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Import Ban and Clean Air: Estimating the Effect of China's Waste Import Ban on the Ozone Pollution

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Abstract

This study investigates the effects of the plastic waste ban on local air quality in China. Using city-level daily ozone concentrations, we examine whether the pollution levels differ between coastal and inland cities in China after the import ban. Obtained results show that the daily ozone concentration lowered by 2.2% in coastal cities after the import ban. Additional analyses suggest that the effect is heterogeneous: the reduction is larger in later period, larger in cities with dirty baseline pollution, and smaller in cities with higher rural population density. These results are suggestive of the impact of import ban as an indirect policy instrument.

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1 Introduction

Air pollution is detrimental to human health and causes substantial loss, particularly in a fast-growing economy like China. In 2017, the Global Burden of Disease estimated that in China, approximately 852,000 deaths were attributable to PM 2.5 exposures and an additional 178,000 chronic respiratory disease-related deaths to ozone (Health Effect Institute, 2019). Air pollution can cause huge economic losses, which were equivalent to 9.92% of China's annual GDP in 2013 (World Bank and Institute for Health Metrics and Evaluation, 2016). Recent studies suggest that the effects of air pollution are diverse, including cognitive performance decline (Zhang, 2018), labor productivity loss (He et al., 2019), and sleeplessness (Heyes et al., 2019).

The Chinese government has taken several actions to reduce the severity of air pollution. As a result, the annual average concentrations of PM 2.5, PM 10, and NO_2 in China gradually decreased from 2014 to 2018. In contrast, the concentration of surface ozone has increased. The surface ozone has become one of the major air pollutants in the cities under Stage I monitoring, based on the amended ambient air quality standard. As Figure 1 shows, while more cities under Stage I monitoring met the standard for many pollutants from 2016 to 2017, fewer cities met the standard for ozone. Despite China seeing a steady decline in PM 2.5 exposures, it had the most population-weighted seasonal concentration of ozone among the world's 11 most populous countries (Health Effect Institute, 2019).

[Figure 1]

Plastic recycling generates volatile organic compounds (VOCs), which react with NOx in the presence of sunlight to form ground-level ozone. China has been the world's largest importer of plastic waste. It processes huge amounts of hard-to-recycle plastics from other countries, accounting for approximately 56% of the global market (Brooks et al., 2018). However, in July 2017, the Chinese government introduced a policy that imposed a ban, effective from January 1, 2018, on the import of several kinds of waste, including plastic waste. As a result of this ban, the volume of plastic waste imported to China has greatly reduced. According to the *China Recycling Industry Report 2019*, it has reduced from 5.83 million tons in 2017 to 0.05 million tons in 2018, by almost 99% (Figure 2). Meanwhile, the supply fell short of demand in the plastic waste market. The market price of plastic waste increased by 6% to 16%, depending on the type of plastic materials.

[Figure 2]

This study investigates the effects of the plastic waste ban on air quality in China by focusing on surface-level ozone. After the import ban, the imports of plastic waste decreased and the market price increased. It supposedly lead to a slowdown of the manufacturing process that releases VOCs, and thus, the VOC emissions also reduced. The reduction of VOCs further reduced the ozone concentration, as VOCs and NOx are the main precursors of ozone formation. Therefore, we can expect that the air quality improved in the areas around the plastic recycling facilities.

This study contributes to the literature on the economics of air pollution in developing countries in two ways. First, many studies on the effect of air pollution control focus on policies that directly affect emission sources, such as shutdown and installation of control equipment (Cao et al., 2009), driving restrictions (Viard and Fu, 2015), and subsidies to winter heating (Almond et al., 2009). Nevertheless, in the case of plastic recycling, the number of pollution sources is large, and it is often difficult to enforce the regulation. Import ban can be regarded as an indirect policy instrument that reduce the amount of plastic waste used by small-scale recyclers. This study exploits the unique event and investigates the impact of a substantial drop in the input for the polluting activity. Second, although several studies have evaluated the global impact of plastic waste ban (Brooks et al., 2018; Qu et al., 2019; Huang et al., 2020), they did not focus on the domestic environmental impact.

One of the aims of the policy is to alleviate local severe pollution; hence, it is necessary to understand whether and how the ban could improve the local environment.

The remainder of this paper is structured as follows. Section 2 briefly describes the policy background and explains air protection control in China related to the ozone concentration. Section 3 reviews previous studies. Section 4 describes our empirical strategy, the model, and the dataset. Section 5 presents the empirical results, robustness checks, and heterogeneous effects. Section 6 concludes our paper.

2 Background

2.1 VOCs Emission During Plastic Recycling

A large volume of plastics is produced and recycled in China. In 2014, the production amount of all kinds of plastics in China was 73.9 million tons, and the corresponding consumption amount was 93.3 million tons. In the same year, the amount of waste plastic recycled was 28.3 million tons, which accounted for approximately 30% of the total consumption amount (Cao et al., 2019).

Plastic recycling includes material recycling, chemical recycling, and energy recovery (Al-Salem et al., 2009; Lazarevic et al., 2010). While there are many material recycling plants in China, melting temperatures in the material recycling method range from 200°C to 300°C, which may produce harmful components, such as VOCs. Pollutants are often emitted into the atmosphere without sufficient treatment. For example, Huang et al. (2013) report that most of the plastic recycling activities in one of the largest plastic recycling centre in China, Xingtan (Guangdong Province) are carried out in open air with no measures to treat the emitted harmful gases. In addition, many devices in small workshops recycling the imported plastic wastes were not qualified which could release harmful exhausts to the air (*China Economic Daily, Blocking foreign garbage completely, 2015/5/28*). He et al. (2015) analyzed the emissions of different kinds of plastic solid waste and found that the melting extrusion of seven different thermoplastics could produce a substantial volume of VOCs. The total VOC concentrations emitted during recycling were highest in ABS, and were lowest in polycarbonates.

