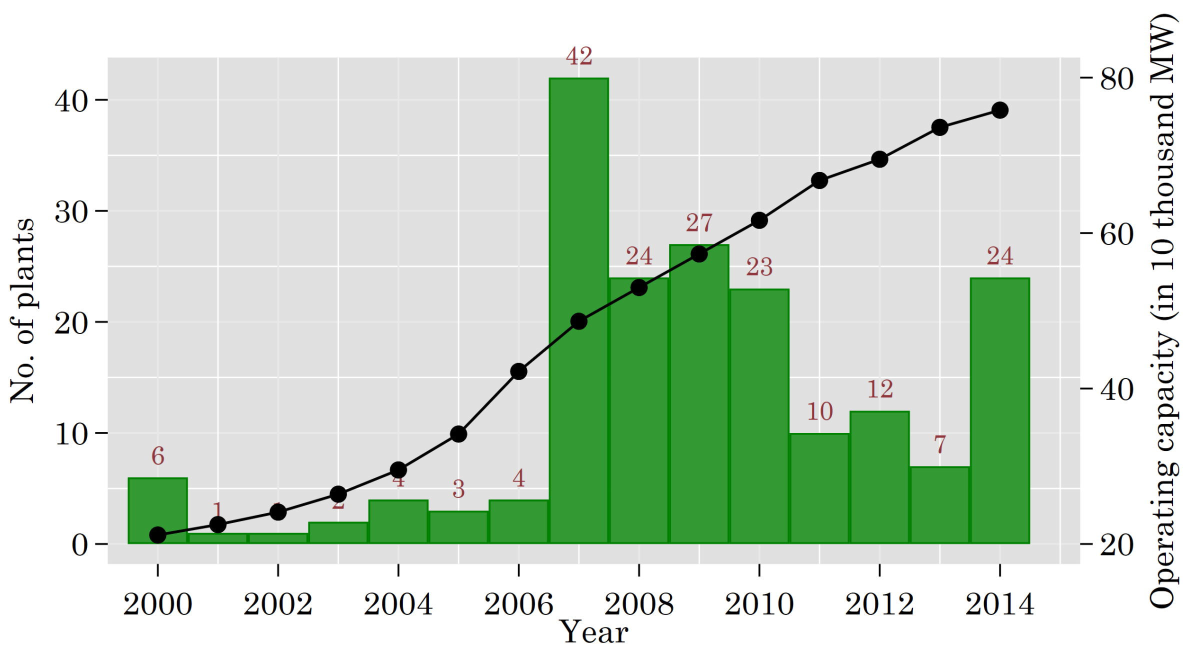

Figure 1: Number of coal-fired power plants retired from 2000 to 2014 across China

As a result, more than 180 coal-fired power plants with a total production capacity of more than 70 million megawatts (MW) were retired across China from 2000 to 2014. For an illustration of on how the Chinese government retired coal-fired power plants over time, and the locations of these plants, refer to Figures 1 and 2 respectively. Dwelling deeper on the characteristics of these retired plants, as observed in Table 1, retired plants are typically smaller, older, are situated around more densely populated communities, and are

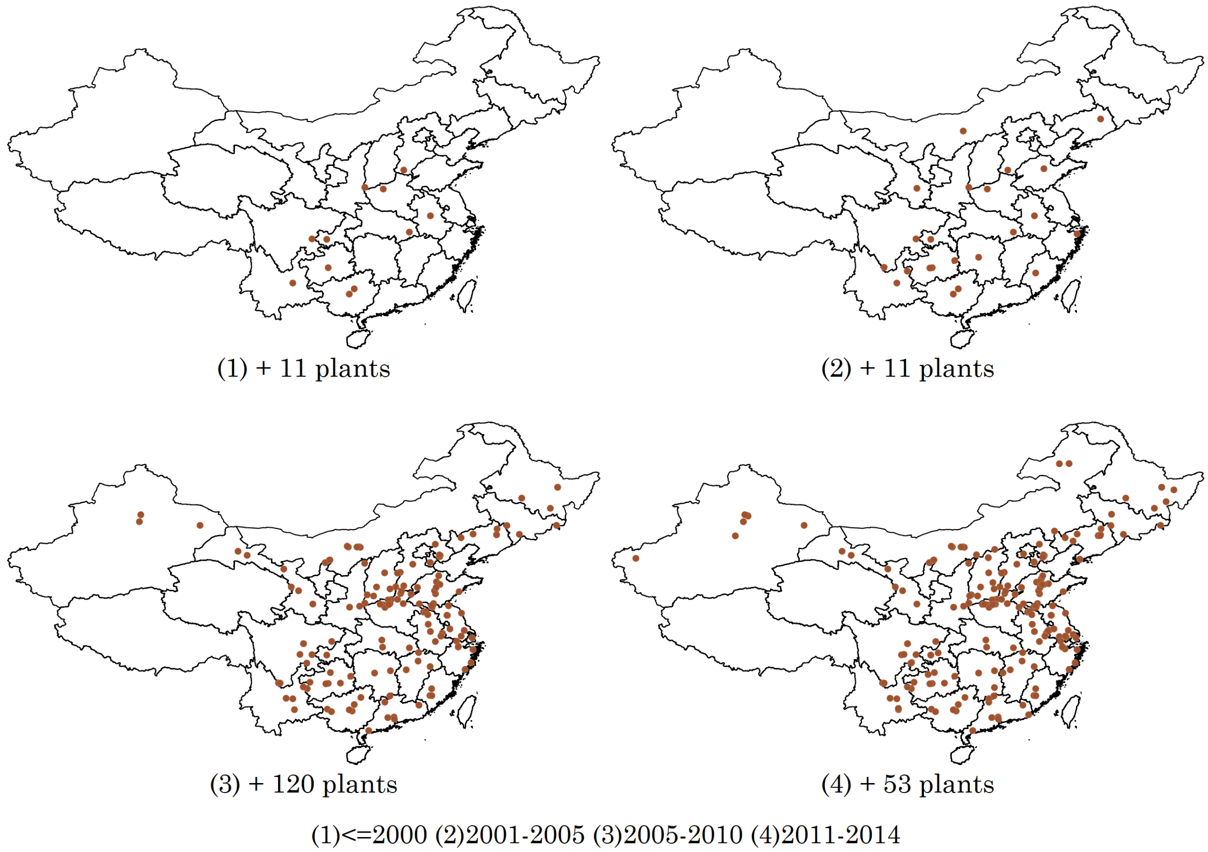

Figure 2: Spatial distribution of coal-fired power plants retired from 2000 to 2014

more pollution inefficient, generating more emissions per unit of electricity generated. Prima facie evidence seems to suggest that planners have accurately identified and retired coal-fired power plants with the largest marginal pollution cost to the society (i.e largest emission per unit of electricity generated, and greatest exposure to human communities).

Given the deleterious environmental effects of coal-fired power plants, many studies focused on how the retirement can significantly impact air quality (Ma et al., 2016; Strasert et al., 2019; Brown and Tousey, 2020b) and, in turn, affect various socio-economic outcomes, including health outcomes (Hao et al., 2007; Yang and Chou, 2018; Komisarow and Pakhtigian, 2021a; Chen et al., 2018, 2021), test scores (Duque and Gilraine, 2022), and school attendance rates (Komisarow and Pakhtigian, 2022). The consensus is that the closures of coal-fired plant contributed to substantial localized improvement in air quality and health outcomes. These studies, however, have only shed light on the partial equilibrium effects from coal-fired power plant closures. Depending on whether the demand on electricity remains constant, and whether electricity production can be allocated to cleaner sources, such as renewable energy, nuclear, or natural gas, the net effect of coal-fired power plant closures on emissions remains unclear. These concerns are warranted as existing literature has documented substantial displacement effects of electricity production when supply of electricity is constricted by shutdowns of power plants.

For instance, Davis and Hausman (2016) have shown that shutting down nuclear power plants in the United States attributed to substantial generation displacement to natural gas plants. This, in turn, led to a substantial increase in carbon dioxide emissions by 9 million tons in a year. Jarvis et al. (2022) also recorded that there is substantial increase in coal-fired electricity production and import of electricity after many nuclear power plants in Germany were closed in 2011 post Fukushima. In addition, Severnini (2017) documented that the closure of two large nuclear power plants in Tennessee Valley Authority due to the Three Mile Island accident in 1979 attributed to one-to-one shift of electricity generation to coal-fired power plants, deteriorating ambient air quality and reducing infant birth weight. Even when electricity production is allocated to cleaner sources such as natural gas, Burney (2020) recorded increases in PM2.5, NO2, and O3 around operational power plants after neighbouring coal-fired power plants are retired. Collectively, it seems evident that the retirement of coal-fired power plants does not necessarily lead to an improvement in air quality, and generation displacement from shutting down electricity sources could attribute to unintended nefarious environmental impacts elsewhere. Therefore, to better understand the net effects of coal-fired power plant closures on emissions, researchers to account for changes in air quality surrounding operating power plants.

Motivated by this gap in the literature, this paper examines the closure and displacement effects on air quality from the closure of 180 coal-fired power plants from 2004 to 2014. We rely on high resolution satellite data measuring monthly sulphur dioxide (SO2) collected at 0.25 by 0.25-degree (or 27km by 27km) latitude and longitude. This data, which is provided by NASA, allows us to measure spatially granular changes in air quality around retired and operating coal-fired power plants. Specifically, we adopt a quasi-experimental difference-in-difference strategy to compare SO2 levels surrounding retired and operating coal-fired power plants before and after the shutdowns. We observe that, unsurprisingly, neighbouring areas within 35km of retired coal-fired power plants experience a 2.5% reduction in SO2 levels relative to comparable areas not more than 50km.

Dwelling further, we document evidence that the reduction in production capacity from closures led to generation displacement to neighbouring operating coal-fired power plants elsewhere. Specifically, areas around operating power plants within 100km from the retired plants experienced a 1.9% increase in SO2 levels. These findings are robust to a battery of empirical specifications that addresses various empirical concerns, providing strong causal evidence of plant closures on air quality. We further show that the displacement of air pollution is largely concentrated within province, suggesting that displacement stems from the distortion in electricity dispatch. Additional analyses also indicate that displacement are attenuated when there are cleaner alternative energy sources around the retired power plant.

Combining these two effects with granular data on population density, we compute net exposure effects from the retirement of coal-fired power plants and report that these effects are merely 11.6% of the closure exposure effects after accounting for generation displacement. These results corroborate with additional analyses that showed that power plant closures do not have any effects on country-wide infant mortality rates. Overall, these results suggest that we could overstate the environmental benefits from the retirement of power plants without considering air quality surrounding operating plants.

In many ways, China provides an interesting and useful laboratory for this study. First, China's war against air pollution led to nationwide shutdowns in coal-fired power plants. This setting allows us to measure the environmental impacts of plant closures from an externally valid representative sample. Second, there are distortions in electricity production allocation and trading in China that could prevent the allocation of production to the "best" locations with the lowest marginal cost of production. Historically, coal-fired power plants across China are allocated equal generating hours and production is not based on economic merit order (Kahrl et al., 2013). Put differently, production could be evenly distributed to less fuel efficient plants that could generate more pollution externalities per unit of electricity produced. Furthermore, generators are compensated based on how much they generate, and there is a strong incentive to oppose reductions in operating hours that might accompany dispatch reforms. Hence, provincial leaders are reluctant to increase electricity imports from other provinces after decommissioning their old coal-fired power plants as this would reduce utilization hours of their own generators increase electricity (Ho et al., 2017). As a result, this could lead to the over-utilization of less efficient power plants even when more efficient plants are available, resulting in excessive fuel usage and the generation of more pollution externalities (Kahrl et al., 2016). This setting allows us to examine whether imperfect electricity dispatch could minimize the environmental benefits from plant retirement.

We improve on the existing literature in at least three ways. This is the first paper to examine the air quality effects from generation displacement due to the decommissioning of older power plants. As mentioned, previous literature focused on localized environmental and health benefits from plant retirement and could have overestimated the benefits of plant closures. Second, we utilize satellite data to measure air quality and there are two notable advantages from using satellite data. For one, they are less susceptible to misreporting compared to pollution monitors (Chen et al., 2012; Ghanem and Zhang, 2014). Furthermore, granular grid data allows us to measure in situ air quality surrounding the power plants without the need of interpolating air quality from pollution monitors further away. Finally, our findings have important policy implications. Phasing out coal electricity generation is increasingly important since the Paris Agreement entered into force in 2016 as many countries are retiring these facilities to reduce carbon footprint. Specifically, our paper not only sheds light on the possible environmental implications associated with coal-fired plant retirement, but also highlight planners can mitigate the deleterious environmental effects associated with energy displacement across space.

The remainder of this paper is structured as follows. Section 2 provides an overview on the power market in China. Section 3 outlines the data and Section 4 illustrates our identification strategy. Findings are then discussed in Section 5 and Section 6 concludes.

2 Institutional Background

In this section, we introduce the electricity market and electricity dispatch in China. We then discuss the phasing out of coal-fired power plants and the development of renewable energy in China.

