

Article

Air Pollution Control: An Analysis of China's Industrial Off-Peak Production Policy through the Quasi-Natural Experiment Method

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Abstract: To reduce frequent heavy air pollution, the Chinese government suspends clinker production during the heating season in most areas of the North, which is known as the Clinker Off-peak Production Policy. The questions regarding such a repressive production policy for environmental purposes are whether this policy is effective in reducing pollutants and whether the marginal cost is high. To explore these policy effects, a quasi-experiment is designed, taking advantage of spatial-temporal variations in policy implementation. With the triple-difference method and environmental satellite data, the effect on air pollution is estimated to be $-1900 \mu\text{g}/\text{m}^2$ ($\sim 2\%$) of SO_2 and $-3200 \mu\text{g}/\text{m}^2$ ($\sim 10\%$) of NO_2 . With daily price information and the difference-in-differences method, the market effect is estimated to be an approximately 10% increase in annual sale prices. The marginal cost estimated through a back-of-the-envelope analysis is 32 k RMB yuan/ton SO_2 or NO_2 , which is 24.88 times the pollutant discharge fee but which better reflects the pollutant shadow price.

Keywords: air pollution control; cement industry; effectiveness of policy; the marginal cost of pollutant reduction



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1. Introduction

Seasonal heavy air pollution due to heating demand and comparatively low atmospheric capability in the autumn and winter [1,2] causes severe health damage and economic loss and has become China's most significant environmental challenge [2,3]. Seeking sustainable development, China has put much effort into air pollution control, such as enacting several new air pollution policies that are included in the Air Pollution Prevention and Control Act (APPCA, 2013–2017) and the Three-year Plan to Fight Air Pollution (2017–2020) [4]. The Clinker Off-peak Production Policy (COPP) is a core policy among these measures in terms of industrial structure adjustment. The basic content is that the COPP suspends cement calcination during seasons in which centralized heating is supplied. The COPP is not only an air pollution control policy but may also affect the market supply-demand relationship, which has caused controversy over the policy's effectiveness. An evaluation of the net effect on air pollution control and the market impacts can help further clarify the policy's purpose and illustrate its actual effectiveness.

As an emergency pollution control measure, the suspension of heavy industrial production has a long history in practice. The previous studies on similar air pollution control measures can provide anticipation on the effectiveness of the enforcement of COPP. The Chinese government suspended and reallocated steeling/coking factories in Beijing in preparation for the 2008 Beijing Olympic Games. Chen et al. (2013) explore the effectiveness of the air pollution control measures in Beijing in the periods of preparation, during the Games, and 13 months after the Games, and find that the control measures significantly

($p < 0.01$) reduced the Air Pollution Index (API) of Beijing by around 35 during the Games and by around 20 after the Games. Further, they divide the whole area into 2.5 km cells and find the effect of closing one plant permanently to at best improve the Aerosol Optical Depth (AOD) within a 5 km radius by 0.091 units, which is much more effective than traffic control for a specific AOD area if considering the average road length within the cell [5]. Additionally, during the 2014 APEC summits (5–11 November) and 2015 Victory-day Parade (3 September), the Ministry of Environmental Protection published the Principles for Formulating the Air Quality Regulatory Program for Beijing and several provinces around Beijing which requires factories that fail to meet discharge standards to shut down. Li et al. (2017) find that both the Victory-day Parade regulation and APEC regulation are effective in air quality improvement. For example, the APEC regulation brought down the AQI by 35.9%, and the concentrations of PM_{2.5}, PM₁₀, SO₂, NO₂, and CO by 41.3%, 48.2%, 56.5%, 38.9%, and 35.5%, respectively [6]. Based on the effective enforcement of similar air pollution control measures in China, COPP is expected to have an effective and immediate air quality improvement effect.

Besides the effectiveness of COPP in air quality improvement, the second part of this paper intends to estimate the market effect. Existing literature has controversies over the market effect of environmental regulations, especially on energy-intensive industries. On the one hand, following the theory that environmental regulations internalize the environmental externalities into enterprises' production, multiple empirical studies have found negative economic effects of environmental policies. For example, Becker and Henderson (2000) explore the unintended effects of the 1978 annual designation of county air quality attainment status and find that this reduced 26–45% births of polluting industries in nonattainment areas [7]. Greenstone (2002) studies the same environmental regulation and finds that there were approximately 590,000 jobs, \$37 billion in capital stock, and \$75 billion (1987 dollars) of output lost in pollution-intensive industries in nonattainment counties compared with attainment ones in the first 15 years of enforcement of Clean Air Act [8]. Linn (2010) conducts an event analysis with stock prices of the regulated firms and finds that the cap-and-trade program on NO_x in the US caused a \$25 billion reduction of the expected profit, which is mainly from the anticipation of the cost increase of coal generators in the regulated areas [9]. The negative effects of environmental regulations also include total factor productivity reduction and the threat to enterprises' survival in energy-intensive industries [10,11]. On the other hand, Porter and his supporters argue that environmental regulations can improve productivity by promoting technology innovation [12,13].

However, the innovation effect of an environmental policy can take years to appear. Since COPP started in 2014, we focus only on the short-term effects. Following Testuji et al. (2018), this paper uses market price to explore the market effect. As COPP targets at cement industry, the market effect not only depends on policy design but also involves the market structure. Several studies discuss the effect of government interference on cement markets and the conclusions vary among different cement market structures. In highly concentrated industries, the output is far less than the optimal amount, and therefore the government's repressive interference in production causes further welfare losses [14]. For example, Ryan (2012) exploits the structure model and estimates that the Clean Air Act has caused approximately 0.81 billion dollars in social welfare loss in the highly concentrated Portland cement industry in the US by increasing entry and exit costs [15]. However, in industries with excess production capacity, the government interference through removing excess production capacity may not cause a significant price effect or social welfare change if the remained capacity can still meet the market demand, such as the capacity reduction carried out in the Japanese Portland cement industry in the 1980s [16]. Industries with excess capacity are prone to attrition wars, which may result in a more serious waste of resources and social welfare loss, as in the case of the Norwegian Portland cement industry before 1968 [17]. This also shows the necessity and positive side of government intervention in the industry. The current Chinese Portland cement market exists excess production capacity, and the cement price experienced a valley in 2015. COPP reduces annual legal

production days, which can increase the price through consumers' anticipation of output reduction. Therefore, a significant price effect is expected of COPP.