2.2 Controlling the VOC Emissions

In January and February 2013, severe haze covered many provinces in China. This led to a widespread environmental concern that pushed the Chinese government to tighten the air pollution regulations (Jin et al., 2016). During 2013 and 2014, China rolled out a new, nationwide air pollution program in three waves across cities to provide real-time monitoring of six air pollutants, including PM2.5, PM10, O_3, CO, NO_2, and SO_2 (Greenstone et al., 2020). Since then, the Chinese government has implemented various policies to alleviate severe air pollution.

The control measures for ozone have largely been untouched in China, however, until the *13th Five-Year Plan for the Prevention and Control of VOCs Pollution* was introduced in 2017 (Health Effects Institute, 2019). Through this policy, the government emphasized the importance of reducing VOCs as the main precursors of ozone. The ozone concentrations in the cities under Stage I monitoring based on the new air quality standard increased by 10.8% from 2013 to 2016. The government then set a target for the local governments of the VOC heavy-polluted areas in 16 provinces to reduce the VOC emissions by 10% before 2020.

2.3 The Ban on Import of Plastic Waste

The Chinese government had been controlling the import of waste for a long time and eventually concluded it with a ban. The government has frequently revised the *Law of the People's Republic of China on Prevention and Control of Environmental Pollution by Solid Waste* in recent years. Since its introduction in 1996, the law has been revised four times in 2005, 2013, 2015, and 2016 (Sun, 2019). Furthermore, the government has been strengthening border control. In 2013, the Green Fence campaign was carried out to enhance border controls. Sun (2019) employed DID methods and found that the Green Fence campaign had a significant effect in reducing the waste imported into China. The government then revised the campaign to the so-called Blue-Sky Campaign and implemented stricter regulations every year from 2017 onward.

The ban on the import of plastic waste was announced in July 2017. The Chinese government set three targets in this policy called the *Implementing Plan for Banning Foreign Trash Imports and Promoting Reform in the Solid Waste Import Management System*. The first target was to reduce the import of solid waste to reduce the environmental damages gradually. The second was to regulate the recycling industry by inspecting illegal behaviors, revising related laws, monitoring smuggling, and promoting job changes. The last one was to increase the recycling rate of domestic waste, improve the recycling technology, and build new and cleaner recycling plants.

As part of the policy, the Ministry of Ecology and Environment of China carried out a campaign in July 2017 to manage and control the recycling industry. The ministry examined the acts of 1,768 large recycling companies and found that 60% of them were operating illegally. The illicit acts included using invalid filters, making fake monitoring data, trading the permit of importing solid waste to other unqualified firms, and building new plants without permission (PRC Central China, 2017).

It should be noted that a company needs to obtain a permit from the authorities to import solid waste. The permits is obtained only by companies with qualified facilities that meet the standards set by the government. However, as mentioned before, some of these companies sell their permits to other firms and small workshops that do not meet the standards or even with no filter installed. The permits illegally sold by qualified companies help those firms and workshops with no permits to obtain materials and process them without enough care for the environment.

3 Method and Data

3.1 Methodology

This paper employs a DID method to identify the treatment effects and mitigate possible endogeneity problems (Meyer, 1995). City-level daily 8-hour average ozone concentration (*Ozone*) is used as a dependent variable to estimate the effect of the plastic waste ban. The baseline model is formulated as follows:

$$Ozone_{it} = \beta_1 After_t + \beta_2 Treat_i + \beta_3 DID_{it} + X_{it} + \xi_t + \epsilon_{it}, \tag{1}$$

where $Ozone_{it}$ denotes the ozone level in city i in day t, and *After* is the dummy variable that equals to 1 for the period after the import ban (January 1, 2018), and 0 otherwise. Treat is a dummy variable for the cities in the treatment group. *DID* is the interaction of *Treat* and *After* that captures the treatment effect. We expect that the coefficient of the interaction term *DID* will be negative if the ban reduces the ozone concentrations. X denotes the control variables including the daily average NO_2 concentrations and the daily maximum temperatures from 2017 to 2018. This is because the formation of ozone is related to VOCs, NOx, and temperature. We use the daily highest temperature to control the effect of the temperature as for the highest ozone concentration of a day should appear around the highest temperature. ξ is the month fixed effects, and ϵ is the error term.

The treatment group contains all the cities in three coastal provinces: Guangdong, Shandong, and Zhejiang, as for most of the plastic recycling firms are located in these provinces and Hebei province (China Recycling Industry Report, 2012 & 2016). Because the plastic is light and bulky, it is not efficient to transfer the imported plastic waste to inland provinces. Although we do not have exact data regarding the location of plastic recycling facilities, anecdotal evidence suggests that these firms tend to concentrate in coastal areas. Hebei province is excluded from our analysis because the province is located in the Jing-Jin-Ji area (including Beijing, Tianjin and Hebei). Because the environmental policies in Jing-Jin-ji area are often different from other areas, it is difficult to control the effect of other policies that could potentially cause estimation bias.

The control group contains all the cities in three inland provinces: Sichuan, Hubei, and Hunan. All provinces in the treatment and control groups are listed in the VOC heavy-polluted areas mentioned in the VOCs reduction policy to control the effect of the country-wide VOCs reduction policy of the 13th 5-Year-Plan. Figure 3 shows the study area where the dark grey area indicates the treatment group and the light grey area is the control group.