2.1 Electricity Market and Electricity Dispatch in China

The electricity system in China, as the second largest worldwide after the U.S., is the engine of its economic growth (Kahrl et al., 2013; Wang et al., 2019). Prior to 2002, the entire electricity sector, including power generation, transmission, distribution, and sales, was owned and managed by the state grid company, operating as a monopoly. The State Council's 2002 Electric Power System Reform Scheme dissolved the monopoly and transformed it into small companies supplying either power generation/distribution or engineering services, to setup a competitive power market (State Council of China, 2002).

After the restructuring, the power system consists of two engineering service companies, two power grid companies, and nine state-owned generation companies known as "Five Giants Four Juniors" responsible for the majority of domestic power generation using coal or other renewable resources.[1] The two power grid companies are responsible for the power transmission and distribution and have established regional and provincial grid companies as subsidiaries.[2] These provincial power grid companies distribute electricity to the city and county power grid companies, which then deliver it to consumers. The entire process, from power generation to electricity transmission, is centrally planned and monitored by the National Energy Administration.

Different from most of the rest of the world, which dispatch generators based on a "merit order" approach according to the marginal cost of production, grid operators in China adopt an "equal shares" system (Kahrl et al., 2016). Specifically, China's operators have allocated operating hours evenly among coal-fired generators, despite of age, size, or efficiency. The merit order approach, on the opposite, guides the generator dispatch based on the cost of fuel (Steinberg et al., 1943). The more fuel efficient a generator is, the higher priority it will receive for dispatch, and the more operating hours it will be allocated. Historically, the lack of merit order dispatch in China was due to chronic shortage of power in almost all year round. The differences in fuel efficiency among generators were slim (Kahrl et al., 2016). However, as the electricity sector expanded in China, the economic inefficiency of the equal shares system became prominent. Furthermore, it worsened pollution as less fuel-efficient and high-emission generators were allocated longer hours than they would have been according to the merit order dispatch.

As a result, the Chinese central government introduced a series of reforms on the dispatch rules from 2007. First, the Differentiated Generation Quota Scheme allocated more utilization hours to larger, more efficient, and less polluting generator units. Second, the formalization of the Generation Rights Trading allowed plants to transfer or sell their generation rights. Notably, this policy allowed decommissioned units to transfer their quotas to operating units. A follow-up policy allowed all generators, not just retired plants, to participate in intra-province and inter-province trading, with the quota allocation based on fuel efficiency. Third, the government proposed the Energy Conservation Dispatch (ECD)

[1] The two engineering service companies are Power Construction Corporation of China and China Energy Engineering Group Corporation, responsible for construction engineering and equipment manufacturing, respectively. The two power grid companies are State Grid Corporation of China and China Southern Power Grid Company. The Five Giants Four Juniors are known as China Huaneng, Datang, Huadian, Guodian, China Power Investment Corporations; China Resources Power, Shenhua Guohua, Guotou Huajing, and China General Nuclear Power.

[2] The State Grid owns 5 regional subsidiary power grids responsible for 27 provincial power grids. The China Southern Power Grid is responsible for the power supply of Guangdong, Guangxi, Yunnan, Guizhou, and Hainan.

to improve the dispatch procedure. The ECD gave priority to renewable power generation over coal-fired one, based on unit energy consumption and pollutant emission levels.[3] Although the ECD improved the resource utilization and significantly reduced emissions, it faced strong opposition from coal-fired power plants and never escalated to the national level (Ho et al., 2017). Coal-fired generators were resistant to trade their quotas with renewable sources even at lower prices. Consequently, the volume of generation right trading mainly relies on the trading from shutdown plants.

Despite the electricity market reforms in China, provinces continue to serve as the primary dispatch zones, granting provincial governments authority over power output and pollution regulations. As a result of disincentives and transmission line-losses, trading across provinces has been discouraged. Each year, provincial governments formulate annual generation plans for power plant units. Generator units are expected to fulfill their allocated hours and maximize target completion rates. Within a province, generators of the same category are assigned similar annual operating hours. When a coal-fired power plant is retired, the provincial government develops a new annual power generation plan and redistributes the generation loss from the closures to other operating plants within the same province. Due to the compensation structure, which is based on generation amounts, provincial governments are discouraged from importing electricity from other provinces after the retirement of their coal-fired power plants (Ho et al., 2017).

Figure A1 illustrates the different types of electricity transactions in China, by inter-provincial vs. intra-provincial and planning-based vs. market-based transactions. Following the reforms, the share of market-based transactions increased. However, a majority of transactions are still within province and planning-based. The inter-provincial transactions constitute a small share, with a significant portion determined by the planning of central government and national-level top down energy policies, such as the west-to-east and north-to-south electricity projects (Ho et al., 2017).

[3]The merit order is: 1. Renewable energy generator units such as wind energy, solar energy and water energy without adjustment capability; 2. Renewable energy generator units such as hydro energy, biomass energy, geothermal energy, etc., with adjustment capability, and garbage power generation that meets environmental protection requirements; 3. Nuclear power generator units; 4. Coal-fired, co-generation units operating in the mode of "heating electricity" or with a comprehensive utilization of waste heat, waste gas, pressure, coal gangue, washed coal and other resources; 5. Natural gas and coal gasification generator units; 6. Other coal-fired generating units. Thermal generator units of the same type are ranked from low to high energy consumption level, and energy saving is given priority; When the energy consumption levels are the same, they will be sorted according to the pollutant level. 7. Fuel generator units.

2.2 Staggered Phasing Out of Coal-Fired Power Plants

In 2020, the thermal power sector was responsible for approximately 68% of China's total electricity generated, with around 90% of that coming from coal burning (Chen et al., 2019; Ye et al., 2019). This heavy reliance on coal power has significant environmental consequences, and with the pressure of the 2060 Carbon Neutrality goal and the global 1.5°C Paris Agreement goal, China is faced with the challenge of phasing out coal power.

Coal-fired power plant closures have been a crucial method to address this challenge. The central government launched the "Great Pressure on Small" Scheme in 2004, which aimed to replace inefficient small generator plants with large efficient ones while limiting the development of new small generator units. Under this scheme, the central government approved the construction of large coal-fired power generator units with a capacity of 1.2-1.6 times that of the total capacity of small plants that they were meant to replace.[4] Additionally, there were 3 waves of large-scale coal-fired power plant closures during the 10^{th} (2001-2005), 11^{th} (2006-2010), and 12^{th} (2011-2015) Five-Year Plans, resulting in the closures of power plants with capacity totalling 25 million, 78 million and 28 million MW, respectively. At the provincial level, governments also reduced energy supply from small thermal power plants through various means, including differentiating electricity prices and supporting the development of large generator units. To meet new standards, new plants were required to mainly use high-parameter and high-efficiency generators with a capacity of at least 300,000 KW.

To reduce SO2 emissions, additional regulations were imposed on existing coal plants in China. In 1995, the Air Pollution Prevention and Control Law was the first policy to advocate for the installation of desulfurization equipment and utilization of clean combustion power generation technology in areas with severe pollution and acid rain. The 12^{th} Five-Year Plan prioritized connection to grids with generator units containing desulfurization infrastructure and offered preferential tax reductions or exemptions to desulfurization equipment. The Two-Control Zone (TCZ) policy, implemented in 1998, demarcated two zones in China, the acid rain control zone and the SO2 pollution control zone, which experienced severe acid rain or dangerous levels of SO2 pollution.[5] Under the TCZ policy, high-sulfur polluting coal-fired

[4]The obsolete plants were thermal power units with a capacity below 50MW; coal-fired power units that had been in operation for 20 years and had a single unit below 100MW; all kinds of units below 200MW serving beyond their designed lifespan; coal-fired units whose standard coal consumption rate was 10% higher than the average level of the province or 15% of the national average level in 2005; units which failed to meet the environmental protection emission standards; or units that should have been shut down in accordance with laws and regulations.

[5]The two zones spanned 175 cities, 27 provinces, and covered approximately 11% of China's territory.

power plants were restricted in utilization, high-energy consumption and heavy-polluting production processes, and equipment were replaced (Wu, 2010). More resources were also dedicated to the installment of desulfurization facilities for thermal power plants. Newly-built or renovated thermal power plants with high sulfur content were mandated to install such facilities. With an exception of thermal power plants by heating, no additional coal-fired power plants were allowed to be built in urban or suburban areas of the two zones. In 2015, China implemented ultra-low emission and energy-saving renovation to further limit the air pollutant emissions. By 2022, the share of desulfurization units in the total installed capacity of thermal power at the national level had increased to 96%; of which 10% completed the ultra-low emission renovations (State Council of China, 2001, 2007, 2013; NDRC, 2016).

2.3 Development of Renewable Energy Sources

As climate change gained prominence in global politics, China began to acknowledge the resource constraints and environmental impact of fossil fuels. Moreover, with the intensified competition for energy resources, China recognized the importance of addressing both the reduction of greenhouse gas emissions and the challenges posed by the volatile fossil fuel market. To tackle these issues, China established goals to promote the adoption of renewable energy sources, enhance energy efficiency, and reform the energy system.

The Renewable Energy Law of the People's Republic of China was enacted on February 28, 2005, establishing a legal framework for the state to support the growth of the renewable energy industry as a core mission. Subsequently, the development of renewable energy in China experienced rapid expansion, particularly in the wind power sector. Between 2005 and 2017, the share of renewable energy in China's energy mix increased significantly, challenging the long-standing dominance of coal power and contributing to the country's industrial growth and economic development.

The proportion of renewables in the electricity mix has continued to grow at a rapid pace, with hydropower and onshore wind power leading the way, followed by solar photovoltaic (PV), biomass, geothermal, and waste-to-energy. Hydropower, wind energy and solar PV have emerged as major power sources in certain regions, while solar thermal, geothermal energy, and biomass have become important alternatives and supplements for clean heating and clean fuels in some urban and rural areas. The expansion of clean renewable energy power plants has exerted downward pressure on the utilization of coal-fired plants. By the end of 2017, China had already established itself as a global leader in renewable energy development, with commercial renewable energy accounting for approximately 12.5% of the country's primary energy consumption (World Bank, 2021).

3 Data

3.1 Data Sources

We restrict our analysis to the period between 2004 and June 2014, as a national Ultra-Low Emissions Policy was introduced after that, which may confound the effect of the staggered power plant closures. Our data on coal-fired power plants during this period comes from the Global Energy Monitor.[6] The dataset includes geographic information on retired and active power plants, as well as the operational status of generator units (e.g., open, retired, cancelled, or under development), starting year, retired year, capacity, and ownership. We define a retired plant as long as at least one of its generator units has been retired; and we specify the retirement year as the year in which the first unit was retired. Our working sample comprises 180 retired plants and 1,367 operational plants.

We measure air quality using NASA's satellite observation dataset, Aura/Ozone Monitoring Instrument level 3 sulphur dioxide (OMSO2e). It has collected hourly data of SO2 concentration at a 0.25 by 0.25-degree ($\approx$ 27km $\times$ 27km) grid since October 2004. We calculate the average monthly SO2 concentration at the grid level, resulting in approximately 2.9 million observations from 2004 to 2014. To analyze the changes in air quality around retired plants, we match the grid-level SO2 data with the closest retired plants and calculate the distance between the centroid of each grid and the nearest retired plant.

Socioeconomic and meteorological information are collected from the National Bureau of Statistics of China and the National Oceanic and Atmospheric Administration, respectively. The former provides provincial annual GDP and population data, while the latter includes monthly data on temperature, dew point, air pressure relative to mean sea level, visibility, wind speed, and precipitation. We combine climate data with SO2 levels at the grid level using Inverse Distance Weighting (IDW).[7]

To investigate alternative energy sources, we manually collect data on 6,211 renewable energy plants in China from the National Energy Administration. This dataset contains information on the name of the plant, its capacity, and the type of renewable power. We use the Gaode Map Application Programming Interface (API) to geocode the addresses of

[6] See https://globalenergymonitor.org/.

[7] The IDW is calculated as $x^* = \frac{\omega_1 x_1 + \omega_2 x_2 + ... + \omega_5 x_5}{\omega_1 + \omega_2 + ... + \omega_5}, \omega_n = \frac{1}{d_n}, (n = 1, ..., 5)$, where d_n is the distance between a grid and each of the 5 nearest climate points.

renewable energy plants and calculate the distance between each plant and the retired coal-fired power plants. We then calculate the number of renewable energy plants within 100km of each retired plant in the same province.

To examine the health consequences of power plant closures, we manually collect annual infant mortality rate (i.e., deaths per thousand of infants) at the county level from the Yearbook of Health in the P.R.China. We aggregate the power plant data to the county level, calculate the annual and cumulative number of retired plants and capacities, and match them with the infant mortality rates. The combined data includes 1,146 counties from 2000 to 2014. We obtain control variables, such as the annual number of maternal and child health hospitals, birth rate, average personal income, female illiteracy, and female employment rate, from the China County Statistical Yearbooks. Table A1 summarizes the data sources and variable definitions.

3.2 Descriptive Statistics

Table 1 displays summary statistics at plant and grid level in Panels A and B, respectively. In Panel A, the statistics are presented for four types of coal-fired power plants sequentially: completely shutdown plants, partially closed plants without new units, partially closed plants with new units, and operational plants. The variables include plant capacity, plant age, monthly SO2 concentrations within a 35km radius of the plant, and county-level socioeconomic variables. To handle negative values in the SO2 data, we replace them with zeros. In a robustness check, we exclude the negative observations.