Based on the literature review, we bring up two main hypotheses to be examined:

Hypothesis 1. *COPP can have an effective and immediate air pollution control effect.*

Hypothesis 2. *As a government-determined production policy, COPP can cause a significant price increase in the clinker market.*

To examine Hypotheses 1 and 2, the quasi-natural experiment method is employed and conducted with Triple Differences (DDD) and Difference-in-Differences (DD) estimators. Greenstone et al. (2009) argue that greater application of experimental and quasi-experimental techniques can identify efficient policies that increase social welfare [18]. Conducted through DDD and DD models, the quasi-natural experiment method can effectively eliminate estimation bias of policy effect from unobservable confounds. Main works that tend to isolate policy's net effect include Auffhammer and Kellogg (2011) that comparatively analyze the effects on O₃ reductions of three gasoline VOCs content policies in the US with DD and RD models [19]; Greenstone and Hanna (2014) that isolate the effectiveness of water protection policy and air pollution control policy in India with DD models [20], and so on. The spatial-temporal variations in the enforcement of the COPP creates an ideal quasi-natural experiment to study its net environmental effects. Different from the policies studied in the above literature, COPP has obvious seasonal variations. Therefore, besides two variations that come from the regulated cities and regulated years, the third difference, seasonal variation, is also compared in this paper. The application of DDD estimator follows Deschênes et al. (2017) that study NO_x budget program (NBP). Since the cap-and-trade market operated only between May 1 and September 30, they use the DDD estimator to compare pollution, defensive expenditures, and health outcomes in the NBP participating and nonparticipating states, before versus after the first policy year, and summer versus winter [21]. Ignoring the seasonal variations will cause potential estimation bias in both cases.

To be noticed, a DD model is employed to estimate the price effect. The response of clinker/cement price to COPP is not as immediate as pollution discharge and the price effect can shift across seasons. Therefore, this paper compares clinker prices in COPP participating and nonparticipating cities, and before versus after the first policy year of each city with the DD model.

This paper is arranged as follows. Section 1 presents the introduction and a brief literature review. Section 2 introduces the policy background. Section 3 introduces the datasets and model specifications. Section 4 presents the regression results and further validation. Section 5 estimates the marginal cost of COPP through a back-of-the-envelope analysis. Section 6 concludes and provides policy implications.

2. Policy Background

Since the 1990s, China has experienced a huge expansion of its cement capacity along with its rapid economic growth and urbanization. According to the Ministry of Industry and Information (MII), there are 1240 clinker plants in mainland China with a total capacity of 5,922,513 tons/day, distributed across 304 prefecture-level cities as of December 2017. Appendix A, Figure A1 displays the total clinker capacity of each city, as well as the distribution and capacity of each clinker production line.

The calcination process in the cement industry accounts for the second-highest level of coal consumption in China, after only thermal power generation. According to The Cement Industry Total Coal Consumption Control Plan and Policy Research from the China Cement Association, in 2012, the total energy consumed in cement production equaled 207 million tons of standard coal, of which 96.6% was from coal-burning and electricity consumption. Excluding the air pollutants discharged from electricity generation, the clinker/cement industry emitted 1.09 million tons of SO₂, 1.98 million tons of NO_x, and

671,000 tons of dust, accounting for 5.7%, 11.9%, and 6.5% of total industrial emissions of those pollutants, respectively.

At the national China People's Political Consultative Conference (CPPCC) held in March 2014, several CPPCC members from the publishing industry proposed implementing an off-peak production coordination mechanism for cement manufacture in Heilongjiang, Jilin, Liaoning, Hebei, and Inner Mongolia. They proposed suspending cement production during heating seasons when market demand is low and heavy smog frequently appears, to adjust cement supply-demand conflicts and improve air quality.

From June to July 2013, the Ministry of Industry and Information Technology (MIIT) conducted field investigations in the proposed regions and agreed on this proposal. Following its tradition of policy experimentation, China initiated four provincial COPP pilots in Xinjiang, Liaoning, Jilin, and Heilongjiang Provinces in 2014. In the following year, MIIT and the Ministry of Environmental Protection (MEP) jointly issued the "Notice on the Comprehensive Trial Implementation of Off-peak Clinker Production in the Northern Heating Region". This was the first national document of the COPP, which imposed full COPP participation on all 13 provinces and 2 municipalities in the North. In October 2016, MIIT and MEP jointly issued the "2016–2020 Clinker Off-peak Production Announcement", which formulates a preliminary plan for the COPP for 2016 to 2020. Beginning in the autumn of 2017, the regulatory targets expanded to include all building material, steel, and coking industries in "2 + 26" cities along the Tianjin-Beijing-Hebei air pollution transmission channel (This is detailed in a central official document, "2017–2018 Notice on the Industrial Sectors of "2 + 26" Cities to Carry Out Off-peak Production in Autumn and Winter").

3. Data and Methods

3.1. Data

3.1.1. Explained Variables

Satellite air pollution data: For the explained variables, the SO₂ and NO₂ daily tropospheric column mass density (TCMD) were selected to represent air quality. SO₂ TCMD is extracted from the time-averaged two-dimensional collections of MERRA2 which is a NASA atmospheric reanalysis for the satellite era (For the data download and Readme file, please search "M2T1NXAER_5.12.4" on the following website: <https://disc.gsfc.nasa.gov/datasets>) [22]. NO₂ TCMD is from POMINO (For the data download and Readme file, please refer to <https://ocean.pku.edu.cn/info/1038/3123.htm>), an improved and validated NO₂ data product based on OMI by Peking University [23]. The unit of each data is a density unit and converted to kg/m². Data cleaning is conducted based on the data quality standards from the Readme files. The MERRA2 data does not need extra cleaning. The POMINO observations with a quality index below 0 and cloud rate bigger than 0.5 are dropped. The reading with a projected location nearest to the municipal center of a prefecture-level city (all less than 100 km (Considering the spatial resolution of satellite data, a 100 km radius is an operation-efficient range that can guarantee at least one observation is obtained for each city)) is used as the reading for that city.

Streets et al. (2013) review the capability of satellite data and present the summary of the major satellite instruments, their characteristics, and the chemical species they can detect. Among these satellite-based atmospheric component monitors, OMI is the most widely applied because of its long duty (2004–), high frequency (daily), and high resolution (13 km × 24 km) [24]. Several research organizations have modified OMI original data using local air mass factor and other parameters and developed level2 and level3 products. POMINO is one of these products.

The satellite-based air quality datasets are generally validated and applied in the atmospheric study but the introduction and application in the environmental economic study are not rich. However, Donaldson and Storeygard (2016) point out the main advantages of satellite data in economic study, which also can be cited to explain why using satellite data is better in this paper [25]: First, the access to obtain information by other

means is difficult. There are no ground-monitored air quality data records that fully cover Chinese cities before May 2014, which has limited relative studies to a period after 2014. Since some cities began to implement COPP in 2014, using ground-monitored data will sacrifice the control observations before the policy year which is crucial for estimation accuracy. Second, satellite data has high spatial resolution and wide geographic coverage. Even if ground-monitored air quality data of most Chinese cities is available after 2014, the number of national ground monitoring stations is limited. The reads for some small cities come from the ground monitoring stations located in a nearby city. Also, many ground monitoring stations are far from the city center and therefore the reads are not within our interested area. Instead, the high spatial resolution of satellite-based data allows the choice of accurate observed locations and the wide geographic coverage allows reads for all cities. Other potential considerations include that the site choice of ground monitoring station is not independent of air pollution distribution [26], and the reads in some Chinese cities may be modified out of political pressure [27].