To confirm the validity of the selection of treatment and control groups, we use the Alibaba online market (https://www.1688.com/) and implemented a keyword search by "Recycled Plastics" in Chinese. As for the online market group the sellers by province, we found there were 1,989 recycled plastic materials sellers in Guangdong, 2,036 sellers in Zhejiang, 1,109 sellers in Shandong and 578 sellers in Hebei. In contrast, there were 103 sellers in Sichuan, 105 in Hubei and 54 in Hunan. The findings are supportive of our selection of the treatment groups and control groups.

[Figure 3]

3.2 Data

This study uses city-level daily data. The data on ozone and NO_2 in cities of these provinces are collected from the China Air Quality Online Monitoring and Analysis Platform.[1] This website collects real-time data on pollutants from the Ministry of Ecology and Environment of China and automatically calculates daily average data. The daily maximum temperature data were obtained from Tianqihoubao,[2] which collects historical weather data covering 34 provinces and provides data at 2,290 counties. The daily data for 47 cities in the treatment group and 43 cities in the control group were collected from 2017 to 2018. Due to data loss between December 1, 2017, and December 12, 2017, we removed the data for the

[1] *http://www.aqistudy.cn*
[2] *http://www.tianqihoubao.com*

corresponding period of 2018.

As Table 1 shows, there are 63,540 observations, and the average concentration of ozone is $94.17\mu\text{g}/m^3$. The average concentration in the treatment group was higher than that in the control group, while the concentration of NO_2 is almost the same.

[Table 1]

The acceptable concentration of ozone set by the WHO is 100 $\mu\text{g}/m^3$. We can see from Figure 4 that China suffers from severe ozone pollution. It is also obvious that compared with 2017, the average daily concentration of ozone in 2018 has reduced. However, it is difficult to understand the trend in both groups from the graph of the daily average concentration from the figure. Therefore, we draw the graph of the monthly average concentration in Figure 5. This reveals that the monthly concentration of ozone exhibits an M-shaped annual trend in both groups. The figure also shows that the trend in both groups was parallel in most months of 2017.

[Figure 4]

[Figure 5]

4 Results and Disscution

4.1 Main Results: DID Estimation

The estimation results are reported in Table 3. Columns 1 and 3 contain month fixed effects, while columns 2 and 4 do not. The result shows a negative relationship between the import ban and ozone concentration. The coefficient of the treatment indicator *DID* is negative and statistically significant at the 1% level in all the columns of Table 2. The estimated effect in column 2 corresponds to a decrease of $2.2\mu\text{g}/m^3$ in the ozone concentration in the coastal provinces, which is about 2.2% of the daily average ozone concentration in the treatment group. The result supports the hypothesis that the import ban from 2018 reduced the ozone concentrations in the coastal cities.

[Table 2]

We also find that both the estimated coefficient for NO_2 and the maximum temperature are positive and significant. Because VOCs, NOx, and temperatures are the major determinants of ozone chemistry (Jin and Holloway, 2015), the result is reasonable. However, the relationship between ozone and VOCs is non-linear and complex. To better understand the mechanism, we explore this point further in the next subsection.

4.2 Robustness Check: Ozone-NOx-VOC Sensitivity

This subsection investigates the robustness of our main findings. We exploited the ozone-NOx-VOC sensitivity to redefine the treatment and control groups to examine the sensitivity of the results. The main result in the previous subsection is based on the list of the VOC heavy-polluted areas at province level published by the government. Considering studies that identify the exact ozone-NOx-VOC sensitivity over China, we redefine the control and treatment groups based on the ozone-NOx-VOC sensitivity as an alternative criterion to choose the study area.

Analysis in this subsection uses the ozone photochemical regime plotted by Jin and Holloway (2015) to reselect the control and treatment groups. We exclude cities in the NOx-limited regime; therefore, cities in both groups were chosen from the VOC-limited regime and transitional regime. This is because, in the NOx-limited regime, the ozone concentration decreases with the reduction of NOx and increases with the reduction of VOCs, which could lead to a biased result. In the VOC-limited and transitional regimes, the ozone concentration decreases with the reduction of VOCs. Defined in this way, we can expect that the control and treatment groups would react similarly to the change in VOCs.

By redefinition, we have 28 cities in the treatment group from Guangdong, Shandong, and Zhejiang provinces. The control group contains 20 cities from Sichuan, Hubei, Hunan, and Anhui provinces. We expect a stronger treatment effect in this regression because the ozone in both groups is more sensitive to the reduction in VOCs. There are 33,888 observations, and the average ozone concentration is $101.5\mu g/m^3$, as shown in Appendix: Table 1.

[Table 3]

The estimation results based on the reselected groups are reported in Appendix: Table 2. The coefficient of the treatment indicator *DID* is negative and statistically significant at 1% level in all the columns. The estimated effect in column 1 corresponds to a decrease of approximately 2.44 $\mu g/m^3$ or 2.4 % of the daily average ozone concentrations in the cities of the treatment group. Although the percentage is almost the same as the main model, the coefficient of *DID* is larger than the main result, as expected.

[Table 4]

4.3 Heterogeneous Effects

In this subsection, we explore the heterogeneity in the treatment effect to better understand the impact of the import ban. We first investigate if the effect of the ban varies as time evolves. Then, we explore the difference in effects among cities with higher or lower baseline ozone concentrations. Further, we examine the difference between the cities among different levels of rural populations to examine the heterogeneous impact among them.