We observe that the completely shutdown plants have the lowest generation capacities on average and a moderate average operational year of 29. However, they have the highest population density and SO2 level in the vicinity, as well as the highest GDP and employment rate in the secondary industry. These pieces of evidence echo the government's policy to shutdown pollution-inefficient plants located in industry-oriented and densely populated regions (Section 2). Comparing partially closed plants without new units to those with new units, the latter have a higher average capacity, longer operational years, lower SO2 level, as well as lower population density and GDP. This reflects the policy tendency to open cleaner new units in less dense and less developed regions. The fully operational plants are the youngest among all and locate in the least populated regions.

Panel B shows summary statistics for treated vs. control groups under closure effect (Columns (1)-(2)) and displacement effect (Columns (3)-(4)). As expected, the average SO2

Table 1: Summary Statistics

	(1)	(2)	(3)	(4)
	Panel A: Plant level			
	Completely close	Partly close w/o new units	Partly close with new units	Fully operating
Average capacity	407.518	1345.926	1491.986	963.34
	(1.779)	(2.158)	(2.471)	(.711)
Age	28.964	32.304	40.646	13.312
	(0.021)	(0.027)	(0.03)	(0.008)
Monthly SO2 (DU)	0.436	0.427	0.36	0.363
	(0.001)	(0.001)	(0.001)	(0.000)
GDP (thousand)	3581.074	3330.338	2155.008	2594.82
	(11.927)	(15.086)	(16.615)	(4.718)
GDP of secondary industry (thousand)	1776.715	1725.023	1113.573	1371.213
	(6.693)	(8.447)	(9.423)	(2.655)
Employment in secondary industry (%)	12.997	12.305	10.223	9.387
	(0.045)	(0.055)	(0.062)	(0.017)
Population (thousand)	5098.86	4411.813	3097.913	2881.829
	(6.371)	(7.726)	(8.847)	(2.546)
Number of plants	167	115	85	1,061
	Panel B: Grid level			
	T^{close}	C^{close}	$T^{displace}$	$C^{displace}$
Monthly SO2 (DU)	0.485	0.438	0.403	0.379
	(0.001)	(0.001)	(0.001)	(0.001)
GDP (thousand)	2,493.458	2,177.565	1,568.651	1,289.399
	(15.277)	(14.991)	(3.332)	(3.090)
GDP of secondary industry (thousand)	1,350.060	1,229.835	879.336	680.128
	(9.087)	(8.871)	(2.058)	(1.921)
Employment of secondary industry (%)	12.001	12.461	7.987	8.121
	(0.081)	(0.082)	(0.039)	(0.035)
Population (thousand)	610.796	634.232	610.237	627.035
	(1.586)	(1.608)	(1.211)	(1.163)
Number of grids	1166	1294	2671	3006

Notes: Plant information is collected from Global Energy Monitor website from 2004 to 2014. SO2 level is obtained from OMSO2e dataset. GDP and employment of industry are from China County Statistical Yearbooks. Population data in Panels A and B are retrieved from World Pop dataset and China County Statistical Yearbooks, respectively. In panel A, "completely close" refers to plants that have closed all generator units; "partly close without new units" refers to plants that shut down part of units but have not opened new units; "partly close with new units" includes plants that shut down part of units and open new units after closure; "Always open" refers to plants without any retired units. Total capacity is the sum of generation capacity of all generator units in a specific plant. Age measures years since the start of a plant. Monthly SO2 is defined as monthly average of SO2 for girds within 35km of plants. $Population_{\leq 35}$ is defined as the total population in grids within 35km of plants. In panel B, T^{close} and C^{close} indicates treatment (within 35km of plants) and control group (35-50km of plants) of retired plants, respectively. $T^{displace}$ and $C^{displace}$ are the treatment (within 35km of plants) and control group (35-50km of plants) of operating plants that are within 100km of retired plants.

level in grids within 35km of retired power plants (0.485 Dobson Units (DU)) is higher than the control group located 35-50km away from the retired plants (0.438 DU), representing an approximately 10% difference.[8] The treated group also exhibits higher overall GDP and GDP

[8] 1 DU=$2.69 * 10^{16} mol/cm^2$.

from the secondary industry, but lower population density. We explicitly control for regional fixed effects in our regression analysis, to account for the correlation between pollution and regional population and industry development. The same pattern is observed for the treated vs. control groups under the displacement effect, where the monthly SO2 level in the vicinity of operational plants within 100km of retired plants (Column (3)) is approximately 6% higher than the control group (Column (4)). Again, the treated group has higher GDP and lower population density, which will be controlled by regional fixed effects.

4 Identification Strategy

To measure the (1) effects of coal-fired power plant closures on air quality, and the (2) displacement effects of closures on air quality around power plants that remain operational, we estimate the following difference-in-difference two-way fixed effects (DID TWFE) equations:

$$ln(SO2_{it}) = \alpha_i + \beta Close_i \times Post_t + X'_{it}\phi + \tau_t + \epsilon_{it} \tag{1}$$

$$ln(SO2_{it}) = \alpha_i + \delta Near_i \times Post_t + X'_{it}\phi + \tau_t + \varepsilon_{it} \tag{2}$$

where, for both equations 1 and 2, our dependent variable, $ln(SO2_{it})$, is the natural logarithm of SO2 levels measured in 0.25 deg latitude and longitude grid i ($\approx$ 27km) in year-month t.

For equation 1, which measures the localized improvement in air quality after coal-fired power plant closure, our key variable of interest is $Close_i \times Post_t$. $Close_i$ is a binary variable taking the value of 1 if the centroid of grid i is within 35km from the retired power plant, 0 otherwise.[9] We define the 35km distance threshold based on previous researches by Brown and Tousey (2020b) and Karplus et al. (2018) that have shown that local pollution externalities from coal-fired power plants are extend to this threshold. $Post_t$ is a binary variable taking the value of 1 in year-month t within 5 years after the power plant retirement, 0 otherwise. Hence, our parameter of interest β measures the average percentage change in the SO2 levels after the closure of neighboring coal-fired power plant. As coal-fired power plants across China are retired at different time periods, we exploit this staggered closure

[9] Figure A2 shows the effects of coal-fired plant closures on air quality in the vicinity defined by 5km distant bands. The result justifies our definition of the treated group within 35km.

timing to estimate the average closure effects of coal-fired power plants on air quality. If coal-fired power plant closures improve local air quality, we expect β to be < 0. To ensure that we are measuring the causal short-run effects of plant closure and displacement effects on ambient air quality, we constraint our analyses to no more than 5 years before and after from each plant closure.

Previous literature have largely focused on estimating the localized air quality and health benefits of power plant closures without accounting for possible displacement in air pollution (Hao et al., 2007; Yang and Chou, 2018; Brown and Tousey, 2020a; Komisarow and Pakhtigian, 2021b). Plant closures lead to shortfall in electricity production that could force operational plants to intensify production to meet demand. Furthermore, as highlighted earlier, distortions in the allocation of electricity production that prevent the production to be allocated to the most pollution efficient power plants, coupled by strong reliance on coal for electricity in China, could further exacerbate displacement effects (Ho et al., 2017).

Hence, we estimate the displacement effects of plant closures on air quality elsewhere with equation 2. Our key variable of interest is the interaction of $Near_i$ and $Post_t$. $Near_i$ is a binary variable that takes the value of 1 if grid i is (1) within 35km from the nearest coal-fired power plant that remains open and is (2) within 100km from the coal-fired power plant that is shut down, and 0 otherwise. $Post$ is a binary variable taking the value of 1 in year-month t after the coal-fired power plant within 100km is retired, 0 otherwise. Our parameter of interest, δ, measures the average percentage change in SO2 levels for areas around operational coal-fired power plants. If these plants are intensifying production to meet the shortfall in electricity supply driven by closures, we expect $\delta > 0$ and air quality to worsen.

For both equations, we further augment a vector of observable time-variant climatic controls, X_{it}, including temperature, dew point, air pressure relative to mean sea level, visibility, wind speed, precipitation, and their second polynomials. Although these local climatic conditions are unlikely to be correlated with plant closures, changes in climatic conditions could affect SO2 levels. Furthermore, we control for year-month fixed effects, τ_t, to control for general changes in $SO2$ levels over time, and grid fixed effects, α_i, to partial out the time-invariant unobservables at a granular level. ϵ_{it} and ε_{it} denote standard errors clustered at grid level.

Consistent estimation of β and δ require $E[\epsilon_{it}, Close_i \times Post_t] = 0$ and $E[\varepsilon_{it}, Near_i \times Post_t] = 0$. These assumptions are likely to be violated if there are unobserved differences between grids closer and further away from coal-fired power plants, whether retired (for equation 1) or operational (for equation 2), or if there are other unobserved correlated shocks associated with coal-fired power plant closures. Put differently, the trends in SO2 between the "treated" and "control" grids are unlikely to be parallel in the absence of plant closures. As mentioned earlier, older and less efficient coal-fired power plants located in more populous areas are more likely to be retired because these plants exposure more pollution externalities to living communities. Hence, to ensure the comparability of the treated and control areas, for equation 1, we restrict our analysis to grids no more than 50km from the nearest closed coal-fired power plant, defining our control group to be grids within 35 to 50km. In similar fashion, for equation 2, we constraint our analysis to grids no more than 50km from operational coal-fired power plants. Besides, we remove the overlapping grids in the control group, which are also in the treatment group of other plants and affected in the period of treatment. For instance, if grids in control group of retired plant A are also within 35km of retired plant B and within 5 years of retirement of plant B, these grids in the control group will be removed. To visualize how treated and control areas are defined for both equation 1 and 2, refer to Figure 3.

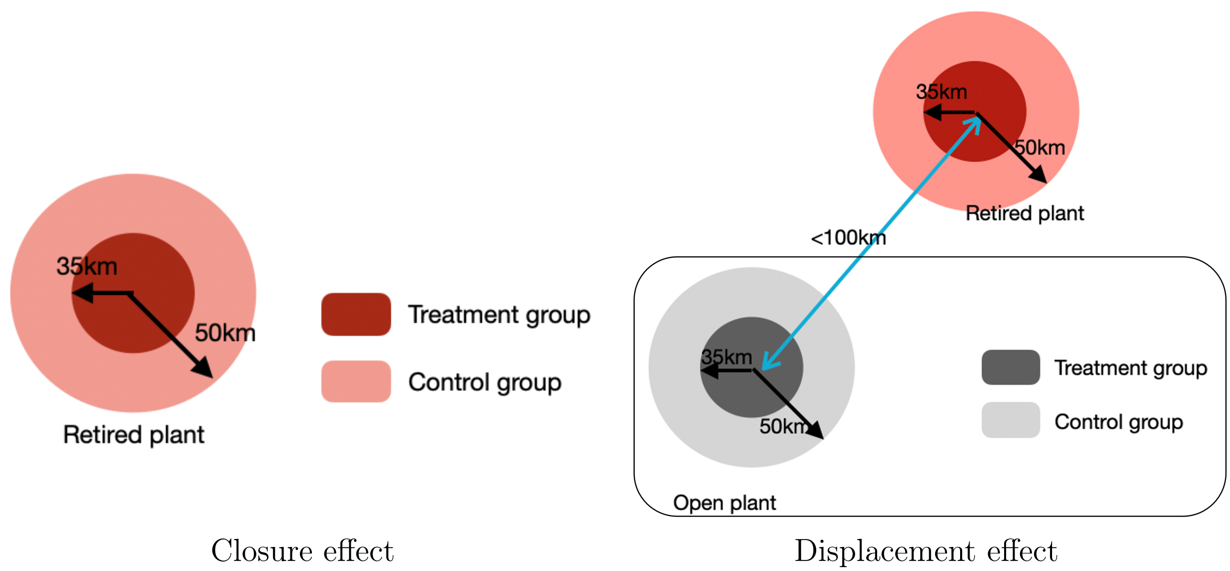

Figure 3: The identification strategies of closure effects and displacement effects

To further relax parallel trend assumption in SO2 between grids closer and further from power plants, we allow trends in SO2 to vary non-linearly across time between provinces by including province-by-year-month fixed effects. We also examine whether there are any pre-differences in $SO2$ trends between treated and control areas with a lead-lag specification. None of these results indicate a concern that the parallel trend assumption is violated, and further details will be provided in the robustness section.

There is a burgeoning literature highlighting that difference-in-difference two-way fixed effects (DID TWFE) estimator (e.g area fixed effects with time dummies) could be biased when there is staggered adoption timing (e.g some areas are being treated earlier, while others are being treated later), when already treated units are being used as control units, and when there is heterogeneous treatment effects over time (De Chaisemartin and dHaultfoeuille, 2020; Goodman-Bacon, 2021; Callaway and SantAnna, 2021). As explained by Goodman-Bacon (2021), in the simplest form, DID TWFE estimator is a weighted average of the different 2-by-2 comparisons (before and after treatment between treated and control groups) from different closed power plants. The weights are determined by both the size and the variance of treatment of the different subgroups. Hence, weights are disproportionately larger for areas that are treated in the middle of the sample as the variance of the treatment is larger, and smaller for those earlier and later treated areas as the variance of the treatment is smaller.