Clinker price data: Clinker prices are from the China Cement website, the largest website with information on the Chinese cement industry that regularly collects price and other information from the cooperative cement facilities, covering over 85% of all facilities. The data are of daily frequency and are available over the observation period 2010–2017, tagged with cement type, brand, manufacturer, and sales agent information. We match the price data with clinker line data via the manufacturer name to control for facility-level factors.

3.1.2. Explanatory Variable

The explanatory variable is a dummy variable indicating whether the observation is within a shutdown period. The specific shutdown dates for each city come from official documents and are verified by news from China Cement. When collecting COPP-relevant documents, we use a top-down approach; that is, we use central government documents first to find regulated regions and then provincial and municipal government documents to find more specific COPP plans, as all COPP-relevant documents are required to be publicly available by MIIT and MEP. The specific shutdown dates are based on the available plans from the lowest administrative level. The COPP proposal was initiated in March 2014, so “off-peak production” was used as a keyword, and 1340 pieces of news were found on the China Cement website. By going through all news items, extra cities that are not required to participate in the COPP by higher-level governments but actually joined independently were located, and the specific participation dates of all cities were verified.

After eliminating observations with either ambiguous shutdown dates or missing satellite data, 214 prefecture-level cities were kept in the treatment group. 27 cities first implemented the COPP in 2014. Then, 74, 33, and 80 new cities joined sequentially from 2015 to 2017. Appendix A, Figure A2 shows the policy year of cities on the map.

3.1.3. Control Variables

Socioeconomic variables: In the price effect estimates, the proportion of cement output to total output and fixed asset investments per capita are controlled for to account for market supply and demand impacts. The regressions also control for city-level characteristic variables, such as GDP per capita, the proportion of the secondary industry to total industry, and government expenditure per capita. The proportion of cement output is from the National Bureau of Statistics, and the other variables are from the Statistical Yearbook of Chinese Cities. Facility-specific variables, such as firm age, are from the China Cement website.

Weather variables: Weather information is used for control variables. The data are also from MERRA2, following the same data cleaning and averaging procedure as for the SO₂ TCMD. Weather variables include temperature, precipitation, wind speed, and direction, all in daily averages.

The observation period for the above datasets is 1 January 2010, to 31 December 2017. The COPP is currently still in effect, but observations from after 2017 are eliminated because more industries have joined the program since then. Additionally, the COPP plans themselves have become more flexible, which means that actual implementation dates and capacities are hard to define. Table 1 lists the definition, units, and sources of all variables and Table 2 presents summary statistics of the variables.

Table 1. Variable definition and data sources.

Variables		Unit	Sources
SO ₂	SO ₂ column density	µg/m ²	M2T1NXFLX_V5.12.4
NO ₂	NO ₂ column density	µg/m ²	POMINO
Temperature	Air temperature scale	°C	M2T1NXFLX_V5.12.4
Precipitation	Total precipitation	kg/m ² s	M2T1NXFLX_V5.12.4
Wind	Wind speed	m/s	M2T1NXFLX_V5.12.4
Eastwind	Eastward wind	m/s	M2T1NXFLX_V5.12.4
Northwind	Northward wind	m/s	M2T1NXFLX_V5.12.4
Price	Clinker price per ton	yuan/ton	China Cements Website
Investment	Fixed-asset investment per capita	yuan/capita	China City Statistical Yearbook
Cement	Cement output proportion	%	National Bureau of Statistics
GDP	GDP per capita	yuan/capita	China City Statistical Yearbook
Second	Secondary industry	%	China City Statistical Yearbook
Fiscal	Fiscal expenditure per capita	yuan/capita	China City Statistical Yearbook
Age	Facility age	Year	List of Cement Clinker Enterprises

Table 2. Summary statistics.

Variables	N	Mean	Min	Max	SD
SO ₂	666,019	30,796.58	27.54	298,950.6	29,129.82
NO ₂	376,004	8765.09	0.039	2,852,611	22,869.98
Temperature	729,714	0.08	−0.92	1.33	0.1
Precipitation	729,714	0.03	0	4.18	0.1
Wind	729,714	5.33	0.92	27.94	2.04
Eastwind	729,714	0.28	−18.73	17.11	3.29
Northwind	729,714	−0.17	−19.76	14.91	3.58
Price	710	232.06	147.19	430.14	43.03
Investment	710	39,475.85	4074.76	219,392.8	24,961.99
Cement	710	0.049	0.007	0.078	0.016
GDP	710	52,448.29	11,383.02	277,857.5	38,547.08
Second	710	49.65	24.81	73.45	8.52
Fiscal	710	7446.04	2012.64	36,840.25	4081.76
Age	707	9.41	1	24	4.27

3.2. Methods

3.2.1. DDD Model Specifications

Since COPP is a seasonal policy, accurate estimation of its air quality effect requires isolating the air quality change during the corresponding dates rather than average air quality change throughout the year, which cannot be solved by DD estimator. Following Greenstone et al. (2012), this paper conducts a DDD model to identify the impact of COPP-regulated suspensions on air quality. The DDD estimator exploits three sources of variations: cities that implement the COPP and those that never implement the COPP, the years for each city before and after it implemented the COPP, and the months of facility shutdowns and those of production. In other words, the city-year-months of production

suspensions are compared with those outside of the regulated suspension periods. The model is given as follows:

$$Y_{icmy} = \gamma Treat_{icmy} + W'_{icmy} \beta + \mu_{cm} + \varphi_{cy} + \omega_{my} + \rho_c + \sigma_y + \tau_m + \varepsilon_{icmy} \quad (1)$$

where $icmy$ indicates the i th observation for each city-month-year. Y denotes the air pollution variable, including SO_2 and NO_2 . $Treat$ is the explanatory variable indicating the treatment status of each observation, and $Treat = 1$ when an observation is within the suspension dates defined by the city-year-month information; otherwise, $Treat = 0$. All three sets of two-way fixed effects should be included in the DDD operation. Due to the efficiency of our calculations, we control for three two-way fixed effects: the city-by-year fixed effects φ_{cy} , which account for all factors common to a city within a year; the month-by-year fixed effects ω_{my} for all factors common to a month and year; and the city-by-month fixed effects μ_{cm} for permanent differences in outcomes across city-months [21]. We also control for city fixed effects ρ_c , year fixed effects σ_y , and month fixed effects τ_m (The month fixed effects are not absorbed by the higher dimensional fixed effects, while the year fixed effects and the city fixed effects are absorbed by higher dimensional fixed effects [25]). In addition to the main fixed effects, we control for a set of variables to address annual, monthly, and weekly cycles in air quality, as well as their interactions with the weather variables. All regressions limit the sample to a balanced panel of city-month-years. The standard errors are clustered at the city-year level.