First, the effect of the ban may not appear immediately because many companies are supposed to keep stock of recyclable materials to maintain a stable supply. Even if the import of plastic waste is banned, many recycling firms can keep processing plastic waste using stocks for some periods. Therefore, the effect of the ban may change with time. We establish the following model to examine the time effect:

$$\begin{aligned} Ozone_{it} =& \beta_1 afterQ1_t + \beta_2 afterQ2_t + \beta_3 afterQ3_t + \beta_4 afterQ4_t + \beta_5 Treat_i, \\ &+ \beta_6 Treat_i * afterQ1_t + \beta_7 Treat_i * afterQ2_t + \beta_8 Treat_i * afterQ3_t, \\ &+ \beta_9 Treat_i * afterQ4_t + X_{it} + \xi_t + \epsilon_{it}, \end{aligned} \tag{2}$$

where $Ozone_{it}$ denotes the ozone level in city i in day t and *Treat* is a dummy variable for the cities in the treatment group. *afterQ1*, *afterQ2*, *afterQ3*, and *afterQ4* are dummy variables for each quarterly period in 2018. X denotes the control variables including the daily average NO_2 concentrations. The maximum temperature is omitted because of collinearity. ξ is the month fixed effects, and ϵ is the error term, which is the same as in the main model. Further, the dataset is the same as that used in the baseline model.

[Table 5]

The results in Table 3 show that the treatment effect increases from the first quarter to the third quarter. We can infer from the result that the recycling firms used the stocks to maintain their production, and many of them used up the stocks before the third quarter. The results indicate that the treatment effect becomes positive in the fourth quarter. It suggest that the result was temporal, because some of the recycling firms might find new sources of plastic waste and worked harder to cover the loss by the import ban.

Second, the effect is likely to be different among cities with different characteristics, for example, the ozone concentrations before the import ban. We employ the difference-in-difference-in-differences (DDD) method to examine the different effects between cities with higher concentrations at the baseline with those with lower concentrations. In other words, we combine three types of variations: the time variation (i.e., before and after the ban on importing plastic waste), the city variation (i.e., coastal cities and inland cities), and the pollution variation (i.e., cities with higher ozone concentrations in 2017 versus cities with lower concentrations). We define cities with concentrations higher than the third quartile as dirty cities. The estimated model is formulated as follows:

$$\begin{aligned} Ozone_{it} = &\beta_1 After_t + \beta_2 Treat_i + \beta_3 Dirty_i + \beta_4 DID_{it} + \beta_5 After_t * Dirty_i, \\ &+ \beta_6 Treat_i * Dirty_i + \beta_7 DDD_{it} + X_{it} + \xi_t + \epsilon_{it}, \end{aligned} \tag{3}$$

where *Dirty* describes the city whose ozone concentration in 2017 is higher than the third quartile. *DID* is the interaction of *Treat* and *After*. *DDD* is the interaction of *Treat*, *After*, and *Dirty* that we are interested in.

[Table 6]

The results are reported in Table 4. The coefficient of the treatment indicator *DDD* is negative and statistically significant at the 1% level in all the columns. The result implies that the effect of the ban in cities with higher baseline ozone concentrations is larger than in other cities. A possible explanation for this is that more plastic recycling firms are located in dirty cities.

Lastly, the rural population density could influence the import ban. As mentioned above, many farmers in coastal provinces are involved in the plastic recycling activity. Because the price of plastic waste is very low, one could even start the business on their own farm in the rural area. Many farmers in China are recycling plastic waste in their farms. Thus, we assume that the number of small recycling workshops will be larger in cities with a larger rural population. According to *People's Daily (Ease the burden of the environment and improve the quality of the eco- nomic growth, 2018/05/05)*, these workshops recycle plastics with low technology and without controlling pollutant emissions. Therefore, we examine whether the effect of the ban in areas with higher rural populations is stronger than that in other areas. We employ a DDD method to investigate this question, and the model is formulated as follows:

$$\begin{aligned} Ozone_{it} =& \beta_1 After_t + \beta_2 Treat_i + \beta_3 Rural_i + \beta_4 DID_{it} + \beta_5 After_t * Rural_i, \\ &+ \beta_6 Treat_i * Rural_i + \beta_7 DDD_{it} + X_{it} + \xi_t + \epsilon_{it}, \end{aligned} \tag{4}$$

where *Rural* is a dummy variable that takes value, 1 if the rural population density in a city in 2017 is higher than the third quartile of the populations in all the cities in 2017 (0.28 thousand people per km^3), and 0, otherwise. *DID* is the interaction of *Treat* and*After*. *DDD* is the interaction of *Treat*, *After*, and *Rural*.

The data of the rural population were obtained from the official websites of the statistical department of each province. The city-level rural population density is calculated by dividing the rural population in the city by the area of the city. As there are two cities lacking rural population data, the dataset includes 88 cities rather than 90 cities in the baseline model.

[Table 7]

The estimation results are reported in Table 5. The coefficient of the treatment indicator *DDD* is positive and statistically significant at the 1% level in all the columns. The results indicate that after the ban, the ozone concentration was higher in cities with higher rural population densities in the treatment area. This implies that the treatment effect is weaker in cities with small workshops. We think this is because the enforcement in rural involves high monitoring costs. In other words, the ban is not very effective in terms of reducing activities of the small recycling workshops, which could cause great damage to the local environment.

5 Conclusions

This study investigated the effects of the ban on the import of plastic waste on air quality using China's city-level daily ozone concentration data. First, the results of our baseline DID model suggest that the ban might help reduce the ozone concentrations in coastal cities where many recycling firms are located. The estimated coefficients suggest that the ban contributes to a decrease in the ozone concentration in the treatment group by about $2.2\mu g/m^3$. We also check the robustness by redefining the treatment and control groups based on the ozone-NOx-VOC sensitivity. Second, we conduct analyses to explore the heterogeneous effects. We find that the effect of the ban gets stronger from the first quarter to the third quarter. Moreover, the result of the DDD methods indicates that the effect of the ban in dirty cities could be larger. In addition, the ozone concentrations in cities with higher rural population density are less affected by the ban. Overall, the results suggest that the ban did help to improve the air quality albeit slightly.