The biggest concern stems from comparing later treated groups with earlier treated groups. Earlier treated units adopted as control units would put negative weights to these groups. This is because these groups are entering the estimation as controls receiving negative weights to be subtracted from treated units when computing average treatment effects. In addition, if treatment effects are heterogeneous, comparing later treated units against earlier treated units (as control groups) could bias the estimates as parallel trend assumption is likely to be violated.[10]

In response, we address these concerns by adopting the CSDID approach proposed by Callaway and SantAnna (2021) that avoids comparing treated units with already-treated units. In particular, CSDID estimation involves computing the average treatment effect on the treated ($ATT(g,t)$) for each sub-group g at when it gets treated in time t (or power plant i when closed at year t in our context) against control units that are never treated. This can be expressed as follows:

$$ATT(g,t) = E(Y_t(g) - Y_t(NT)) - E(Y_{t-1}(g) - Y_{t-1}(NT)) \tag{3}$$

where NT denotes the "good" control units that are never or not-yet treated, and $t-1$ denotes pre-treatment period one year before treatment. Next, to compute the aggregated average treatment effects on the treated ($AGTT$), we will need to compute the weighted

[10]If earlier treated units receive treatment and these treatment effects changes over time, the trends in outcome are unlikely to be comparable with other treatment groups.

average of the $ATT(g,t)$ across the different sub-groups g and that can be represented as:

$$AGTT = \frac{\sum(W_{g,t} \times ATT(g,t))}{\sum(W_{g,t})} \tag{4}$$

where $W_{g,t}$ is the group-specific weights given to each subgroup g. This approach allows for treatment effects heterogeneity and dynamic effects by constructing different aggregated causal parameters flexibly. For instance, it summarizes the "Group-specific effects" by the timing of treatment; "Calendar time effects" by year; "Event study" by the length of exposure using different weighting functions.

5 Impact of Coal-Fired Power Plant Closures on Pollution

We begin this section by providing graphical evidence of the closure and displacement effects and then present the DID estimates, along with a battery of robustness checks. Next, we present a back-of-the-envelope calculation of the net exposure effect, followed by a discussion of the determinants of displacement.

5.1 Graphical Evidence

Figure 4a depicts the SO2 level before and after power plant closures, contingent on distance from the retired plants. To create this figure, we first obtain the residuals from regressing log(SO2) on all control variables in equation 1, along with grid, year-month, and province-by-year fixed effects. We plot the residuals against the distance from retired plants for 5 years before and after the retirement, with 95% confidence intervals.

The closure effect is clearly demonstrated. Prior to closure, the SO2 level is positive and gradually decreases with distance from the retired plants. However, after closure, the SO2 level drops significantly until approximately 35km. This distance is consistent with the treatment group specification used in Brown and Tousey (2020b) and Karplus et al. (2018). The difference in SO2 level gradually diminishes and becomes statistically insignificant thereafter, until the two lines intersect as approaching 50km. This justifies the boundary for our control group.

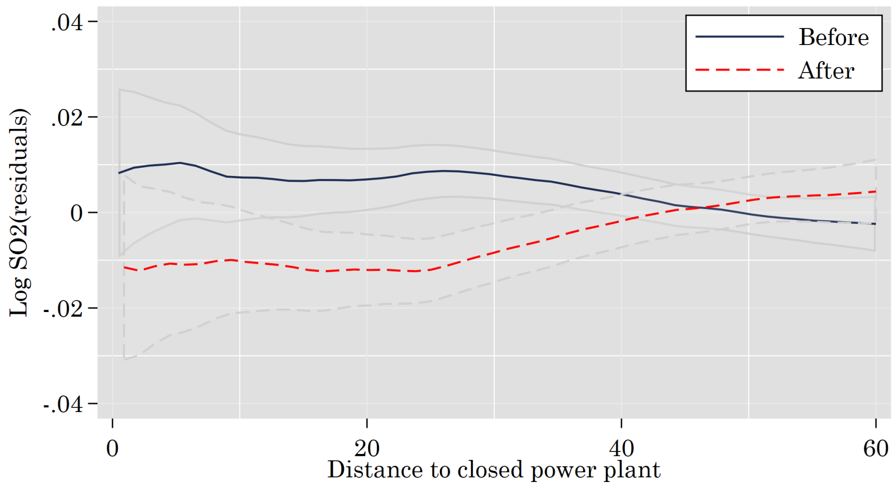

Figure 4a: Closure effect

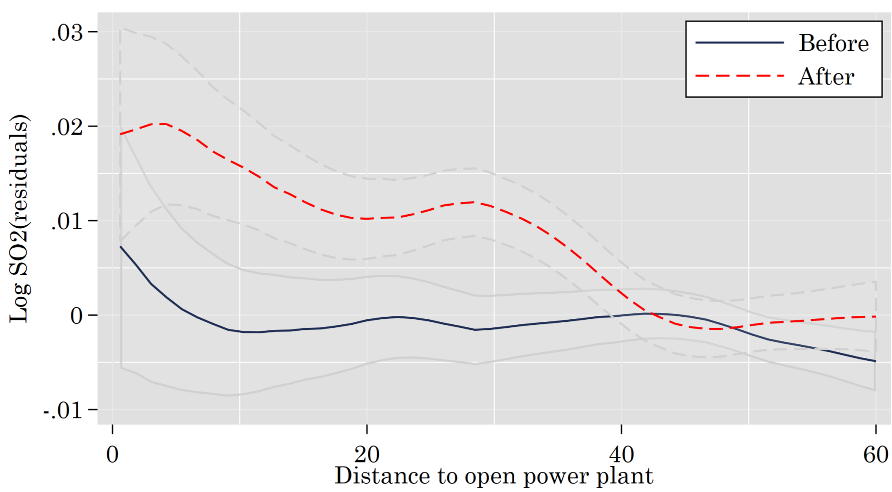

Figure 4b: Displacement effect

Figure 4: Graphic Evidence on Closure and Displacement Effects

Notes: Residuals are obtained from regressing ln(SO2) on all sets of control variables, grid, year-month and province-by-year fixed effects. Standard errors are clustered at the grid level. Observations of 5 years before and after plant closures are included.

Figure 4b depicts the displacement effect by displaying the changes in SO2 levels with distance from operational plants before and after the closures of adjacent plants. The figure is constructed using the same method as Figure 4a, but using data near operational plants within 100km of retired plants (see Figure 3 for illustration).

The displacement effect is graphically demonstrated. Prior to the retirement of nearby coal-fired power plants, the SO2 level in the vicinity of operational plants remains stable around 0. After plant closures, nevertheless, the SO2 level around operational plants significantly increases and then gradually declines with distance from operational plants. The difference in the SO2 level before and after treatment is not statistically significant until around 35km. In other words, air quality near active plants deteriorates after the closures of adjacent plants, likely due to an intensification of electricity production in operational plants.

5.2 Baseline Results

Closure Effect: Table 2 presents the DID estimates on closure effect (Panel A) and displacement effect (Panel B).[11] Columns (1)-(4) display the estimates with regional fixed effects at different levels. Each specification includes a full set of control variables, as described in Section 4, and year-month fixed effects. The treatment group is defined as being within 35km of target plants, while the control group is defined as being between 35km and 100km as in Columns (1)-(5). We further specify more refined control group as being within 75km or 50km in Columns (6) and (7), respectively.

Our results, consistent with the graphic evidence, show that the monthly SO2 level in the vicinity of retired coal-fired plants falls by approximately 2.6% after closure, controlling for climatic variables, province, and year-month fixed effects (Column (1) of Panel A). The estimate is statistically significant at the 5% level. To account for unobserved time invariant regional factors at granular geographic levels, we further refine the regional fixed effects at city, county, and grid levels. Results are presented in Columns (2)-(4) sequentially, showing that the declining SO2 level in the surrounding areas of retired power plants remains robust, with reasonable variations in the magnitude between 2.8% and 3.3%. All estimates are statistically significant at a high 1% level. To further control for unobserved time-varying factors across regions that cannot be captured by existing climatic controls, we include Province$\times$Year fixed effect in addition to the year-month and grid fixed effects. Estimates

[11]The full regression results for the closure effect and displacement effect are reported in Tables A2 and A3, respectively.

Table 2: Baseline Estimates on Closure and Displacement Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Closure Effect						
Close ∗ Post	-0.026**	-0.028***	-0.033***	-0.033***	-0.029***	-0.029***	-0.025***
	(0.013)	(0.010)	(0.009)	(0.007)	(0.006)	(0.006)	(0.008)
Observations	848563	848563	848563	848563	848563	484667	220765
R2	0.37	0.43	0.46	0.48	0.49	0.49	0.50
Mean Dep Variable	0.44	0.44	0.44	0.44	0.44	0.45	0.48
	Panel B: Displacement Effect						
Near ∗ Post	0.035***	0.025**	0.016*	0.006	0.010*	0.015***	0.019***
	(0.012)	(0.010)	(0.009)	(0.007)	(0.006)	(0.006)	(0.006)
Observations	2795840	2795840	2795840	2795840	2795840	1434559	559401
R2	0.33	0.39	0.42	0.44	0.45	0.45	0.45
Mean Dep Variable	0.37	0.37	0.37	0.37	0.37	0.39	0.40
Year month FE	Y	Y	Y	Y	Y	Y	Y
Province FE	Y						
City FE		Y					
County FE			Y				
Grid FE				Y	Y	Y	Y
Province*Year FE					Y	Y	Y

Notes: *p < 0.10; **p < 0.05; ***p < 0.01. Dependent variable is natural log of monthly SO2 from 2004 to 2014. Regression sample in Column (1)-(5) includes observations within 100km of retired plants or operating plants. Column (6) restricts the sample to be within 75km and Column (7) restricts the sample to be within 50km of power plants. All regressions include all sets of control variables. Standard errors are clustered at grid level. Detailed regression results are in Table A2 and A3.

are displayed in Column (5). Again, our findings remain robust and statistically significant, indicating that the closure of coal-fired power plants decreases SO2 level in the vicinity by approximately 2.9%.

One concern is that the chosen control group (35-100km away from retired plants) may include areas affected by other operational or retired power plants simultaneously, making the control group a treated group for other plants. To mitigate this concern, we restrict control group to be within 75km or 50km, respectively, as shown in Columns (6) and (7). The analysis includes year-month, grid, and Province×Year fixed effects, as well as the full set of climatic variables. The estimates remain stable, with reasonable variations in magnitude and level of statistical significance. The most refined control group (35-50km in Column (7)) yields the smallest estimate of -2.5%, suggesting that the broadly defined control group may include regions affected by other retired power plants during China's large-scale phasing out of coal-fired power plants. We consider estimate in Column (7) as our preferred one, because it is based on the most refined control group, includes time-invariant fixed effect at grid level, and captures time-varying factors at province by year level.

The magnitude of our estimated closure effect is consistent with Burney (2020) and Chen et al. (2018), but smaller than the one in Karplus et al. (2018), who study the impact of China's implementation of a national air emissions standard in 2014 on SO2.[12] In contrast, we examine the effect of the staggered phasing-out of coal-fired power plants on air quality between 2004 and 2014.

Displacement effect: In addition to the closure effect, a displacement effect is highly possible though has been little investigated. If plant closures induce nearby active plants to increase operating hours in order to compensate for the falling electricity supply, it may increase SO2 level around the operational plants. We use equation 2 to estimate the displacement effect. Results are presented in Panel B of Table 2. The format of Panel B assembles that of Panel A, but our coefficient of interest is $Near \times Post$, to capture the change in SO2 around operational plants after adjacent plants within 100km shut down.

We find a significant increase in the SO2 level within 35km of operating plants near the retired ones, controlling province and year-month fixed effects (Column (1)). The estimate is 3.5% and statistically significant at a high 1% level, indicating the presence of a displacement effect. With refined regional fixed effects at the city, county, and grid levels, the estimates shrink but remain positive and statistically significant at conventional levels in most specifications (Columns (2)-(4)). We further consider time-varying unobservables and control for Province×Year fixed effects in addition to the grid fixed effects. The estimate under this specification is again positive with statistical significance at the conventional level (Column (5)).

To address the concern about the control group specification, we further restrict the control areas to be within 75km or 50km, as under the closure effect. Results are displayed in Columns (6) and (7), respectively. Controlling for year-month, grid, and Province×Year fixed effects, we observe a statistically significant rise of 1.5% in the SO2 level surrounding operational plants, with control areas defined as 35-75km from operational plants (Column (6)). A similar pattern repeats when using the most refined control group within 50km (Column (7)), with an estimate of 1.9% at a high 1% level of statistical significance. Following the closures of coal-fired power plants, operational plants in the vicinity of retired ones indeed intensify the electricity generation, resulting in a 1-3.5% worsening of the SO2 level in the surrounding areas. We consider the estimate of 1.9% (Column (7)) as our preferred one, as

[12] Burney (2020) reports a decline of 0.013 DU in SO2 due to the decommissioning of coal-fired power plant units in the U.S. Our estimated decline of 2.5% under the closure effect can be translated into a reduction of 0.012 DU in the vicinity of retired plants. Chen et al. (2018) demonstrate that a 1% increase in the scale of power plants in China leads to a 0.7%-2% increase in the SO2 emissions.

it uses the most refined control group and includes granular grid level and Province×Year fixed effects.