3.2.2. DD Model Specifications

The response of clinker price to COPP is not as immediate as the pollution discharge and the price effect can shift across seasons through consumers' expectation of the output reduction. We estimate the annual average price effect of COPP rather than the effect that appears during certain months. We conduct the following DD model to compare the price difference in cities that implementing COPP versus those not implementing COPP, and years before the policy versus after:

$$Y_{icy} = \gamma Treat_{icy} + X'_{icy} \beta + \rho_c + \sigma_y + \varepsilon_{icy} \quad (2)$$

where icy indicates the observation of i th facility in each city-year. Y denotes the annual clinker sale price. $Treat$ indicates whether the observation is within the COPP treatment period, and $Treat = 1$ when the facility is within a suspension year; otherwise, $Treat = 0$. X' is a vector of control variables, including city-level control variables such as GDP per capita, the ratio of the industry output value, fiscal expenditure per capita, foreign investment per capita, and the proportion of clinker output, as well as facility-level control variables such as facility age and facility age squared. We also control for city fixed effects ρ_c , and year fixed effects σ_y . The standard errors are clustered at the facility-year level.

To validate the DD model, the dynamic price effect is explored to observe yearly differences and examine the common trend assumptions between the two groups. The model specification is as follows:

$$Y_{icy} = \sum_{t=-5}^3 (\delta_t D_{icy}^t) + X'_{icy} \beta + \rho_c + \sigma_y + \varepsilon_{icy} \quad (3)$$

where t gives the standard treatment year that ranges from -5 to 3 , with 2014 as the base year. D indicates whether the observation in year t is in the treatment group ($D = 1$) or control group ($D = 0$). δ_t gives the dynamic effect coefficient of the COPP in year t . The other terms are the same as those in model (2).

The econometric process is conducted via STATA 16 software.

4. Results

4.1. Effect on Air Pollution

Figure 1 reflects air quality using SO₂ (Panel A) and NO₂ (Panel B) TCMDs within and outside of the shutdown period regulated by the COPP in Heilongjiang Province. For the years 2016–2017, Heilongjiang experienced clinker production suspension from 1 November to 31 March of the next year. In 2017 only, there were 3 suspensions conducted from May to September, and each was approximately 20 days. From Figure 1, both the SO₂ and NO₂ TCMDs during most of May–September 2017 were lower than those during the same period in 2016. The seasonal patterns support the feasibility of the DDD method for estimating the effect on air pollution control.

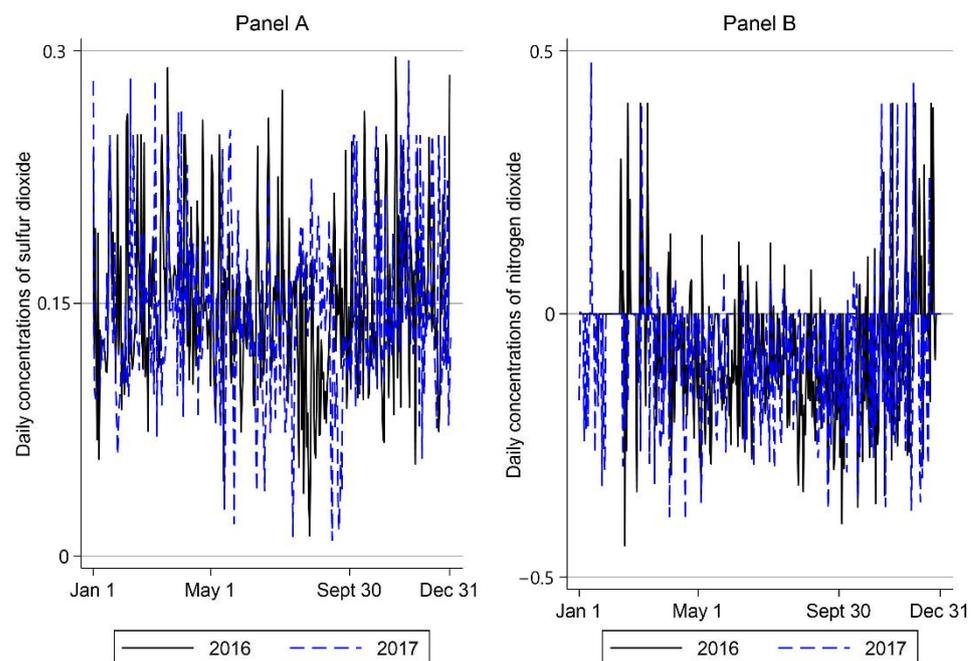


Figure 1. A comparison of the within-year pattern of atmospheric pollutants between 2016 and 2017: Panel A daily SO₂ and Panel B daily NO₂ TCMDs, taking Heilongjiang Province as an example. The values were obtained from an OLS regression of SO₂ and NO₂ TCMD on six day-of-week indicators, weather variables, and a constant. The values in the graph are equal to the constant plus the regression residual. The graph depicts fitted values for the reference category (Monday). Daily TCMDs on the y -axis are measured in $\mu\text{g}/\text{m}^2$.

Table 3 displays the regression results for the DDD regression and the robustness checks. Columns (1)–(4) use the SO₂ TCMD as the explained variable and (5)–(8) use the NO₂ TCMD. Columns (1) and (5), which include city fixed effects, year fixed effects, month fixed effects, and their two-way interaction, show that the COPP significantly reduced daily SO₂ by 1762 $\mu\text{g}/\text{m}^2$ and the daily NO₂ TCMD by 2712 $\mu\text{g}/\text{m}^2$, both at the 0.01 significance level. Columns (2) and (6), which additionally control for DOW, DOY, Season FE, Region FE, and their interactions, estimate the causal effect of the COPP on daily SO₂ and NO₂ TCMDs to be $-1863 \mu\text{g}/\text{m}^2$ and $-2807 \mu\text{g}/\text{m}^2$, respectively. Columns (3) and (7) add Weather and its interactions with DOW and DOY. Columns (4) and (8) add Trend as an extra control. There is an amplification of the coefficient of interest, γ , along with the introduction of additional control variables, which validates the choice of fixed effects used in this model. For the results of SO₂, the robust standard errors are within the range of 230–250. The estimates are all significant at 1% level. R^2 is around 0.6. For the results of NO₂, the robust standard errors are within the range of 227–231. The estimates are all significant at 1% level and R^2 reaches 0.14. The results are robust across models which indicates the credibility of the estimations. The COPP's causal effects on the daily SO₂

TCMD can be fairly accepted as $-1900 \mu\text{g}/\text{m}^2$ and those on the daily NO_2 TCMD as $-3200 \mu\text{g}/\text{m}^2$.

Table 3. The effects of the Clinker Off-peak Production Policy (COPP) on air pollution.