Because we are not able to capture the exact location and the situation of the plastic recycling firms and workshops, it is challenging to define the treatment and control groups at the exact city level or even monitoring-point level. Moreover, as the ban was implemented recently, the availability of other outcome variables is limited. Despite these limitations, our approach allows us to examine the impact of import ban in a simple framework.

In the long-run, the import ban will lead to an increase in recycling of domestic plastic waste. Several big cities in China, such as Shanghai, have already started waste sorting from 2019. It will increase the domestic supply of recyclables, reviving the domestic plastic waste recycling industry. To maintain the local air quality, the plastic recycling industry need to transform its process with adoption of new technologies.

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Tables

Table 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
All					
Ozone(μg/m^3)	63,540	94.17	44.84	1	586
NO2(μg/m^3)	63,540	30.91	17.00	2	176
Max_Temp($^{\circ}C$)	63,540	23.06	9.222	-20	41
Treat(*dummy*)	63,540	0.522	0.500	0	1
After(*dummy*)	63,540	0.500	0.500	0	1
DID(*dummy*)	63,540	0.261	0.439	0	1
Treatment Group					
Ozone(μg/m^3)	33182	99.16	47.42	1	586
NO2(μg/m^3)	33182	30.96	17.12	2	168
Max_Temp($^{\circ}C$)	33182	23.53	9.4	-20	41
Treat(*dummy*)	33182	1	0	1	1
After(*dummy*)	33182	0.5	0.5	0	1
DID(*dummy*)	33182	0.5	0.5	0	1
Control Group					
Ozone(μg/m^3)	30358	88.72	41.14	1	300
NO2(μg/m^3)	30358	30.86	16.80	2	176
Max_Temp($^{\circ}C$)	30358	22.54	9	-5	41
Treat(*dummy*)	30358	0	0	0	0
After(*dummy*)	30358	0.5	0.5	0	1
DID(*dummy*)	30358	0	0	0	0

Table 2: The effects of the ban on the ozone concentrations

Ozone	(1)	(2)	(3)	(4)
After	-2.567***	-2.784***	-3.130***	-3.125***
	(0.361)	(0.372)	(0.398)	(0.472)
Treat	9.081***	8.896***	12.16***	12.17***
	(0.432)	(0.443)	(0.463)	(0.518)
DID	-2.210***	-2.168***	-3.442***	-3.447***
	(0.579)	(0.597)	(0.620)	(0.702)
NO2	0.351***	0.296***		
	(0.00995)	(0.00965)		
Max_Temp	2.447***	2.616***		
	(0.0280)	(0.0169)		
Month FE	Y	N	Y	N
Constant	16.77***	22.00***	56.48***	90.28***
	(0.681)	(0.603)	(0.467)	(0.345)
Observations	63,540	63,540	63,540	63,540
R-squared	0.322	0.279	0.228	0.017

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Descriptive statistics: ozone-NOx-VOC sensitivity

Variable	Obs	Mean	Std. Dev.	Min	Max
All					
Ozone(μg/m^3)	33,888	101.5	49.78	1	324
NO2(μg/m^3)	33,888	37.24	20.65	2	269
Max_Temp($^{\circ}C$)	33,888	22.15	9.662	-19	41
Treat($dummy$)	33,888	0.583	0.493	0	1
After($dummy$)	33,888	0.500	0.500	0	1
DID($dummy$)	33,888	0.292	0.455	0	1

Table 4: The effects of the ban: ozone-NOx-VOCs sensitivity

Ozone	(1)	(2)	(3)	(4)
After	-5.249***	-5.342***	-4.254***	-4.350***
	(0.611)	(0.640)	(0.658)	(0.791)
Treat	5.565***	5.488***	7.746***	7.746***
	(0.628)	(0.659)	(0.675)	(0.796)
DID	-2.437***	-2.400***	-3.220***	-3.196***
	(0.855)	(0.891)	(0.909)	(1.077)
NO2	-0.141***	-0.158***		
	(0.0155)	(0.0137)		
Max_Temp	2.701***	2.698***		
	(0.0419)	(0.0240)		
Month FE	Y	N	Y	N
Constant	42.60***	47.85***	57.63***	100.1***
	(1.042)	(0.965)	(0.657)	(0.581)
Observations	33,888	33,888	33,888	33,888
R-squared	0.359	0.306	0.286	0.008

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: The effects of the ban for different periods

VARIABLES	(1)	(2)	(3)	(4)
afterQ1	0.440	-20.82***	-0.706	-20.82***
	(0.590)	(0.588)	(0.582)	(0.587)
afterQ2	-3.175***	16.71***	-4.434***	16.70***
	(0.778)	(0.678)	(0.793)	(0.675)
afterQ3	-1.673**	13.67***	-2.524***	13.65***
	(0.754)	(0.655)	(0.764)	(0.646)
afterQ4	-3.400***	-25.10***	-5.080***	-25.09***
	(0.754)	(0.746)	(0.767)	(0.745)
Treat	12.02***	12.16***	12.16***	12.16***
	(0.458)	(0.518)	(0.463)	(0.518)
Treat*afterQ1	-1.251	-1.584*	-1.585**	-1.585*
	(0.785)	(0.877)	(0.780)	(0.878)
Treat*afterQ2	-3.175***	-3.872***	-3.875***	-3.875***
	(1.024)	(1.068)	(1.046)	(1.068)
Treat*afterQ3	-12.13***	-12.71***	-12.71***	-12.71***
	(0.955)	(1.004)	(0.972)	(1.005)
Treat*afterQ4	4.674***	5.622***	5.626***	5.626***
	(0.939)	(1.083)	(0.939)	(1.082)
NO2	0.373***	0.00163		
	(0.0104)	(0.0107)		
Month FE	Y	N	Y	N
Constant	39.13***	90.23***	54.78***	90.29***
	(0.689)	(0.477)	(0.514)	(0.345)
Observations	63,540	63,540	63,540	63,540
R-squared	0.248	0.088	0.232	0.088