To summarize, our findings provide robust and statistically significant evidence for the closure effect and displacement effect that occur following the retirement of coal-fired power plants. We show that while the closure of plants induces a reduction of SO2 in the vicinity, pollution redistributes to operational plants within 100km distance of retired plants, resulting in a significant increase in SO2 levels. By combining our preferred estimates on the closure effect and displacement effect, we calculate the net exposure effect and evaluate its health consequences as measured by infant mortality at the county level. Results will be presented in Sections 5.4 and 6.

5.3 Robustness Checks

In this section, we present robustness checks on the parallel pre-trend assumption, using an alternative way to construct the SO2 measure, removing outliers, clustering at different levels, using a sub-sample of operating plants that did not receive multiple treatments, performing an alternative CSDID model, and varying the distance between retired and operational plants.

Pre-trend assumption: A key assumption for the validity of the DID specification is the presumably parallel trend between the treated and control groups before the treatment. To test this assumption, we present the coefficients for the $Year \times Treatment$ interaction for five years before and after the power plants closures, along with the 95% confidence intervals. To account for variation in treatment timing and heterogeneous treatment effects as discussed in Section 4, we use the CSDID approach and present graphic evidence presented in Figure 5.

We find that prior to the closures, the coefficients for closure effect remain stable and hover around 0 across all years. Nevertheless, after the closures, the coefficients decrease and become negative from year 2 onwards, indicating an improvement in the air quality. The parallel pre-trend assumption for the displacement effect is also supported by the data. Similar to the closure effect, the coefficients prior to treatment are insignificant and hover around 0. However, after the treatment, the coefficients become positive and statistically significant in most years, suggesting redistribution of pollution and a deterioration in air quality around active plants following retirement of power plants in the vicinity. These patterns hold even ignoring the heterogeneous treatment effects (Figure A3).

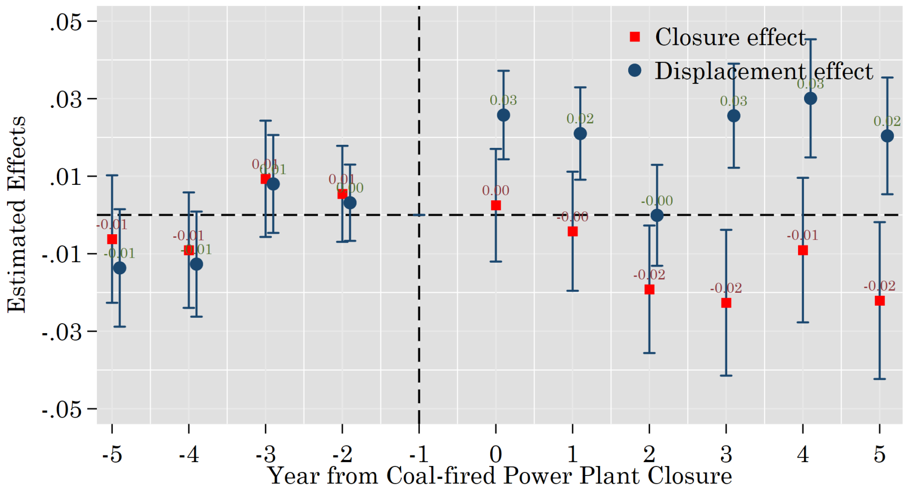

Figure 5: Pre-trend of Closure and Displacement Effects using CSDID

Notes: A full set of controls, grid, year-month and province by year fixed effects are included. Standard errors are clustered at grid level. The effect $\theta^{event}(e) = \frac{\sum \omega_{g,t} ATT(g,t)}{\sum \omega_{g,t}}$ where $\omega_{g,t}$ are based on the number of treated observations of t-g=e, which is average effect of participating in the treatment for the group of units that have been exposed to the treatment for exactly e time periods.

Alternative way to construct SO2 measure: In the baseline analysis (Column (1) of Table 3), negative SO2 data is replaced with zero values. In this robustness check, we drop those the negative SO2 values and re-calculate the grid-level monthly average SO2. Results on the closure and displacement effects are presented in Column (2) in Panels A and B, respectively. Consistent with the baseline results, estimates under this alternative specification remain robust and statistically significant, with reasonable variation in the magnitudes. These findings support our conclusion that there is a reduction in air pollution surrounding retired power plants but an increase in the air pollution in the vicinity of nearby operational plants.[13]

Removal of outliers: To mitigate potential bias from outliers, we exclude grids with monthly SO2 level in the top and bottom 1%. Results are presented in Column (3) of Table

[13]The complete regression results for the robustness checks of closure effect and displacement effect are presented in Tables A4 and A5, respectively.

Table 3: Robustness Checks on Closure and Displacement Effects

	(1) Baseline	(2) Replace negative SO2 with missing	(3) Remove outliers	(4) Cluster county	(5) Cluster province	(6) Sub-sample	(7) CSDID
				Panel A: Closure Effect			
Close * Post	-0.025^{***}	-0.016^{***}	-0.026^{***}	-0.025^{***}	-0.025^{***}	-0.021^{**}	-0.013^{***}
	(0.008)	(0.006)	(0.007)	(0.008)	(0.007)	(0.010)	(0.003)
Observations	220765	220765	215185	220765	220765	139871	19871
R2	0.50	0.50	0.51	0.50	0.50	0.50	
Mean Dep Variable	0.48	0.48	0.46	0.48	0.48	0.52	
				Panel B: Displacement Effect			
Near * Post	0.019^{***}	0.012^{**}	0.017^{***}	0.019^{***}	0.019^{***}	0.028^{**}	0.016^{***}
	(0.006)	(0.005)	(0.006)	(0.007)	(0.006)	(0.012)	(0.002)
Observations	559401	559401	550406	559401	559401	199053	24826
R2	0.45	0.46	0.47	0.45	0.45	0.41	
Mean Dep Variable	0.40	0.40	0.39	0.40	0.40	0.31	

Notes: *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$. Dependent variable is natural log of monthly SO2 from 2004 to 2014. Coefficients in panel A and B are derived from equation (1) and (2), respectively. Control group is defined as between 35 and 50km from the retired or operating plants. In Column (6), we use retired plants without new-built units after closure to analyze the sub-sample closure effects; we remove the open plant with overlapped treatment period to estimate displacement effects. All regressions include a full set of control variables, grid, year-month and province by year fixed effects. Standard errors are clustered at grid level unless otherwise stated. Detailed regression results are in Table A4 and A5

3. Consistent with the baseline results, the estimates remain robust under this specification, with only minor variations in magnitudes.

Different clustering levels: In the baseline estimation, we cluster standard errors at the granular grid level. In this set of robustness check, we relax the restriction and cluster at county or province level, with estimates shown in Columns (4) and (5), respectively. There are no discernible changes in standard errors, and the estimates for the closure and displacement effects remain statistically significant and robust.

Sub-sample without multiple treatment years: Another potential concern is that an operational plant may be located within 100km of various retired plants, resulting in a multiple-treatment issue. To address this concern, we use a sub-sample consisting of operational plants located within 100km of a single retired plant only in the periods of 5 years before and after the closure. In other words, we impose a restriction of a minimum 10-year time interval between any treatments. Column (6) presents the results. Similar to the baseline pattern, estimates from this sub-sample analysis show a closure effect with a magnitude of 2.1% and a displacement effect with magnitude of 2.8%, respectively. Both estimates are statistical significance at the 5% level.

CSDID model: Burgeoning literature highlights the potential bias in estimates under conventional DID settings due to variation in treatment timing and heterogeneous treatment effects (De Chaisemartin and dHaultfoeuille, 2020; Callaway and SantAnna, 2021; Goodman-Bacon, 2021). To address this concern, we conduct an alternative CSDID model. We aggregate SO2 data from monthly to yearly level and match the grids with the nearest retired/operational plants. Note that under this specification, the control group is composed of grids which are never treated within 35-50km of the retired/operational plants, as discussed in Section 4.

Results of the CSDID model are reported in Column (7), where the estimate of the closure effect is -1.3% with statistical significance at the 1% level (Panel A). The magnitude is smaller than the baseline one (Column (1)) due to the weighted average of heterogeneous effects. The estimate of the displacement effect is 1.6% with statistical significance at the 1% level (Panel B), slightly smaller than the baseline result. Thus, our main estimates are not likely contaminated by the concern of heterogeneous treatment effects.

Alternative specification on distance between retired and operating plants: In our main specification of the displacement effect, we restrict the sample of operational plants located within 100km of retired plants. To examine the robustness of this cutoff, we estimate an alternative specification using a sample of operational plants locating 100-200km away from retired plants. The specification follows equation 2 and the results are reported in Table A6, which has a similar structure to Table 2. Unlike the positive and statistically significant estimates in the baseline analysis, most estimates under this alternative specification are statistically insignificant. Our findings support that the displacement effect primarily occurs within a 100km radius of retired power plants.

5.4 Net Exposure Effects

We have so far estimated the average closure and displacement effects on air quality associated with the retirement of coal-fired power plants. However, these relative effects do not inform us about the net exposure of pollution to human settlements, without taking into account population density and absolute levels of air quality. To measure net exposure, we augment granular population data at the 1×1 km^2 cell from the World Pop website. Specifically, we identify cells with centroids within 35km of the retired plants and sum up population of those cells. We then calculate the average annual population within 35km of each plant from 2004 to 2014. The net exposure effect is calculated as follows:

$$\text{Net Exposure} = \overbrace{\left[\beta \times \sum_{i=1}^{n} \left(Popsize_i^{d<=35km} \times \overline{SO2_i}\right)\right]}^{\text{Closure reductions}} - \overbrace{\left[\delta \times \sum_{j=1}^{n} \left(Popsize_j^{d<=35km} \times \overline{SO2_j}\right)\right]}^{\text{Displacement increments}}$$

where β and δ are our preferred estimates of the closure effect and displacement effect, respectively (Column (7) of Table 2). $Popsize_i$ and $Popsize_j$ represent the average population within the 35km vicinity of retired plant i and operational plant j, respectively, after the closure of plant i. $\overline{SO2_i}$ and $\overline{SO2_j}$ refer to the average SO2 levels in the respective vicinity.

We present a back-of-envelope calculation on the net exposure effect in Table 4. The closure of coal-fired power plants is associated with a drop of approximately 16.5 million DU in SO2 levels in the vicinity of retired plants (Panel A). However, the displacement effect offsets this reduction by approximately 14.59 million DU (Panel B). Thus, the net reduction in SO2 is only equivalent to about 11.6% of the reduction from the closure effect (Panel C). This suggests that other operational plants may intensify electricity production after the retirement of coal-fired plants, offsetting the reduction in air pollution due to closures.

Table 4: Net exposure effects from closed and operating coal-fired power plants

Panel A - Closure		Panel B - Displacement	
Estimated effects	-2.5%	Estimated effects	1.9%
SO2 levels (DU)	0.528	SO2 levels (DU)	0.384
Total Population size (<=35km)	1,250,000,000	Total Population size (<=35km)	2,000,000,000
Net Closure exposure [A]	- 16,500,000	Net Displacement exposure [B]	14,592,000
Panel C - Overall			
Net exposure [A + B]	≈-1,908,000		
Net exposure/Net closure [A]	≈ 11.6%		

5.5 Determinants of Displacement

So far, our results have shown that retiring obsolete coal-fired power plants across China contribute to nefarious effects on air quality elsewhere due to energy displacement. These effects are not benign as the net exposure effects from the retirement of older power plants is close to zero after accounting for these pollution displacement effects. Hence, it is imperative for policy makers to understand how to retire dirty energy sources without shifting electricity production and pollution around.

Conceptually, substantial displacement in air pollution surrounding power plants that remain in operation could stem from various reasons. For one, the distortions in electricity dispatch between provinces could prevent the allocation of energy production to the "best" locations with the lowest marginal damage with the smallest exposure to human settlements. As mentioned, provincial leaders have little or no incentives to import electricity from other provinces as this will reduce production capacity from their own generators. Another reason is the lack of cleaner alternate energy sources, such as natural gas, nuclear and/or renewable energy, to supplement energy production after the retirement of coal-fired power plants. Production quotas are likely to be redistributed to other coal-fired power plants with little or no reduction in the marginal external environmental damage for every unit of electricity produce.

In this section, we leverage on the detailed information on power plant locations and electricity trading to understand how planners could minimize displacement effects from retiring power plants.

Distortion in electricity dispatch: As highlighted earlier, one reason why there is displacement is because provincial leaders have no incentives to import electricity from other provinces that have cleaner generation technologies. While detailed trading information between areas is unavailable to us, we rely on our dataset to measure displacement effects within and between administrative boundaries.

Table 5: Determinants of pollution displacement effects from plant closures

	(1) Province	(2) City	(3) County	(4) Renewable	(5) Energy (RE)
Near × Post × SameArea	0.019***	0.015*	0.049***		
	(0.006)	(0.008)	(0.016)		
Near × Post × DiffArea	0.003	0.014**	0.017***		
	(0.010)	(0.007)	(0.006)		
Near × Post × WithRE				0.014**	
				(0.006)	
Near × Post × W/ORE				0.025*	
				(0.013)	
Near × Post × AboveMeanRE					0.005
					(0.009)
Near × Post × BelowMeanRE					0.020***
					(0.007)
Observations	559401	559401	559401	559401	559401
R2	0.45	0.45	0.45	0.45	0.45
Mean Dep Variable	0.40	0.40	0.40	0.40	0.40

Notes: *p < 0.10; **p < 0.05; ***p < 0.01. Dependent variable is natural log of monthly SO2 from 2004 to 2014. Columns 1,2 & 3 report three-way interactions allowing displacement effects to vary between neighboring operating power plants that are in the same and different provinces, cities and counties. Columns 4 and 5 report three-way interactions allowing displacement effects to vary between areas with and without renewable energy plants, and to vary between areas with above and below mean counts of renewable energy plants. All regressions control for a standard set of observables as before, and include grid, year-month and province by year fixed effects. Standard errors are clustered at grid level.