Variables	(1)	(2)	(3)	(4)
Panel A				
SO ₂	−1762 *** (252.0)	−1863 *** (251.8)	−1920 *** (232.9)	−1936 *** (233.2)
N	648,684	648,684	648,684	648,684
R ²	0.610	0.611	0.649	0.649
Panel B	(5)	(6)	(7)	(8)
NO ₂	−2712 *** (229.6)	−2807 *** (228.7)	−3132 *** (231.3)	−3212 *** (227.5)
N	370,352	370,352	370,352	370,352
R ²	0.138	0.140	0.148	0.149
City FE	X	X	X	X
Year FE	X	X	X	X
Month FE	X	X	X	X
Month-Year FE	X	X	X	X
Month-City FE	X	X	X	X
Year Fes-City FE	X	X	X	X
Weathers			X	X
DOW FE-Weathers			X	X
DOW FE-Season FE		X	X	X
DOW FE-Region FE		X	X	X
DOY-Weathers			X	X
DOY-Season FE		X	X	X
DOY-Region FE		X	X	X
Trend				X
Cluster at city-month	X	X	X	X

*** $p < 0.01$. Robust standard errors clustered at the city-month level are reported in parentheses in columns (1)–(8). Weather (a matrix of daily average temperature, precipitation, and wind measurements) is included since these variables may have significant nonlinear effects on the atmospheric environment [28]; day-of-week fixed effects (DOW), day-of-year fixed effects (DOY), and their interactions with Weather are included; season fixed effects (Season FE), province fixed effects (Region FE), and their interactions with DOY or DOW are also included; and finally, Trend, the province trend effects specific to treated cities and control cities within each province, is also included.

4.2. Effect on Clinker Price

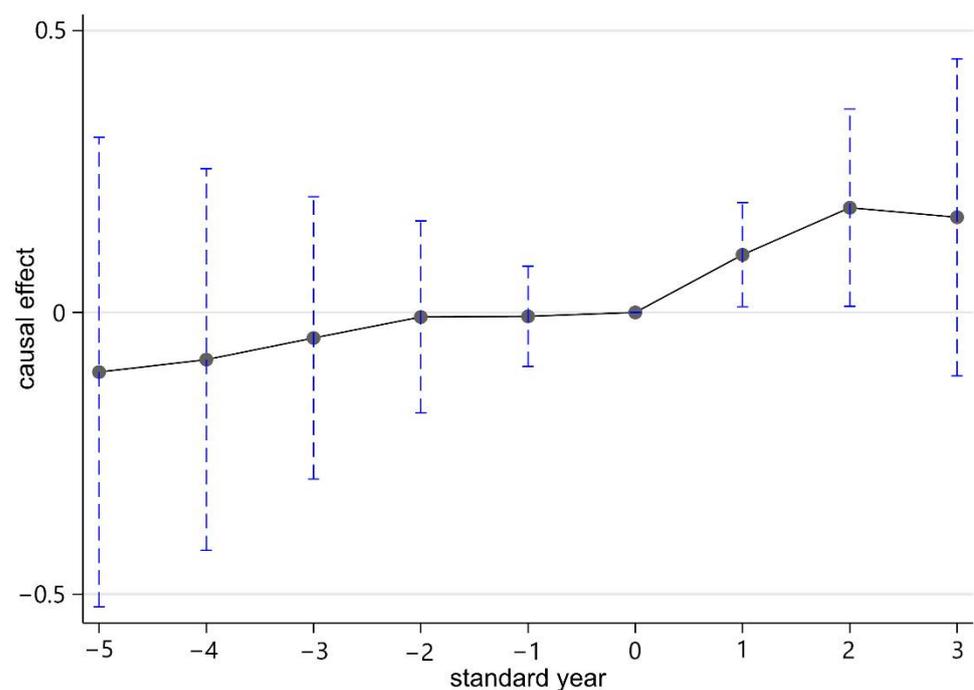
The questions regarding government interference with clinker production are the extent to which such interference affects market power and whether it causes significant social welfare loss. The product sale price is a key index for measuring social welfare changes [16]. To explore the market effect, the plant-level daily clinker sale price and model (2) are employed. Table 4 shows the regression results. Column (1) controls for total investments in fixed assets averaged over the population and the proportion of cement output to total output for each city. Column (2) adds GDP per capita, government fiscal expenditure, and the ratio between the gross value of secondary industry production and GDP. Column (3) additionally controls for facility age and the square of facility age. The robust standard error is around 0.19 and R^2 is around 82%. The estimates of the price effect are significant at the 1% confidence interval, and the effect of the COPP on annual clinker prices is approximately 10%. This result is robust across regressions. The above statistical parameters validate the reliability of the models.

Table 4. The effects of the COPP on the annual average of clinker sale prices.

	(1)	(2)	(3)
Log(price)	Clinker	Clinker	Clinker
Treatment	0.0845 *** (0.0194)	0.0948 *** (0.0187)	0.100 *** (0.0188)
Investment	-6.28×10^{-7} (7.71×10^{-7})	-1.25×10^{-6} (8.37×10^{-7})	-1.22×10^{-6} (8.49×10^{-7})
Cement	7.36×10^{-6} (7.21×10^{-6})	3.01×10^{-6} (6.96×10^{-6})	1.50×10^{-6} (6.88×10^{-6})
GDP		-1.14×10^{-6} (1.57×10^{-6})	-1.88×10^{-6} (1.63×10^{-6})
Second		0.00977 *** (0.00246)	0.0103 *** (0.00246)
Fisical		8.92×10^{-6} (9.34×10^{-6})	1.26×10^{-5} (9.44×10^{-6})
Age			0.0511 ** (0.0222)
Age square			1.88×10^{-6} ** (8.15×10^{-7})
Facility FE	Y	Y	Y
Year FE	Y	Y	Y
N	710	710	707
R ²	0.817	0.825	0.828

*** $p < 0.01$, ** $p < 0.05$. The clinker price data is collected at the facility-level, so other than regional-level variables, the facility-specific variables are controlled here.

We also estimate the dynamic effect of the COPP on clinker prices using model (3). The regression results are plotted in Figure 2. We find that in the pretreatment period, these estimates are approximately 0 and insignificant. Immediately after the COPP was implemented, there was a clear increase in the estimated effect, and it remained significantly positive. This result demonstrates no differential time trend before the treatment and validates the DD results.

**Figure 2.** Common trend analysis of the COPP's effects on clinker prices.

4.3. Placebo Test

This subsection intends to further examine if the significant effects are caused by potential unobserved variables by employing a placebo test. The idea of a placebo test is that if the effects that the model estimates are due to unobservable variables, the distribution of the results from randomized trials must be very different from the standard normal distribution. In the spirit of Chetty et al. (2009) and Martin et al. (2017), we first keep only cities in the treatment group and then randomly assign them a year as they started to implement COPP. Then regressions are conducted to estimate the effect of the placebo policy [29,30]. Since the policy event is not real, the estimate is expected to be insignificant. This exercise is repeated 200 times. For each iteration, we run the following regressions for each outcome of interest:

$$Y_{icmy} = \gamma Random_{icmy} + W'_{icmy} \beta + \mu_{cm} + \varphi_{cy} + \omega_{my} + \rho_c + \sigma_y + \tau_m + \varepsilon_{icmy} \quad (4)$$

$$Y_{icy} = \gamma Random_{icy} + X'_{icy} \beta + \rho_c + \sigma_y + \varepsilon_{icy} \quad (5)$$

The randomly assigned treatment is distinguished from true treatment by year to avoid confounding.

