# Discharge Fees, Pollution Mitigation, and Productivity: Evidence from Chinese Power Plants

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**Abstract**

The economy of China has experienced a dramatic transformation in recent years but a cost of development has been pollution. Starting in 2003, Chinese provinces started to assess discharge fees for two main air pollution measures, $SO_2$ and $NO_2$. This study obtains detailed data on ambient pollution and discharge pollutants, fuel inputs, and firm productivity for power plants, which comprise the majority of these emissions from fixed sources. We identify the impact of discharge fees on pollution and productivity outcomes using a difference-in-difference for monitors and firms in local border areas within 50 KM of a provincial border with fee changes. We find some evidence that pollution fees caused ambient pollution to drop. Pollution fees led to large reductions in emitted $SO_2$ and $NO_2$ with elasticities ranging from $-22\%$ to $-45\%$. Power plants reduced their coal inputs and may have increase their natural gas inputs following fee changes. Fees appear to have led to a drop of productivity, with an elasticity of $-22\%$. Fee increases appear to make labor relatively less productive and capital relatively more productive.

**JEL Codes: Q4, D2, L2**
**Keywords: sulfur dioxide, nitrous oxides, coal, natural gas**

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# 1 Introduction

A potentially important cost of China's massive economic growth and development has been pollution. As China has gotten wealthier and the scope of the pollution problem has emerged, there is more demand in China to reduce pollution. Over the past 15 years, pollution reduction has become a priority of the Chinese national government and of regional authorities in China. For instance, the 11th Five-Year Plan, which is the official government planning document for the years 2006-10, emphasized the need to reduce air and water pollution and proposed specific targets for pollution reduction. The 12th Five-Year Plan, implemented in 2011, set further reductions in targeted pollution levels.[1]

Despite these measures, pollution remains a huge problem in China. A large literature has found that air and water pollution in China remain at very high levels (Vennemo et al., 2009; Jin et al., 2016; Zheng and Kahn, 2017). There is also evidence that the pollution is seriously affecting the health and longevity of its residents (Chen et al., 2013; Ebenstein, 2012), the productivity of its workers (Fu et al., 2017; Chang et al., 2016), and that there is substantial willingness to pay for lower pollution (Barwick et al., 2017; Ito and Zhang, 2016).

The fact that pollution remains a central problem for China suggests that it may be very costly to mitigate pollution, in terms of lost productivity and revenues. This view is supported by the finding of substantial productivity costs of pollution mitigation in the U.S. context. For instance, Greenstone (2002) found that the U.S. Clean Air Act caused $75 billion in lost output in its first 15 years and Greenstone et al. (2012) finds that the Act caused a 4.8 percent decline in total factor productivity over its first 21 years. Despite the above findings, there is comparatively little evidence on the costs of pollution mitigation, in China and in other countries. Tanaka et al. (2014) and Ankai (2016) find that increases in Chinese environmental stringency led to increased productivity. This view is supported by the "Porter hypothesis" (Porter and Van der Linde, 1995), that postulates that environmental policies lead to greater productivity. However, He et al. (2016) find that environmental regulations lower productivity in China.Altogether, the evidence on the impacts of pollution mitigation

[1] See the Chinese Ministry of Environmental Protection: `http://www.zhb.gov.cn/gzfw_13107/ghjh/wngh/`.

on productivity is mixed.

Besides affecting productivity, environmental regulations may also have substantial distributional consequences. For instance, environmental regulations may favor capital-intensive technologies, since it may be easier to mitigate environmental harm with these technologies. To the extent that environmental regulations lower labor productivity, they may lower wages but increase rents on capital. The distributional impact of pollution mitigation in China has also not been fully studied.

This paper has two goals. First, we seek to evaluate whether Chinese policies to lower pollution have been successful. Second, we seek to quantify the productivity and distributional costs of these policies. We will investigate these research questions for both the power generation sector, and the manufacturing in general. We single out the power generation sector, as it generates approximately 60% of the sulfur dioxide air pollution from fixed sources, and we can study the changes in fuel use in response to the regulations.

Our study exploits variation from fee changes in the prices of pollution in China, together with detailed ambient pollution data, environmental discharge data, and firm production data. During the time period 2003-15, China implemented a number of pollution reduction programs. Many policies were implemented at the national level, starting with the Chinese government's tenth five year plan, which started in 2001. As part of the national pollution reduction policies, the Chinese government delegated provincial governments to set water and air pollution fees in order to help meet national pollution reduction targets. This resulted in province-level variation in pollution fees over time.