Given that dispatch decisions are made within provinces, we expect displacement to be salient within but not between provinces. In other words, when, for instance, an inefficient coal-fired power plant is retired in Beijing, we expect the quota to be allocated to other operating plants within Beijing, but not to operating plants in neighboring Tianjin. We are able to provide educated answers to this question as we measure in situ air quality measures surrounding all the operating power plants. Results, summarized in column (1) of Table 5, provide support to this notion. Specifically, an operating power plant in another province, despite being geographically proximate (within 100km) to the retired power plant, experiences an immaterial displacement effect that is close to zero. Conversely, as illustrated in Columns (2) and (3), we record significant displacement effects for neighboring operating power plants across counties and cities but within the same province. Collectively, these results suggest to us that impediments to electricity trading between province could be a reason why production quotas are allocated to less pollution efficient plants.

Alternative energy sources: Another reason why we document pollution displacement is because electricity generation quotas are transferred to plants that are pollution inefficient. If these quotas are given to cleaner renewable plants, do we observe an attenuation of displacement effects? To address this question, we augment additional data on the location of renewable energy power plants (e.g hydro-electric, wind power) and examine whether coal-fired power plant closures attribute to smaller pollution displacement when these plants are surrounded by cleaner energy sources. Results, summarized in Column (4) of Table 5, are consistent with our predictions. Specifically, we document that the displacement effects for operating plants without renewable energy power plants averages around 2.5% , while a smaller effect of 1.4% is recorded for operating plants with at least one renewable energy power plant within the vicinity of 100km. These effects are more precisely estimated when we divide our sample into above and below mean based on the counts of renewable energy power plants within 100km. In particular, operating plants that are below mean experience more precise displacement effects of around 2.5%, while the effects associated with plants above mean are close to zero and not statistically significant at any conventional levels.

6 Health Implication

Last, we evaluate the impact of closures of coal-fired power plants on infant mortality as a measure of health outcome, taking both closure and displacement effects into account:

$$ln(Y_{ct}) = \alpha_c + \gamma Plant_{c,t-1} + X'_{ct}\phi + \lambda_c + I_t + \epsilon_{ct} \tag{5}$$

where Y_{ct} is the infant mortality rate at county c in year t from 2000-2014. $Plant_{c,t-1}$ is the independent variable of interest, measured either by the number of retired plants or retired capacity (in MW) in county c at year $t-1$. Cumulative measures of number and capacity by year $t-1$ are also used as alternative measures. X_{ct} is a vector of control variables, including county-level GDP, population, number of maternal and child health hospitals, birth rate, average income, female illiteracy rate, and female employment rate. λ_c and I_t represent county and year fixed effects, respectively. Standard errors are clustered at the county level.

Table 6 presents the results. Columns (1)-(4) display estimates using the number and capacity at year $t-1$ to measure $Plant_{c,t-1}$, while Columns (5)-(8) show the results using alternative cumulative measures until year $t-1$. It is found that the number of retired plants does not have statistically significant impact on the subsequent infant mortality rate, either estimated using non-trimmed (Column (1)) or trimmed data excluding top and bottom 1% observations (Column (2)). The measure of capacity yields some significant results, though at

Table 6: Impact of Power Plant Closure on Infant Mortality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Levels				**Cumulative**			
	Number		Capacity		Number		Capacity	
	ln(infant)	ln(infant)trim	ln(infant)	ln(infant)trim	ln(infant)	ln(infant)trim	ln(infant)	ln(infant)trim
L.Yearly_retireplant	0.074	0.083						
	(0.098)	(0.098)						
L.Yearly_retirecapacity			-0.053*	-0.054*				
			(0.028)	(0.029)				
L.Cumulative_retireplant					-0.057	-0.037		
					(0.080)	(0.077)		
L.Cumulative_retirecapacity							-0.020	-0.023
							(0.034)	(0.035)
Observations	2934	2880	2934	2880	2934	2880	2934	2880
R2	0.79	0.82	0.79	0.82	0.79	0.82	0.79	0.82

Notes: County-level infant mortality rates are from manual collection from Yearbook of Health in the P.R.China, matched with the power plant data collapsed into county level. Standard errors are clustered at the county level. *P < 0.10; **P < 0.05; ***P < 0.01; All columns includes county and year fixed effects; Year_retired plants is the number of retired plants each year, Year_retired capacity is the retired capacities each year, Cum_retired capacity is the cumulative retired capacities of the county divided by 100, Cum_retired plant is the cumulative retired plants of the county; ln(infant)_trim removes the outliers of top 1% and bottom 1%; All regressions contain GDP, population, number of maternal and child health hospital, birth rate, average income, female illiteracy rate and female employment rate controls and restriction of positive number of coal-fired power plants in the province.

the 10% level of statistical significance. With an additional megawatt of retired capacity, the infant mortality rate drops by 5.3-5.4%. None of the estimates using cumulative measures, however, show statistically significant effect on the infant mortality rate (Columns (5)-(8)). It appears that the closures of coal-fired power plants have little impact, if any, on health outcomes as measured by infant mortality, likely due to the displacement effect.

7 Conclusion

In this paper, we estimate the closure effect and displacement effect of coal-fired power plants retirements on air quality in China, using its staggered retirement of mass power plants as a quasi-experiment. Our results indicate that the closures of power plants lead to a reduction of 2.5% in SO2 levels near the retired plants. However, this reduction is counteracted by a 1.9% increase in SO2 levels in the vicinity of operational plants nearby, which may result from an intensification of electricity generation to compensate for the lost capacity. The displacement is more pronounced within the same administrative boundaries and in areas with limited alternative renewable energy sources. Taking both effects into account, we find that the net reduction in SO2 levels from the closure of coal-fired power plant is only 11.6% of the gross reduction in SO2 around retired plants, which likely explains the small or insignificant effects of plant closures on country-wide infant mortality rates.

Improving air quality is a key target of China in achieving carbon neutrality by 2060. Our analysis suggests that the retirement of highly polluted coal-fired power plants alone may not lead to a significant reduction in air pollution, but only a redistribution of pollution to surrounding areas with operational plants. We highlight the need for greater policy attention on developing alternative cleaner energy sources, such as renewable energy, to alleviate the displacement effects.

Our paper has caveats. Due to data limitations, our infant mortality data does not cover all counties in China and we use the starting year of sponsor companies of renewable energy plants as a proxy for the opening of renewable plants. Future research is warranted when more refined health and renewable energy data are available.

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Online Appendix

A1. Data Linkage of Retired Plants and Grid

We define a retired plant if at least one of its generator units is retired, and specify the earliest retired year as the treated year of the power plant. The working sample of the coal-fired power plants includes 180 retired plants and 1,367 open plants. We then aggregate all units in the same plant to calculate the total capacity of the plant and use the earliest commissioning year of the unit as the start year of the power plant. Ages of plants are measured as the number of years since the start year.

We then link the retired plant data with grid pollution data, as well as the climate control variables to estimate the closure effects. Based on the latitude and longitude information of retired plants and grid centroids, we identify grids located within 100 km of retired plants to construct plant-grid pairs. For grids that are located within 100 km of multiple power plants, we count one observation for each plant-grid pair. After converting the paired data of plants and grids into panel data at the monthly level spanning from 2004 to June 2014, we proceed to match it with the monthly SO2 levels, climate data of the corresponding grids in the specific year month and retire year of the plant. Power plants with unknown retired years are excluded from the sample.

In the combined data, grids within 35 km of a retired plant are divided into the treatment group, and the rest are assigned to the control group (35-100 km or 35-50 km). We assign a value of "post=1" for observations over the period of 0-5 years after the plant closure. Since power plants may be located in close proximity to one another, some grids may be included in both the control group of retired power plant A and the treatment group of retired power plant B. This could result in those grids being influenced by plant B's closure within a 5-year period. To prevent contamination in the control group, we exclude data of control groups of plant A pertaining to overlapping grids within 5 years of plant B's retirement.

A2. Qualification of Operational Plants

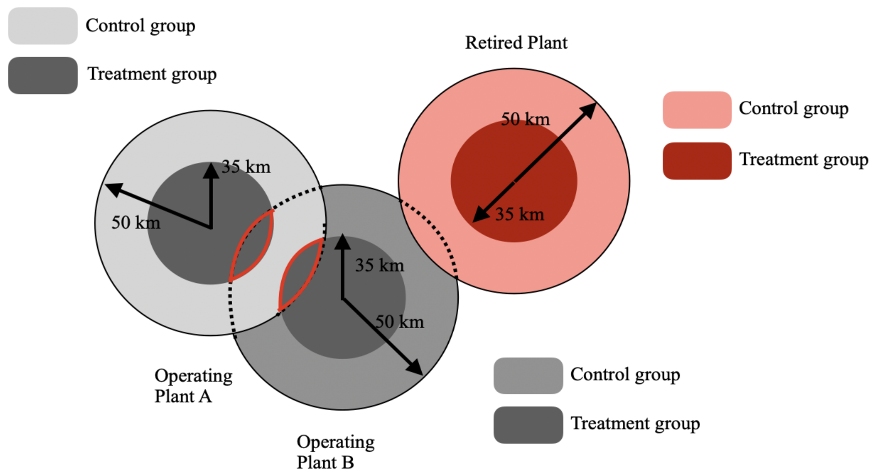
We begin by selecting power plants that are qualified as displaced operating plants to estimate the displacement effects. The specific process involves the following steps: 1. We use the retired plants with a nonmissing retired year to cross with the dataset of all coal-fired plants; It creates a large dataset consisting of all pairwise combinations of retired plants and all plants, as well as the pair of a retired power plant with itself.2. We calculate the distance between each retired plant and paired plants. After that, we keep the paired plants within 100km of retired plants, supported by the heterogeneous analysis across jurisdiction districts in section. There are no significant displacement effects for plants within 100 to 200 km of retired plants. That is, power plants that are located far away from retired plants are less likely to displace and generate power. 3.When identifying operating power plants that have the potential to make up for lost generation following a plant closure, we consider three cases: first, power plants that are continuously operational are capable to displace and provide power generation at all times; second, plants that retired part of generator units still have active units to generate power. We also classify these plants as displaced operating plants; third, for the paired plants are closed completely, we believe that even if the paired plants close before the retired plants based on the comparison of retired year (the earliest retired year of plants), the remaining generator units that close after the retired plant may displace to generate. Therefore, we identify the year in which the latest generator unit of the paired plant was closed, and keep the paired plants with larger latest retired years than the retired year of retired plants. As we mentioned before, the dataset includes the pair of a retired power plant with itself. If the retired power plant has any generator units that were closed after the earliest retired year, we include the pair of the retired power plant with itself in the analysis. Finally, we obtain the 6152 pairs of combinations of displaced operating plants and retired plants.

In this case, if an operating plant is located within 100 km of more than one retired power plant, we will include one observation for each retired power plant-operating plant pair. This means that some operating plants may potentially be displaced operating plants and impacted by the closure of several retired power plants. In the primary specifications, we find all retired plants paired with a specific operating plant and sort them by the retired year. We then reshape the long form data into wide form, to construct the dataset for each unique operating plant. The wide form contains the unique operating plant id, their multiple treated years such as treated year1, treated year2… treated year 20 and different provinces 1-20, cities 1-20, counties 1-20 and retired capacities 1-20 of the multiple retired plants. Treated year 1, retired capacity 1, province 1, city 1 and county 1 refer to the retired year, retired capacity and jurisdiction of the first retired plant within 100 km of the operating plant. This dataset of multiple treatments also indicates that operating plants are within 100 km of at most 20 retired plants. As the previous pairwise combination data may have repeated operating plants, which contribute one observation for each retired plant-operating plant pair, we remove duplicate operating plants to ensure only unique operating plants are preserved. We then match the dataset of multiple treatments with the pairwise combination of operating plants and retired plants based on the operating plant id. The final displaced operating plant data includes 1367 operating plants.

As the operating plants may be located within 100 km of multiple retired plants and have multiple treated years, the sample periods of five years before and after treated years may overlap. If treated years are close to each other, such as 2007 and 2010, the observations of five years prior to second treated year will be affected by the five-year treatment period of first treated year. To address the overlap contamination, we then select the subset of operating plants, which have no overlapped treated years. The sample period of five years prior to and after each treated year will not be impacted by other treatments, indicating that there must be a minimum interval of 10 years between these treated years. Operating plants with only one treated year do not face such issues; hence, we have retained all operating plants with a one treated year.

Similarly, after obtaining the retired and operating plant pairs, we integrate the operating plant data with grid data and climate control values to estimate the displacement effects. We start by using the latitude and longitude information of operating plants and grid centroids to identify the grids located within 100 km of operating plants. Then, we convert the data of plant-grid pairs into panel data from 2004 to June 2014 at the monthly level. After that, we match this data with the monthly SO2 levels and climate data of the corresponding grids based on the year and month. Again, power plants with unknown retired years are excluded from the sample. We define the treatment group as grids within 35 km of operating plants, and the rest are assigned to the control group (35-100 km).