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: The effect on dirty cities

Ozone	(1)	(2)	(3)	(4)
After	-5.184***	-5.016***	-5.117***	-5.150***
	(0.365)	(0.378)	(0.411)	(0.487)
Treat	-12.35***	-9.844***	1.139*	1.138*
	(0.616)	(0.620)	(0.670)	(0.654)
Dirty	21.45***	19.68***	12.40***	12.35***
	(0.571)	(0.564)	(0.568)	(0.641)
DID	2.296***	2.194***	1.207	1.229
	(0.794)	(0.822)	(0.897)	(0.893)
Treat*Dirty	17.18***	15.49***	8.788***	8.824***
	(0.782)	(0.803)	(0.850)	(0.861)
After*Dirty	9.948***	10.50***	10.91***	10.88***
	(0.651)	(0.670)	(0.724)	(0.882)
DDD	-13.57***	-14.08***	-14.91***	-14.91***
	(1.100)	(1.137)	(1.223)	(1.338)
NO2	0.193***	0.226***		
	(0.00991)	(0.00950)		
Max_Temp	3.368***	2.825***		
	(0.0329)	(0.0168)		
Month FE	Y	N	Y	N
Constant	13.00***	18.69***	55.89***	89.71***
	(0.682)	(0.588)	(0.486)	(0.343)
Observations	63,540	63,540	63,540	63,540
R-squared	0.389	0.342	0.253	0.042

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: The effect on cities with higher rural population

Ozone	(1)	(2)	(3)	(4)
Treat	10.20***	10.09***	13.34***	13.34***
	(0.497)	(0.511)	(0.534)	(0.593)
After	-2.313***	-2.540***	-2.624***	-2.687***
	(0.416)	(0.427)	(0.457)	(0.532)
Rural	9.109***	9.162***	8.635***	8.638***
	(0.628)	(0.644)	(0.694)	(0.829)
DID	-3.612***	-3.506***	-5.166***	-5.125***
	(0.669)	(0.689)	(0.712)	(0.801)
Treat*Rural	-4.525***	-4.843***	-4.520***	-4.523***
	(1.027)	(1.054)	(1.101)	(1.234)
After*Rural	-0.999	-0.920	-1.748*	-1.647
	(0.842)	(0.868)	(0.941)	(1.135)
DDD	4.067***	3.918***	5.208***	5.064***
	(1.366)	(1.408)	(1.474)	(1.670)
NO2	0.356***	0.303***		
	(0.0100)	(0.00972)		
Max_Temp	2.440***	2.596***		
	(0.0282)	(0.0171)		
Month FE	Y	N	Y	N
Constant	14.42***	19.81***	54.55***	88.03***
	(0.709)	(0.634)	(0.503)	(0.389)
Observations	62,128	62,128	62,128	62,128
R-squared	0.323	0.279	0.228	0.021

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figures

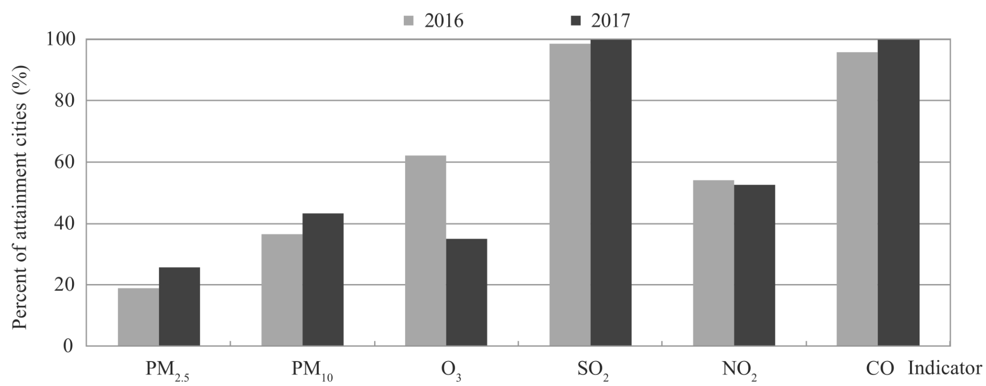

Figure 1: Cities Meeting the Stage I Monitoring Standard
Source: Report on the State of the Ecology and Environment in China 2018