To study these questions, we utilize ambient pollution data from pollution monitors, firm-level data on pollution discharges and matched production data, which we describe in Section 2. The ambient data derive from Ebenstein et al. (2017) and include annual information on ambient pollution for $SO_2$, $NO_2$, and PM10 for a variety of sites in China.

The pollution discharge data comes from the Chinese Environmental Survey (CES), which we observe from 2003 to 2015. This dataset reports environmental discharges for manufacturing plants. These data derive from information collected the Chinese Ministry of Environmental Protection (MEP). Since the 1980s, the MEP has established an environmental monitoring system to collect administrative data regarding ambient environmental quality and the pollution of industrial firms. The monitoring system covers major industrial polluting firms that contribute to approximately 85% of China's total pollution in terms of major pollutants. Our data measure two air pollutants: sulfur dioxide ($SO_2$) and nitrous oxides ($NO_X$). Covered firms are required to report levels of discharge for these pollutants on an annual basis. The information is verified by the local environmental protection bureau, compiled at the MEP, and finally used to construct the CES dataset and produce the Chinese Environmental Yearbook. The CES dataset is thus regarded as the most comprehensive and reliable environmental microeconomic data in China. However, the CES data were kept secret and have only recently become accessible to researchers.

We use the production data for power plants from the Chinese Annual Survey of Industrial Production (ASIP). These data derive from annual surveys conducted by the National Bureau of Statistics (NBS). These data have been used in a number of papers on firm productivity (Brandt et al., 2017a; Chen et al., 2017). These data report annual firm-level data for the period 1998-2013 on all industrial firms with sales above 5 million RMB (roughly 800,000 U.S. dollars).

We develop a simple model where firms produce multiple outputs: an output good and a variety of pollution outputs, which are valued negatively. Changes in environmental policies shift the relative prices of the pollution outputs, which allow us to trace out the production function of firms in different sectors, as firms reoptimize their level of the output good and pollution levels given the implicit prices of pollution. We propose to characterize the tradeoffs that firms face between output and pollution, and to understand the heterogeneity in these tradeoffs across different industrial and energy sectors and across different types of pollution. Ultimately, we believe that by better characterizing the production possibility frontier for pollution and industrial output, our paper can help policymakers design more effective pollution mitigation strategies.

Our main results come from three sets of regression specifications. First, we analyze how environmental fee changes affect ambient pollution as reported by pollution monitors. Second, we analyze how they affect power plant emissions of the two pollutants noted above.

Finally, we examine how they affect firm productivity.

Our regressions rely on sources of identification that we believe are credible. We focus on environmental discharge fees that were implemented by Chinese provinces and became effective following a 2003 state order, and that vary over province and time. These fees specify amounts that firms must pay for discharging pollutants, specifically the air pollutants of sulfur dioxide ($SO_2$) and nitrous oxides $NO_2$. At different points in our sample, a number of Chinese provinces raised these fees while neighboring and similar provinces did not. However, a simple "difference-in-difference" strategy that compares provinces that raise the fees vs. provinces that do not will not take into account the differential output/growth trends across Chinese provinces in the last two decades. In order to mitigate the effect of differential growth rates across provinces, we focus on cities located near the borders between provinces. The idea is to compare firms that are located on the side of the border that has changed pollution discharge fees vs. firms on the other side of the border where fees have not changed, accounting for region level trends. Since provinces share borders with multiple other provinces, our research design allows us to construct multiple comparison groups for firms within a given province.

Our detailed data on power plants also allows us to evaluate how firms change their behavior in response to pollution regulation. Specifically, we study how power generators change their fuel mix in response to the regulations. We also study the heterogeneity in firms' response to pollution regulation, especially with regards to the labor vs. capital intensity of the technology they utilize.

In a first set of analyses, we study the effect of increases in fees for air pollutants on ambient air pollution. For this study, we utilize measurements obtained from ambient pollution monitoring stations. Our main results indicate that air pollution fees lead to drops in ambient pollution levels.[2] This analysis also highlights the important of accounting for regional level trends. Specifications that do not control for these trends yield the highly robust and unintuitive result that increased pollution fees are associated with higher levels of ambient air pollution.

[2] Our reported results are statistically significant but alternative specifications show that this statistical significance does not hold across other similar specifications.

The effect of increased air pollution fees on firms' reported discharges of these pollutants is much stronger. We find, in our preferred specification with provincial borders and accounts for region level trends that doubling fees is associated with a 33% to 45% decline in $SO_2$ and 22% to 35% decline in $NO_X$ discharges for the power plants in our sample.