Table 5, Panel A shows the results from one of the 200 placebo runs, while Panel B summarizes the number of runs that were significantly above or below 0 at the 10% level for each outcome of interest. For most outcomes, 20 or fewer runs were significant at the 10% level. Overall, 7.5% of the NO₂ results were significant, and 0 of the SO₂ results were significant. The clinker price outcome did have 26 runs (13%) that were significantly different from 0, 24 of which were negative, which is the opposite direction from the true results. Panel C shows an empirical cumulative distribution function (CDF) from the 200 placebo results for NO₂, SO₂, and clinker price. As expected from a successful placebo test, the true coefficients for the effects on NO₂ and SO₂ are at the far left of the CDF, and the true coefficient for the effect on clinker price is at the far right of the CDF. Therefore, the placebo test validates that the pollutant reduction and price increase are caused by the COPP.

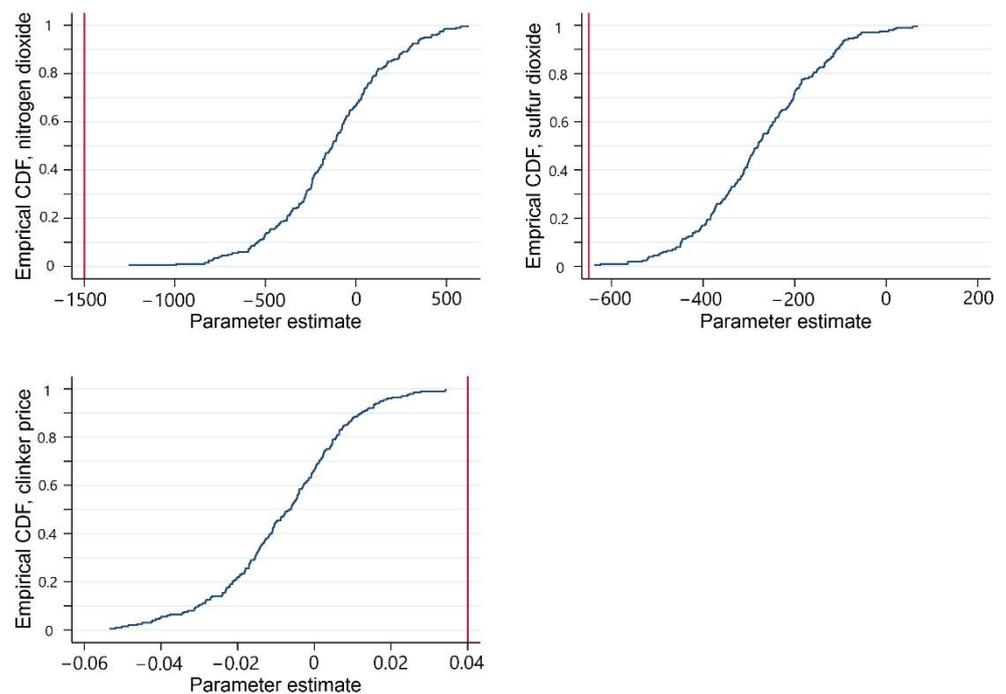
Table 5. Placebo test.

	(1) NO ₂	(2) SO ₂	(3) Clinker Price
Panel A: Placebo test			
Placebo effect	−330.6 (368.1)	−334.5 (470.3)	−0.00835 (0.0181)
Control variables	Y	Y	Y
Fixed effects	Y	Y	Y
N	18,573	21,312	707
R ²	0.798	0.974	0.816

Panel B: Results of 200 iterations of placebo sampling, number of estimates landing above, below, and within 95 percent confidence interval around 0

	Significant		
	Above 0	Below 0	Insignificant
NO ₂	1	14	185
SO ₂	0	0	200
Clinker price	2	24	174

Panel C: Results of 200 iterations of placebo sampling for NO₂, SO₂ and clinker price



Results from Table 5 in which COPP treatment timing is randomly assigned across all potential observations. Placebo treatments were assigned 200 times. Panel A shows an example of one placebo run. The control variables in columns (1) and (2) are the same as those in columns (4) and (8) of Table 3, and the control variables in column (3) are the same as those in column (3) of Table 4. Panel B shows the number of runs in which each outcome of interest was above or below 0 and significant at the 10% level versus not significant at the 10% level. Panel C shows an empirical cumulative distribution function (CDF) of 200 placebo runs, as well as the true coefficients, for the effects on SO₂, NO₂, and clinker price. The vertical lines show the direction of the true coefficients for the COPP. Standard errors are clustered at the city-year level.

5. Back-of-the-Envelope Analysis

5.1. Total Pollutant Mass

Satellite pollutant data in this paper gives the daily mass over the projected area of the tropospheric air column, which can theoretically be integrated across city areas and shutdown days to estimate the total mass reduction caused by the COPP. The integration of TCMD has been widely used to retrieve pollutant burden and emission rates via top-down methods, such as Beirle et al. (2011), and Laughner and Cohen (2019) [31,32]. The daily

SO₂ and NO₂ TCMD reduction coefficients are equal to -1.9 kg/km^2 and -3.2 kg/km^2 , respectively. The results show the impact of COPP on the air quality at city centers. However, considering that the clinker facilities in different cities are randomly distributed around city centers, it is reasonable to assume in this back-of-the-envelope analysis that COPP has an equal impact on air quality across the city. Integrations are conducted using the average effect coefficients, the municipal area (from China City Yearbook), and the number of shutdown days within the whole year for those cities that participated in the COPP from 2014 to 2017. For comparison with market costs, the total mass reduction is converted to province-year level, as shown in Table 6. The average annual tropospheric SO₂ mass reduction was 8.7, 22.5, 32.8, and 45.9 kt per province-year for 2014–2017. The average annual tropospheric NO₂ mass reduction was 14.6, 37.9, 55.2, 77.3 kt per province-year for 2014–2017.

Table 6. Results of the back-of-the-envelope analysis.