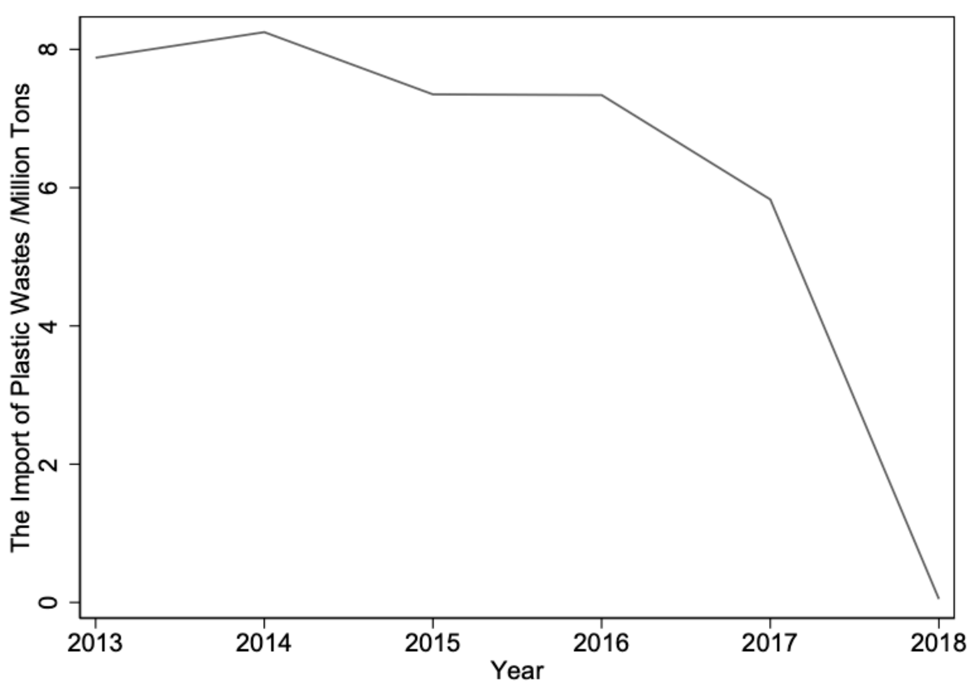

Figure 2: Import of Plastic Waste of China*Source: China Recycling Industry Report 2019*

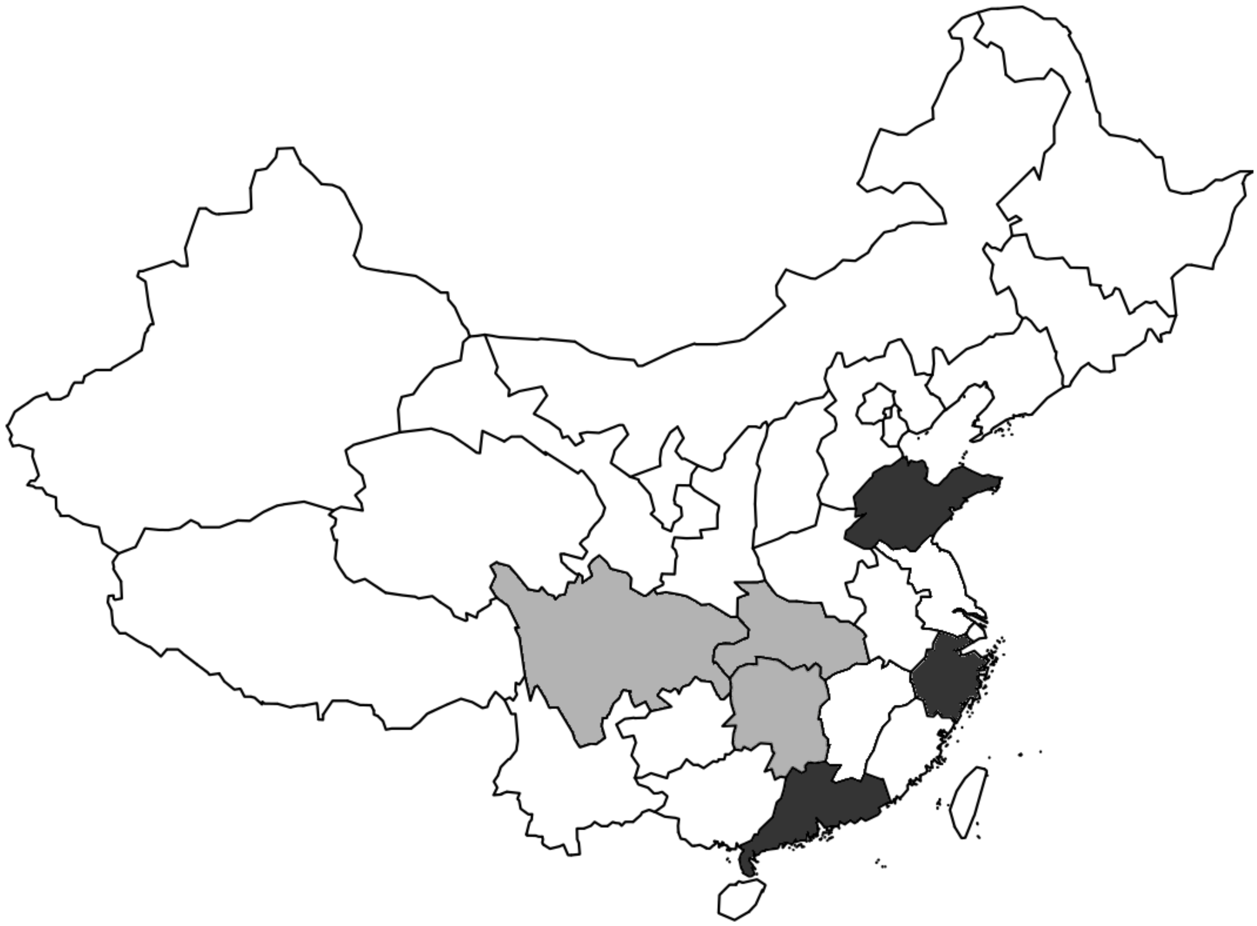

Figure 3: The Control Group (Light grey) and Treatment Group (Dark grey)