The fact that grids may be paired with more than one operating plant raises a similar question that grids are present in both the control group of operating plant A and the treatment group of operating plant B. It causes that control groups may be influenced by plant B's operation within 5 years of displacement. To prevent contamination in the control group, we drop data of overlapping grids in control groups and within 5 years of plant B's displacement. For instance, operating plant A is close to the retired plant that was retired in 2005, while operating plant B is treated in 2014. The control group for plant B will exclude observations in years between 2005 and 2010, as they overlap with the treatment group of plant A and are in the treatment period of plant A. Considering the issue of a combination of closure effects and displacement effects for operating plants that have retired units, we exclude observations of such operating plants within 5 years of the retirement of any of their units. Besides, observations beyond the year when the latest retired units ceased to operate are disregarded because the operating plant is unable to contribute to power generation.



We define post=1 for observations over the period of 0-5 years after the treated year. As the operating plants have multiple treated years as mentioned above, we define the post-treatment to be 1 if the year is within 5 years of any treated year, otherwise it would be zero. For example, for plantid=1, it has three retired plants nearby, which were closed in 1994, 2001 and 2006 respectively. Then post equal to 1 for years from 2001-2006, and 0 in 2000; from the second treatment period 2006-2011, post equal to 1 and 0 for 2012-2014.

plantid	treat_year1	retired_capacity1	treat_year2	retired_capacity2	treat_year3	retired_capacity3
1	1994	200MW	2001	500MW	2006	100MW
year	post	cumulative retired capacity				
2000	0	0				
2001	1	200				
2002	1	200				
2003	1	200				
2004	1	200				
2005	1	200				
2006	1	700				
2007	1	500				
2008	1	500				
2009	1	500				
2010	1	500				
2011	1	500				
2012	0	0				
2013	0	0				
2014	0	0				

A3. Construction of CSDID

CSDID can estimate the heterogeneous treatment effects with multiple periods. Since the closure time of the plant is measured at the year level, and the cohorts (treatment groups) are identified based on the retired plants in each year, it is necessary to aggregate the monthly grid data, including SO2 and climate variables, to the yearly level from 2004 to 2014. As we mentioned before, When matching grids within 100 km of the plants using geographical information, some grids will be within 100 km of more than one plant. Consequently, these grids will appear multiple times, once for each plant-grid pair, resulting in multiple treated years for those grids. However, when using panel data in CSDID, observations cannot change cohorts across time, indicating one grid is matched with only one retired plant. In this case, we cannot match the yearly grid variables with the plant data using previous methods. To resolve this problem, we match each grid with its closest retired plant to ensure that each grid is associated with a unique retired plant and treated year. It is important to note that some retired plants may be the closest plant to several grids, because we have 15405 grids, but 180 retired plants in our dataset. Finally, we define the treatment and control group in a similar way. Observations with unknown retired years are dropped from the sample.

For the displacement effect analysis using CSDID, we identified and selected operating plants to displace in the preceding step. We now match the yearly grid data with these selected plants by linking each grid to its closest operating plant. To ensure that the estimate is accurate, we remove observations after the latest retired year of the operating plants, as well as those observations that the operating plants are in the period of closure. Since CSDID assumes that once a group is treated, it always remains treated. As part of our methodology, we drop observations in the vicinity of operating plants after they have been closed. In addition, to measure a clear displacement effect, we exclude the grids that are within 35 km of the nearest retired plants.

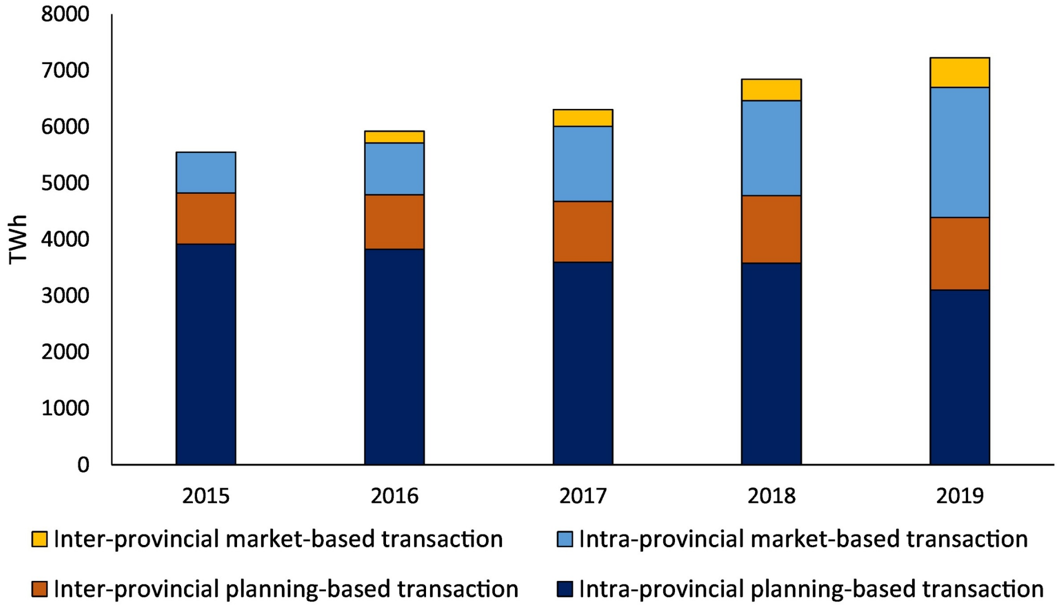


Figure A1: China Electricity Transaction from 2015 to 2019

Notes: The graph is from Chen et al. (2022) Figure 1

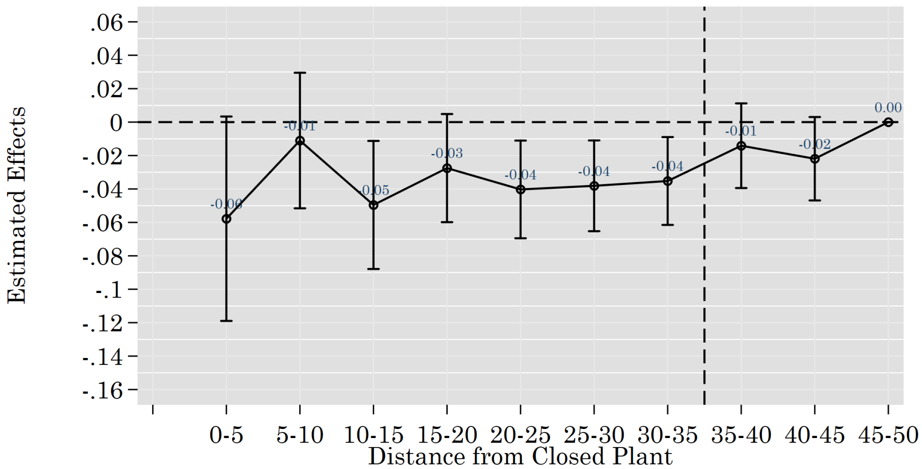


Figure A2: Closure Effects of Different Treatment Group

Notes: The regression uses treatment group defining areas 0-5, 5-10...45-50 km from the retired plants and restricts to area within 50 km of retired plants. Observations five years before and after the plant closure from 2004 to June 2014 are used. A full set of controls, grid, year-month and province by year fixed effects are included. Standard errors are clustered at grid level.

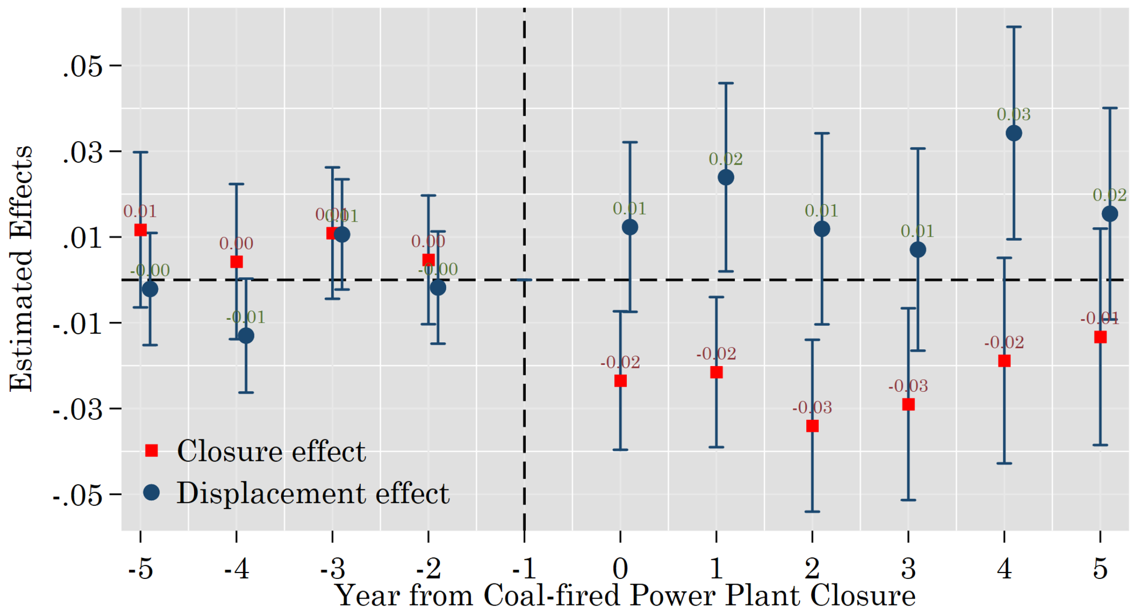


Figure A3: Pre-trends of Closure and Displacement Effects

Notes: This figure presents the Year × Treatment coefficients for 5 years before and after plant closures. Treatment is defined as within 35 km of retired or operating power plants. To test for the displacement effects, operating plants are restricted to be within 100 km of retired plants. A full set of controls, grid, year-month and province by year fixed effects are included. Standard errors are clustered at grid level.

Table A1: Data Source and Variable Definition

Variable	Data	Definition
Dependent variable		
$SO2_{it}$	OMSO2e dataset	SO2 emission of grid i in month t
$Infantmortalityrate_{ct}$	Yearbook of Health in the P.R.China	Infant mortality rate (deaths per thousand of infants) of county c in year t
Independent variable		
$Treat_i$		Treat is a dummy variable to identify the treatment and control group, which equals to 1 if grid i is within 35 km of retired plants.
$Post_t$		Post equals to 1 when year-month t is post the treatment.
$Near_i$		Near is a dummy variable to identify the treatment and control group of displacement, which equals to 1 if grid i is within 35 km of open plants near the retired plants.
$RE\_plantcount$	National Energy Administration	$RE\_plantcount$ is the number of renewable energy plants within 100 km of retired plants and in the same province
$Capacity_{it}$	Global Energy Monitor website	$Capacity_{it}$ is the dummy variable to measure five plant groups with different cumulative retired capacities: 0-100, 100-200, 200-300, 300-500, 500-1000MW
Control variables		
$temp_{it}$	National Oceanic and Atmospheric Administration	The monthly average temperature of grid$i$ in month t, calculated by IDW
dew_{it}	National Oceanic and Atmospheric Administration	The monthly average dew points of grid$i$ in month t, calculated by IDW
slp_{it}	National Oceanic and Atmospheric Administration	The monthly average air pressure relative to mean sea leve of grid$i$ in month t, calculated by IDW
$visibility_{it}$	National Oceanic and Atmospheric Administration	The monthly average visibilty of grid$i$ in month t, calculated by IDW
$wdsp_{it}$	National Oceanic and Atmospheric Administration	The monthly average wind speed of grid$i$ in month t, calculated by IDW
$prcp_{it}$	National Oceanic and Atmospheric Administration	The monthly average precipation of grid$i$ in month t, calculated by IDW
GDP	National Bureau of Statistic	The yearly GDP values of each province
$Popsize_i$	World Pop website	The number of population of grid i
$Numberofhealthhospitals_{ct}$	China County Statistical Yearbook	The number of maternal and child health hospitals of county c in year i
$Birthrate_{ct}$	China County Statistical Yearbook	Birth rate of county c in year i
$Personalincome_{ct}$	China County Statistical Yearbook	Average personal income of county c in year i
$Femaleilliteracy_{ct}$	China County Statistical Yearbook	The ratio of female illiteracy of county c in year i
$Femaleemployment_{ct}$	China County Statistical Yearbook	Employment rate of female of county c in year i

Table A2: Baseline Estimates on Closure Effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat	0.177***	0.155***	0.079***	0.005	0.010***	0.010**	0.011*
	(0.014)	(0.010)	(0.008)	(0.004)	(0.003)	(0.004)	(0.006)
Post	0.027***	0.010***	0.009***	0.010***	0.005***	0.011***	0.016***
	(0.005)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.006)
Close ∗ Post	-0.026**	-0.028***	-0.033***	-0.033***	-0.029***	-0.029***	-0.025***
	(0.013)	(0.010)	(0.009)	(0.007)	(0.006)	(0.006)	(0.008)
Temperature	-0.009***	-0.007***	-0.005***	-0.004***	-0.005***	-0.007***	-0.007***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Temperature square	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dew point	0.020***	0.014***	0.010***	0.009***	0.010***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dew point square	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sea level pressure	0.045***	0.015***	0.014***	0.007***	0.009***	0.009***	0.009***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Wind speed	0.100***	0.018	-0.056***	-0.063***	-0.065***	-0.062***	-0.070***
	(0.016)	(0.012)	(0.011)	(0.011)	(0.011)	(0.013)	(0.019)
Wind speed square	-0.010***	-0.004***	-0.000	-0.001	-0.001	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Precipitation	-0.434***	-0.287***	-0.208***	-0.238***	-0.231***	-0.257***	-0.271***
	(0.070)	(0.056)	(0.053)	(0.051)	(0.053)	(0.061)	(0.079)
Precipitation square	0.889***	0.569***	0.439***	0.433***	0.428***	0.401***	0.372***
	(0.098)	(0.085)	(0.084)	(0.084)	(0.086)	(0.101)	(0.127)
Constant	-47.363***	-16.818***	-14.735***	-7.967***	-10.283***	-10.064***	-10.013***
	(2.058)	(1.461)	(1.599)	(1.148)	(1.144)	(1.379)	(1.848)
Observations	848563	848563	848563	848563	848563	484667	220765
R2	0.37	0.43	0.46	0.48	0.49	0.49	0.50
Mean Dep Variable	0.44	0.44	0.44	0.44	0.44	0.45	0.48
Year month FE	Y	Y	Y	Y	Y	Y	Y
Province FE	Y						
City FE		Y					
County FE			Y				
Grid FE				Y	Y	Y	Y
Province*Year FE					Y	Y	Y

Notes: *p < 0.10; **p < 0.05; ***p < 0.01. Dependent variable is natural log of monthly SO2 from 2004 to 2014. Regression sample in Column (1)-(5) includes observations within 100 km of retired plants. Column (6) restricts the sample to be within 75 km and Column (7) restricts the sample to be within 50 km of power plants. All regressions include all sets of control variables. Standard errors are clustered at grid level.