The decline in pollution discharge is accompanied by very marked changes in fuel use. We find that the elasticity of coal usage with respect to the pollution fee is almost -1; suggesting that a 50% increase in fees is associated with a 50% decline in coal use. We also find that increases in pollution fees is associated with an increase in the use of alternative fuels such as oil and gas; however, the elasticity of oil/gas usage is far below 1 and closer to 0.2, suggesting that these fuels are only imperfect substitutes for coal, at least in the short- to medium-run.

We study the effect of pollution regulation on productivity, using regression specifications motivated by the model in Section 3. Along with the decline in coal usage and switching over to alternative fuels, we find sharp declines in the productivity of power plants. We find that the elasticity of productivity with respect to air pollutant fees is about $-0.2$, suggesting that a doubling of fees would lower productivity by 20%.

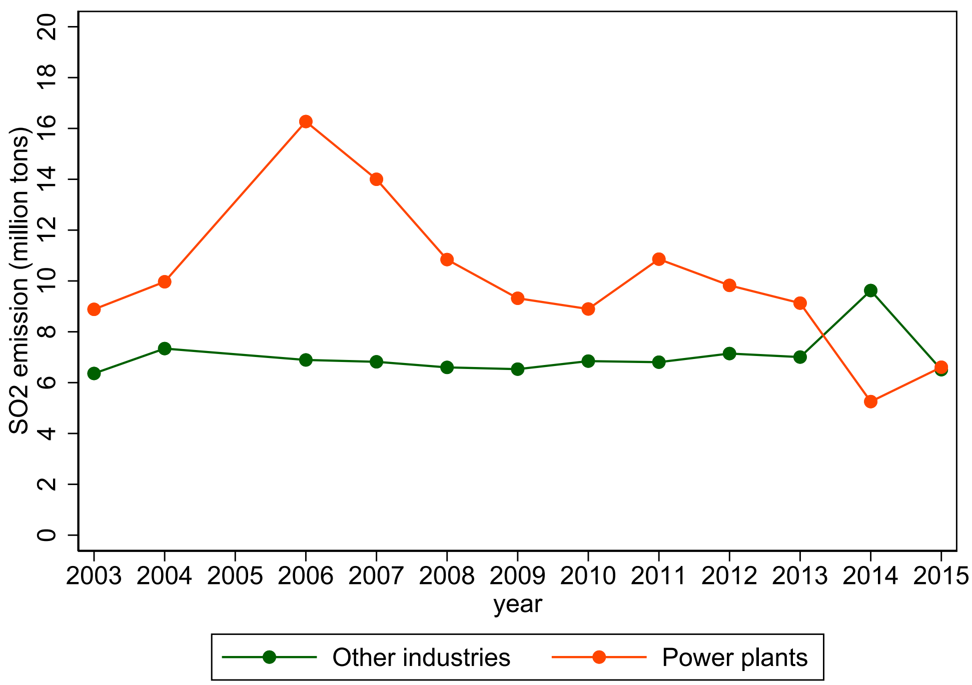
The effect of increased air pollutant fees on productivity is robust when we allow for trans-log vs. Cobb-Douglas production functions. We also find that the air fees have a larger negative effect on firm productivity for firms that are more labor intensive. This suggests that the incidence of the pollution fees falls more heavily on more labor intensive power plants, which may be using an older technology.

We believe that our paper contributes to the literature on the tradeoffs between productivity and environmental discharges in important ways. We are among the first to combine firm-level panel datasets on industrial production for manufacturing firms, on production and investment power plants, and on air pollution discharges. A number of recent studies have used Chinese industrial production data to consider research questions such as state ownership and productivity (Chen et al., 2017), trade and productivity (Brandt et al., 2017a), and the demand for exporting (Roberts et al., 2017). We use these data to understand the impact of environmental policies. Our study also uses detailed data on Chinese power plants, including their output, capital stock, labor inputs, along with fuel inputs.

The remainder of the paper is structured as follows: Section 2 provides a description of China's environmental regulations and the data sets used in this study. Section 3 provides the analytic foundation for our estimation and discusses our identification and estimation assumptions. Section 4 presents our results: we first analyze ambient pollution measures, then reported pollutant discharge data, and power plant fuel use patterns. We then analyze the connection between pollution fees and productivity, allowing for the heterogeneity of the impact across different production technologies. Section 5 concludes.