Province	Year	Market Cost (Million RMB yuan)	SO ₂ Reduction (kton)	NO ₂ Reduction (kton)	Marginal Cost (k RMB yuan/ton)	Pollution Discharge Fee (k RMB yuan/ton)	Ratio
Heilongjiang	2015	344.48	85.75	144.41	1.49669	1.26	1.187849
Jilin	2014	-	5.74	9.66	-		
	2015	-	25.89	43.61	-		
Liaoning	2014	697.84	1.19	2.00	218.865	1.26	173.7024
	2016	516.66	32.00	53.90	6.014622	1.26	4.77351
	2017	684.25	76.06	128.10	3.351425	1.26	2.659861
Inner Mongolia	2016	455.52	56.13	94.54	3.023157	1.26	2.399331
	2017	458.75	227.75	383.57	0.750432	1.26	0.595581
Ningxia	2015	-	1.76	2.96	-		
	2016	-	10.20	17.19	-		
Qinghai	2015	235.10	1.31	2.21	66.86795	1.26	53.0698
	2016	234.96	1.53	2.57	57.28096	1.26	45.46108
	2017	211.18	5.16	8.70	15.23483	1.26	12.09113
Shandong	2017	2135.81	32.95	55.49	24.14944	1.26	19.16622
Shanxi	2015	328.15	21.70	36.54	5.634655	1.26	4.471949
	2016	409.30	31.32	52.74	4.869182	1.26	3.86443
	2017	547.56	36.97	62.26	5.518282	1.26	4.379589
Shannxi	2015	695.07	10.86	18.29	23.85042	1.26	18.9289
	2017	801.07	23.58	39.71	12.65719	1.26	10.04539
Jiangsu	2017	1229.17	4.56	7.68	100.461	1.26	79.73093
Jiangxi	2017	1276.13	-	-	-		
Hebei	2015	785.74	18.66	31.43	15.68739	2.40	6.536414
	2016	869.58	37.32	62.86	8.680605	2.40	3.616919
	2017	1220.91	51.50	86.74	8.831621	2.40	3.679842
Henan	2015	1236.29	18.34	30.89	25.11237	1.26	19.93046
	2016	1161.20	23.48	39.55	18.42229	1.26	14.62086
	2017	1809.84	25.94	43.70	25.98827	1.26	20.62561
Zhejiang	2017	1150.13	4.54	7.64	94.46524	1.26	74.97241
Hubei	2017	948.93	-	-	-		
Hunan	2017	1320.12	-	-	-		
Guangdong	2017	1947.84	-	-	-		
Guangxi	2017	1355.08	-	-	-		
Fujian	2017	893.37	15.95	26.86	20.86668	1.26	16.56086
Sichuan	2017	1820.71	-	-	-		
Chongqing	2017	892.20	-	-	-		
Average					32.00332		24.88

5.2. Market Cost

The definition of market cost here is the part of social welfare change caused by the price effect, which is the extra money consumers paid to purchase the same amount of clinker that is caused purely by the COPP or could be regarded as the cost the consumers paid to reduce tropospheric pollutant mass through the COPP. The market cost for each province is the price increased multiplied by the clinker output each year. The average market costs are 535.97, 662.89, 731.25, and 1150.16 million RMB yuan per province-year for 2014–2017, which equals 82.46, 101.98, 112.5, and 176.95 million US dollars.

5.3. Marginal Cost

After balancing the province-year pollutant reduction and market cost data, 24 province-year observations are kept to further calculate the unit cost of SO₂ and NO₂ reductions through the COPP, as shown in Table 6. The average cost of reducing each ton of tropospheric SO₂ or NO₂ through the COPP was 32 k RMB yuan from 2014–2017 (Since the pollution discharge fee is the same for SO₂ and NO_x, the value of a reduction of one unit of SO₂ and NO_x is assumed to be identical here. The ratio of NO_x to NO₂ in the atmosphere is not addressed here because the uncertainty in the back-of-the-envelope analysis is larger than that). China has established 11 pilot provincial markets for trade in pollutant permits since 2007 and adjusted pollution discharge fees after 2007. The unit prices for pollutant discharge and pollutant permits can both provide a reference for the marginal price of pollutant reduction. Table 6 gives the provincial discharge fees, which range from 1.26–2.4 k RMB yuan/ton [33]. In other words, the marginal cost of pollutant reduction through the COPP is 24.88 times the pollutant discharge fee. The price of pollution permits ranged from 1–15 k RMB yuan/ton between 2001–2017 among pilot provinces. The SO₂ shadow price between 2011 and 2014 is reported in the literature to be approximately 72.5 k RMB yuan/ton [34]. Additionally, for the province with the highest permit trade price, Hunan, the shadow prices reported in the literature are 3.02 k RMB yuan/ton for SO₂ and 58.09 k RMB yuan/ton for NO_x [35]. Therefore, the marginal cost of reducing pollutants through the COPP is higher than the marginal costs given by discharge fees and pollution permits but is within the range of rational shadow prices given in the literature.

6. Discussions and Policy Implications

The main findings of this article are concluded as follows: (1) the net of the COPP effect on pollution is $-1900 \mu\text{g}/\text{m}^2$ of SO₂ and $-3200 \mu\text{g}/\text{m}^2$ of NO₂; (2) the average tropospheric SO₂ mass reduction is 8.7, 22.5, 32.8, and 45.9 kt per province-year from 2014–2017 and the average tropospheric NO₂ mass reduction is 14.6, 37.9, 55.2, 77.3 kt per province-year from 2014–2017; (3) the effect of the COPP on annual sale prices is approximately 10%, which caused consumers to pay extra costs of 535.97, 662.89, 731.25, and 1150.16 million RMB yuan per province-year from 2014–2017, or 82.46, 101.98, 112.5, and 176.95 million US dollars; and (4) the marginal cost of pollutant reduction through the COPP is 32 k RMB yuan/ton, which is 24.88 times the pollution discharge fee and is higher than the discharge permit trade price, but is closer to pollutant shadow prices estimated in the literature.

First, the air pollution control effect implies that the enforcement of “Chinese style” air pollution control policy under the leadership of the Chinese government is effective and immediate. This conclusion is generally consistent with the findings of effectiveness analysis of air pollution control policies of China. For example, Wang et al. (2021) find that the central environmental inspection mechanism of China significantly improved air quality and argue that this system has had an immediate effect in general [36]. The literature has found that the effectiveness of air pollution policy enforcement relies largely on public concern under a weak environmental institution. However, for the case of China, the literature has argued that the focus of the Chinese government plays a significant role in the effectiveness of air quality improvement [5]. Therefore, it is of great significance to explore how the Chinese government design and implement air pollution control policies,

especially those of the “Chinese style”, to promote effective environmental governance and sustainable development.

Second, the market effect implies that the administrative air pollution control measures in energy-intensive industries increase the market price and possibly bring a higher marginal cost of air pollutant reduction compared with market-based measures. Similar works that study air pollution policies of China mainly focus on the policy effectiveness and seldom estimate the policy cost. For example, Li et al. (2020) estimate the benefits of fuel standard upgrade but fails to estimate the cost. They point out that the economic realities are not transparent for oil refineries and the profit estimate is rough [37]. In this paper, we find that the marginal cost of COPP is much higher than the pollution discharge tax rate. Fowlie et al. (2016) calculate the social benefits of carbon abatement with emission tax rate and argue that reductions in product market surplus and allocative inefficiencies due to market power in the US cement market counteract the benefits [38]. From this view, we argue that COPP requires government and residents to assign a high marginal value to pollutant reduction to avoid the potential cost-and-benefit distortion. In other words, the sustainability of COPP as an air pollution control policy depends on the government’s and the resident’s willingness to pay.