Table A3: Baseline Estimates on Displacement Effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat	0.085***	0.075***	0.037***	0.004	0.002	0.001	-0.003
	(0.010)	(0.007)	(0.005)	(0.003)	(0.002)	(0.002)	(0.003)
Post	0.088***	0.028***	0.004	0.002	0.001	-0.001	0.008
	(0.008)	(0.005)	(0.004)	(0.003)	(0.002)	(0.003)	(0.006)
Near ∗ Post	0.035***	0.025**	0.016*	0.006	0.010*	0.015***	0.019***
	(0.012)	(0.010)	(0.009)	(0.007)	(0.006)	(0.006)	(0.006)
Temperature	-0.005***	-0.004***	-0.003**	-0.002	-0.004***	-0.006***	-0.008***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Temperature square	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dew point	0.019***	0.011***	0.009***	0.008***	0.009***	0.010***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dew point square	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sea level pressure	0.040***	0.014***	0.012***	0.008***	0.010***	0.012***	0.013***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Wind speed	0.055***	-0.020**	-0.064***	-0.060***	-0.062***	-0.069***	-0.065***
	(0.014)	(0.010)	(0.008)	(0.009)	(0.009)	(0.010)	(0.013)
Wind speed square	-0.006***	-0.001	0.001***	-0.000	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation	-0.527***	-0.305***	-0.232***	-0.264***	-0.346***	-0.362***	-0.312***
	(0.070)	(0.064)	(0.064)	(0.064)	(0.065)	(0.078)	(0.087)
Precipitation square	0.858***	0.475***	0.356***	0.364***	0.462***	0.458***	0.268*
	(0.106)	(0.111)	(0.116)	(0.117)	(0.119)	(0.159)	(0.158)
Constant	-42.293***	-15.726***	-13.403***	-8.869***	-11.286***	-12.648***	-13.764***
	(1.830)	(1.565)	(1.446)	(1.287)	(1.269)	(1.453)	(1.626)
Observations	2795840	2795840	2795840	2795840	2795840	1434559	559401
R2	0.33	0.39	0.42	0.44	0.45	0.45	0.45
Mean Dep Variable	0.37	0.37	0.37	0.37	0.37	0.39	0.40
Year month FE	Y	Y	Y	Y	Y	Y	Y
Province FE	Y						
City FE		Y					
County FE			Y				
Grid FE				Y	Y	Y	Y
Province*Year FE					Y	Y	Y

Notes: *p < 0.10; **p < 0.05; ***p < 0.01. Dependent variable is natural log of monthly SO2 from 2004 to 2014. Regression sample in Column (1)-(5) includes observations within 100 km of operating plants. Column (6) restricts the sample to be within 75 km and Column (7) restricts the sample to be within 50 km of power plants. All regressions include all sets of control variables. Standard errors are clustered at grid level.

Table A4: Robustness Checks on Closure Effect

	(1) Baseline	(2) Replace negative SO2 with missing	(3) Remove outliers	(4) Cluster county	(5) Cluster province	(6) Sub-sample
Treat	0.011*	0.006	0.012**	0.011*	0.011	0.003
	(0.006)	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)
Post	0.016***	0.010**	0.014***	0.016***	0.016	0.010
	(0.006)	(0.005)	(0.005)	(0.006)	(0.010)	(0.007)
Close ∗ Post	-0.025***	-0.016***	-0.026***	-0.025***	-0.025***	-0.021**
	(0.008)	(0.006)	(0.007)	(0.008)	(0.007)	(0.010)
Temperature	-0.007***	-0.002	-0.004**	-0.007**	-0.007	-0.012***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.007)	(0.003)
Temperature square	0.000***	0.000***	0.000	0.000**	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dew point	0.010***	0.006***	0.008***	0.010***	0.010**	0.013***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)	(0.002)
Dew point square	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sea level pressure	0.009***	0.009***	0.008***	0.009***	0.009*	0.006**
	(0.002)	(0.001)	(0.002)	(0.003)	(0.006)	(0.003)
Wind speed	-0.070***	-0.045***	-0.045***	-0.070**	-0.070	-0.100***
	(0.019)	(0.015)	(0.017)	(0.028)	(0.056)	(0.027)
Wind speed square	-0.002	-0.002*	-0.003**	-0.002	-0.002	0.000
	(0.002)	(0.001)	(0.001)	(0.002)	(0.005)	(0.002)
Precipitation	-0.271***	-0.413***	-0.280***	-0.271***	-0.271	-0.253***
	(0.079)	(0.065)	(0.071)	(0.090)	(0.190)	(0.094)
Precipitation square	0.372***	0.404***	0.341***	0.372**	0.372**	0.411***
	(0.127)	(0.107)	(0.122)	(0.156)	(0.153)	(0.139)
Constant	-10.013***	-9.408***	-8.582***	-10.013***	-10.013*	-6.470**
	(1.848)	(1.516)	(1.640)	(2.591)	(5.721)	(2.985)
Observations	220765	220765	215185	220765	220765	139871
R2	0.50	0.50	0.51	0.50	0.50	0.50
Mean Dep Variable	0.48	0.48	0.46	0.48	0.48	0.52

Notes: *p < 0.10; **p < 0.05; ***p < 0.01. Dependent variable is natural log of monthly SO2 from 2004 to 2014. Coefficients are derived from equation (1). Control group is defined as between 35 and 50 km from the retired plants. All regressions include a full set of control variables, grid, year-month and province by year fixed effects. Standard errors are clustered at grid level unless otherwise stated.

Table A5: Robustness Checks on Displacement Effect

	(1) Baseline	(2) Replace negative SO2 with missing	(3) Remove outliers	(4) Cluster county	(5) Cluster province	(6) Sub-sample
Treat	-0.003	-0.002	-0.003	-0.003	-0.003	-0.003
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Post	0.008	0.005	0.008	0.008	0.008	-0.036^{***}
	(0.006)	(0.005)	(0.006)	(0.006)	(0.008)	(0.011)
Near ∗ Post	0.019^{***}	0.012^{**}	0.017^{***}	0.019^{***}	0.019^{***}	0.028^{**}
	(0.006)	(0.005)	(0.006)	(0.007)	(0.006)	(0.012)
Temperature	-0.008^{***}	-0.000	-0.005^{***}	-0.008^{**}	-0.008	0.010^{***}
	(0.002)	(0.002)	(0.002)	(0.004)	(0.007)	(0.002)
Temperature square	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{**}	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dew point	0.011^{***}	0.005^{***}	0.009^{***}	0.011^{***}	0.011^{***}	-0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)	(0.002)
Dew point square	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sea level pressure	0.013^{***}	0.011^{***}	0.011^{***}	0.013^{***}	0.013^{**}	0.011^{***}
	(0.002)	(0.001)	(0.001)	(0.002)	(0.005)	(0.002)
Wind speed	-0.065^{***}	-0.032^{***}	-0.057^{***}	-0.065^{***}	-0.065^{*}	-0.017
	(0.013)	(0.010)	(0.011)	(0.018)	(0.034)	(0.014)
Wind speed square	-0.001	-0.002^{**}	-0.001	-0.001	-0.001	-0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Precipitation	-0.312^{***}	-0.323^{***}	-0.283^{***}	-0.312^{***}	-0.312^{*}	0.001
	(0.087)	(0.078)	(0.077)	(0.101)	(0.173)	(0.106)
Precipitation square	0.268^{*}	0.193	0.209	0.268	0.268	-0.222
	(0.158)	(0.146)	(0.144)	(0.176)	(0.244)	(0.156)
Constant	-13.764^{***}	-11.619^{***}	-11.789^{***}	-13.764^{***}	-13.764^{**}	-12.794^{***}
	(1.626)	(1.331)	(1.491)	(2.296)	(5.042)	(2.015)
Observations	559401	559401	550406	559401	559401	199053
R2	0.45	0.46	0.47	0.45	0.45	0.41
Mean Dep Variable	0.40	0.40	0.39	0.40	0.40	0.31

Notes: *p < 0.10; **p < 0.05; ***p < 0.01. Dependent variable is natural log of monthly SO2 from 2004 to 2014. Coefficients are derived from equation (2). Control group is defined as between 35 and 50 km from the operating plants. All regressions include a full set of control variables, grid, year-month and province by year fixed effects. Standard errors are clustered at grid level unless otherwise stated.

Table A6: Baseline Regression on Displacement Effect across Different Distances

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Near $*$ Post	0.017^{*}	0.018^{**}	0.002	0.008	0.003	0.001	0.003
	(0.009)	(0.008)	(0.006)	(0.006)	(0.004)	(0.004)	(0.005)
Observations	3840337	3840337	3840337	3840337	3840337	2046763	837323
R2	0.31	0.37	0.40	0.42	0.43	0.43	0.43
Mean Dep Variable	0.36	0.36	0.36	0.36	0.36	0.36	0.37
Year month FE	Y	Y	Y	Y	Y	Y	Y
Province FE	Y						
City FE		Y					
County FE			Y				
Grid FE				Y	Y	Y	Y
Province*Year FE					Y	Y	Y

Notes: *p $<$ 0.10; **p $<$ 0.05; ***p $<$ 0.01. Dependent variable is natural log of monthly SO2 from 2004 to 2014. Operating plants are within 100-200 km of retired plants. Regression sample in Column (1)-(5) includes observations within 100 km of operating plants. Column (6) restricts the sample to be within 75 km and Column (7) restricts the sample to be within 50 km of power plants. All regressions include all sets of control variables. Standard errors are clustered at grid level.

Table A7: Determinants of pollution displacement effects from plant closures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Province	City	County	Electricity Import	Renewable Energy		Natural Gas	
Near × Post × SameArea	0.019^{***}	0.015^{*}	0.049^{***}					
	(0.006)	(0.008)	(0.016)					
Near × Post × DiffArea	0.003	0.014^{**}	0.017^{***}					
	(0.010)	(0.007)	(0.006)					
Near ∗ Post ∗ Withimportabovemean				0.007				
				(0.010)				
Near ∗ Post ∗ Noimportbelowmean				0.022^{***}				
				(0.007)				
Near × Post × WithRE					0.019^{***}			
					(0.007)			
Near × Post × W/ORE					0.001			
					(0.008)			
Near × Post × AboveMeanRE						0.022^{**}		
						(0.009)		
Near × Post × BelowMeanRE						0.002		
						(0.007)		
Near ∗ Post ∗ WithGas							-0.007	
							(0.014)	
Near ∗ Post ∗ NoGas							0.022^{***}	
							(0.006)	
Near ∗ Post ∗ WithGasabovemean								-0.011
								(0.015)
Near ∗ Post ∗ NoGasbelowmean								0.021^{***}
								(0.006)
Observations	559401	559401	559401	559401	559401	559401	559401	559401
R2	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
Mean Dep Variable	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40

Notes: *p < 0.10; **p < 0.05; ***p < 0.01. Dependent variable is natural log of monthly SO2 from 2004 to 2014. Columns 1,2 & 3 report three-way interactions allowing displacement effects to vary between neighboring operating power plants that are in the same and different provinces, cities and counties. Columns 4 and 5 report three-way interactions allowing displacement effects to vary between areas with and without renewable energy plants, and to vary between areas with above and below mean counts of renewable energy plants. All regressions control for a standard set of observables as before, and include grid, year-month and province by year fixed effects. Standard errors are clustered at grid level.