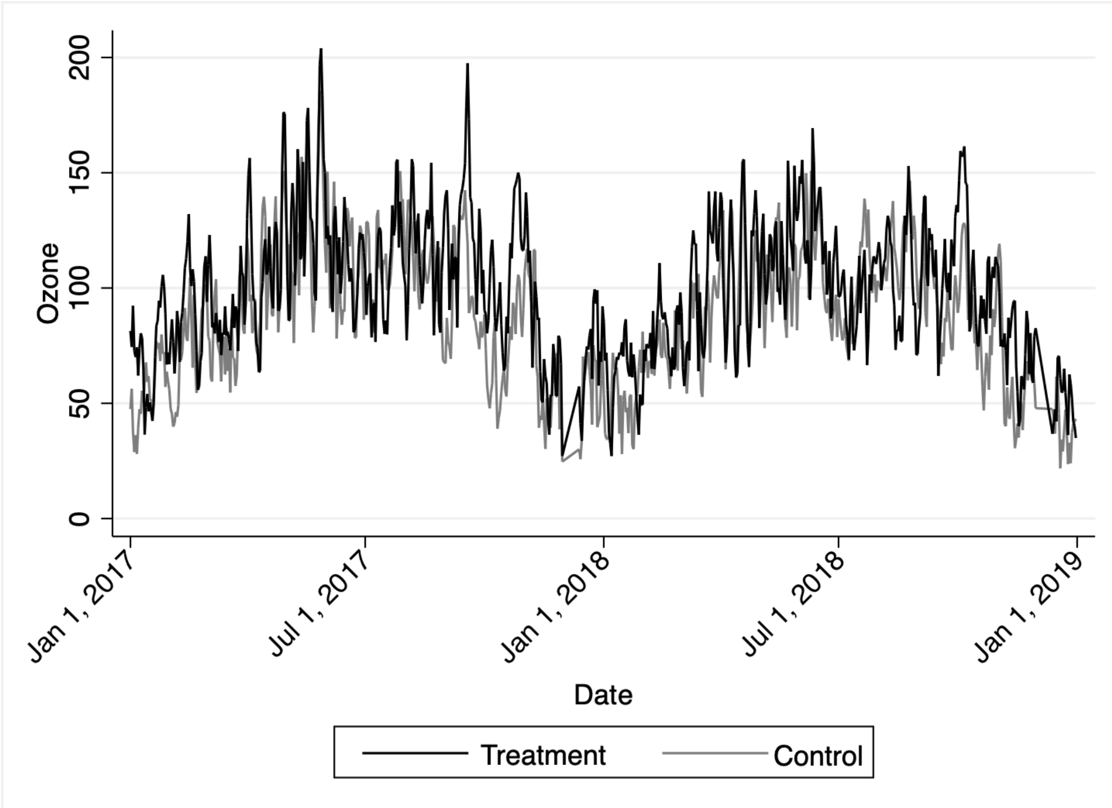

Figure 4: Daily Average Ozone Concentrations

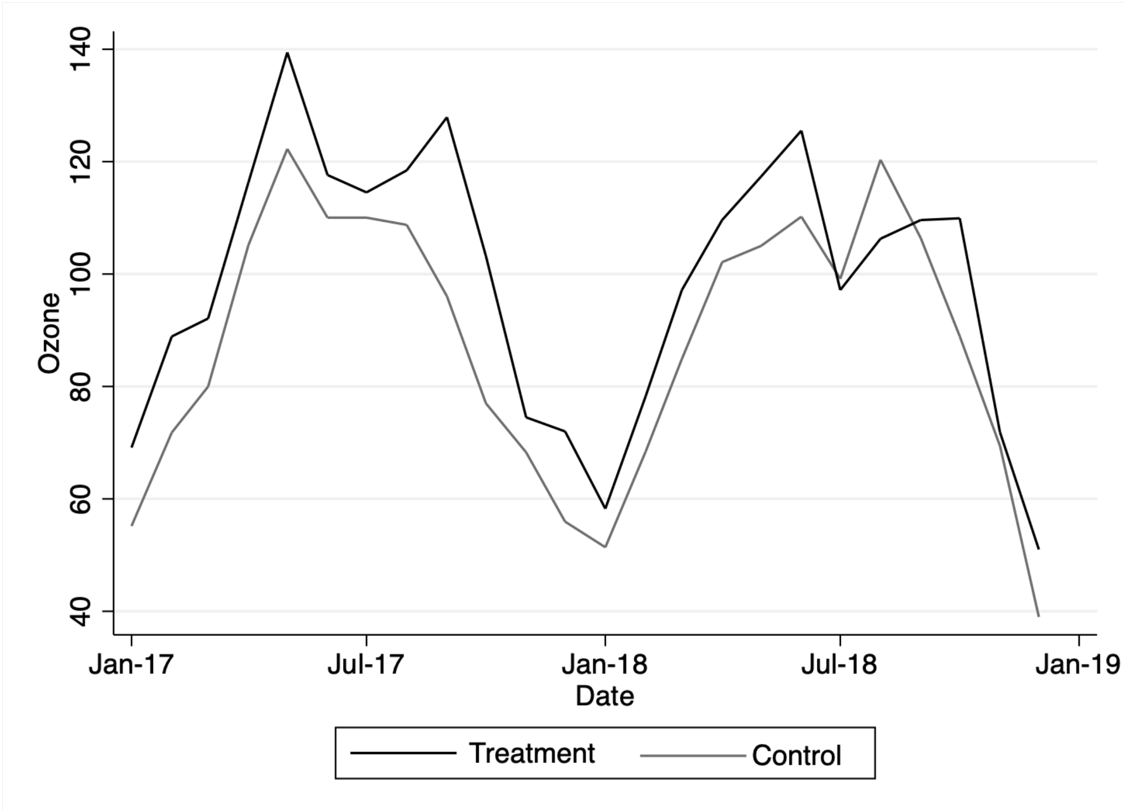

Figure 5: Monthly Average Ozone Concentrations