Therefore, the performance of the COPP generates the following policy implications for the environmental governance in energy-intensive industries. (1) Repressive production policies are an effective and immediate measure for reducing tropospheric pollutant mass and are therefore of high practical value for emergency control of heavy pollution. (2) Although the literature argues that the government’s repressive production policies in industries with excess capacity do not cause significant social welfare loss, the optimal level of government production interference is hard to determine. In other words, it is not easy for a direct production interference policy to avoid having a significant price effect or leading to social welfare change. (3) Direct repressive production control policies can impose a high marginal cost for pollutant reduction, given the far lower pollution discharge fee and pollution discharge permit price in China, but these high marginal costs better reflect pollutant shadow prices. There is a rational motivation for the government to enforce the COPP. (4) Such a production control policy requires the government to assign a high marginal value to pollutant reduction; therefore, enforcement strongly depends on governments’ and residents’ willingness to pay for environmental protection. To enjoy better air quality, the marginal cost is roughly estimated to be 32 k RMB yuan/ton, which is 24.88 times the current pollution discharge fee.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

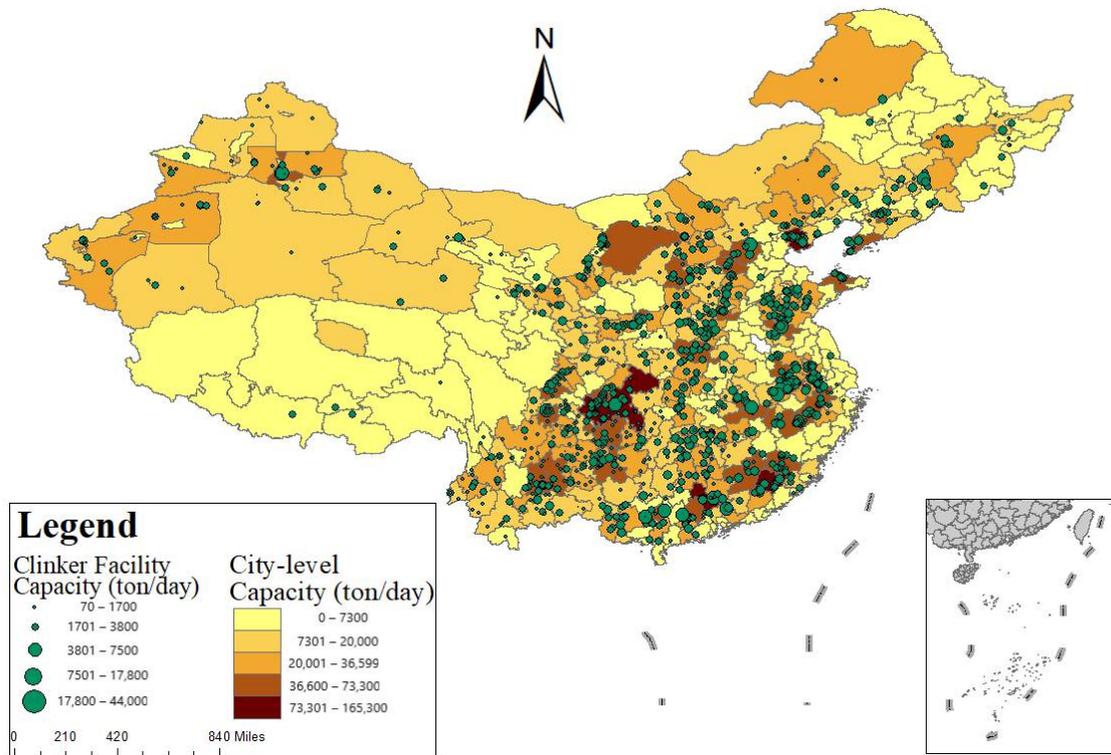


Figure A1. Graphic summary of the geographical distribution of clinker capacity at facility-level and city-level of China.

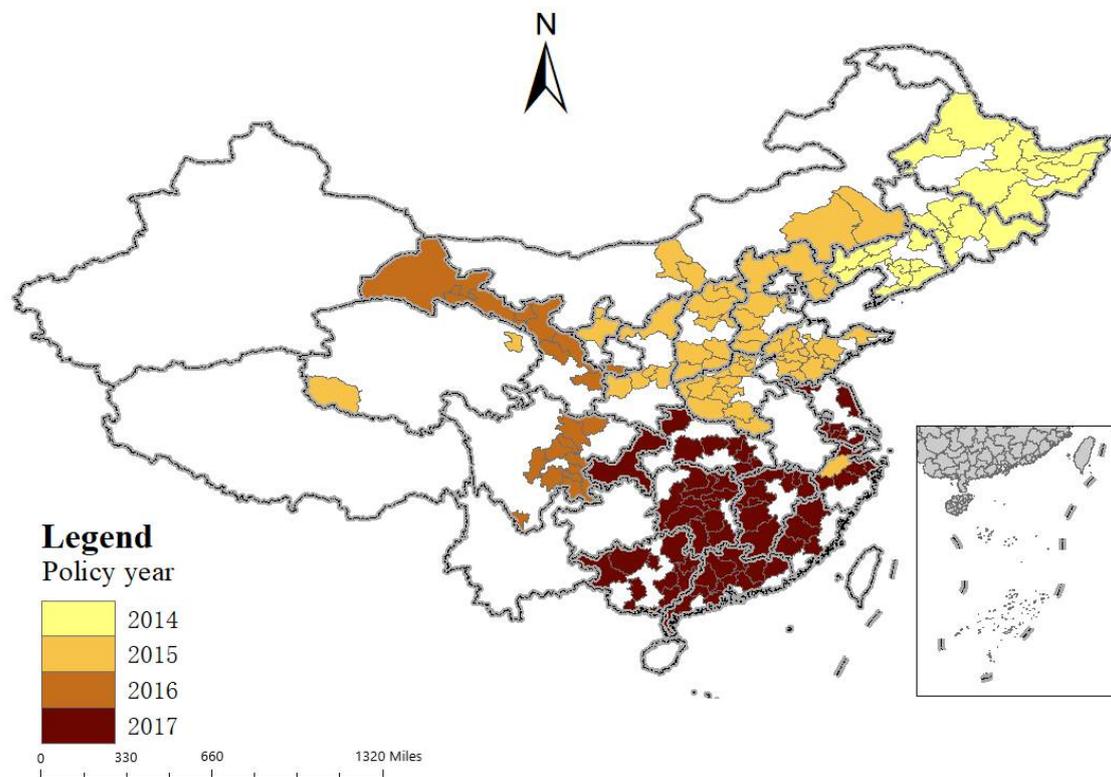


Figure A2. Spatial and temporal variation in COPP implementation. The policy year indicates when cities initially implemented the COPP.

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