# 2 Data

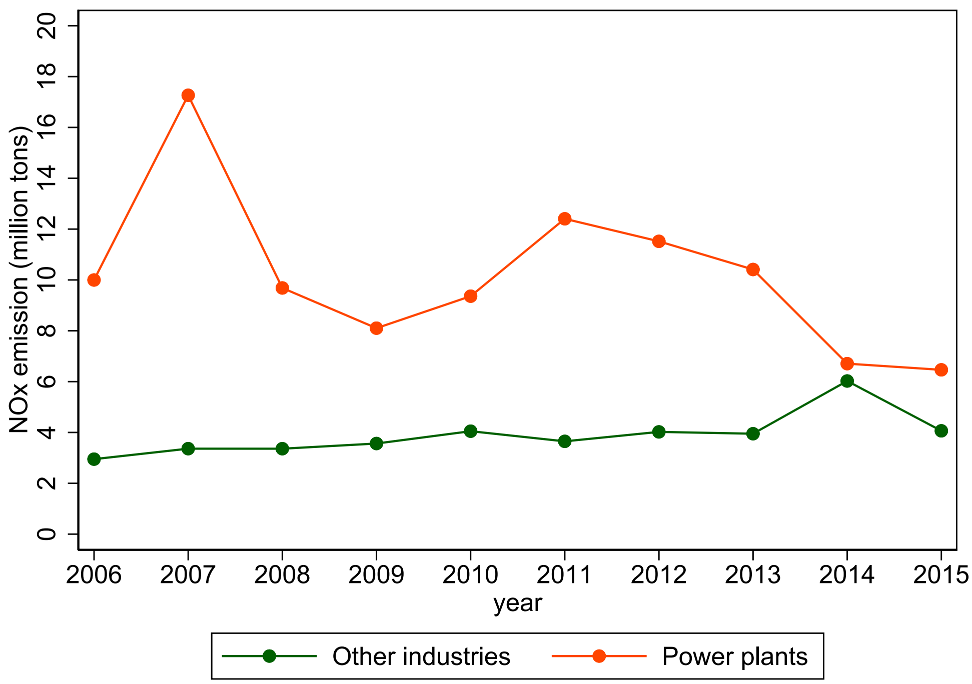
Figure 1: Total sulfur dioxide ($SO_2$) emissions by power plants and other industrial sources




Source: authors' calculations based on CES data.

Our study focuses on air pollution emitted by power plants. Power plants are the largest fixed source of air pollution in China. Figures 1 and 3, respectively, show the total $SO_2$ and $NO_X$ air pollution emitted by power plants and other industrial facilities in China. Power

Figure 2: Total nitrous oxide ($NO_X$) emissions by power plants and other industrial sources




Source: authors' calculations based on CES data.

plants account for well over half of the fixed source air pollution in China for these two pollutants.

Focusing on power plants, we evaluate the effect of environmental discharge fees on ambient pollution, discharge pollutants, and production. Accordingly, we use four main sources of data. First, we use province-year level data on environmental discharge fees assessed to firms. Second, we use annual data from ambient pollution monitors. Third, we use firm-year level data from the Chinese Environmental Survey (CES). Finally, we use firm-year level data from the Chinese Annual Survey of Industrial Production (ASIP). We now discuss each of these data sources.

## 2.1 Environmental Discharge Fees

Our first data source is information on environmental discharge fees for air pollution and policies. China's Environmental Protection Law, passed in 1979, and enacted in its final form in 1989, officially established discharge fees for air pollution by power generation and manufacturing firms. However, these fees were generally considered ineffective until a 2003 state order that implemented a system for their effective collection.

In 2003, most Chinese provinces started charging fees of CNY 0.21 (approximately USD 0.03) per kilogram of $SO_2$ with similar fees per kilogram of $SO_2$.[3] These fees were doubled in 2004 and raised again by 50% in 2005. However, the fees were the same across provinces until 2007, when Jiangsu province raised its fees. Over the following several years, a number of other provinces raised their fees above the national standards.

The variation in fees across provinces stemmed in part from mandated reductions in $SO_2$ at the provincial level as specified in the 11th and 12th Five-Year Plans.[4] These plans were formally submitted by the State Council in 2006 and 2011, respectively. They specified an aggregate pollution level change in the total discharges of these two pollutants for each

[3]The exception is Beijing, which charged a higher $SO_2$ fee in 2003.

[4]The environmental measures in the 11th and 12 Five-Year Plans can be found at http://zfs.mep.gov.cn/fg/gwyw/200711/t20071126_113414.shtml and http://www.zhb.gov.cn/gkml/hbb/bgth/201212/t20121205_243258.htm, respectively. Guo and Fang (2017) used these mandated reductions.

province over the five year period.[5]

We collected fees for $SO_2$ and $NO_X$ pollution by examining source documents from Chinese provinces. We created a panel of these fees for each year and Chinese province over the period 2003-2015.The four centrally administered cities—Beijing, Chongqing, Shanghai, and Tianjin—also implemented fees. We treat these cities as equivalent to provinces in our analysis. The $SO_2$ and $NO_X$ fees are very similar for a given province/year. For instance, the correlation coefficient between them is 0.953. Given this level of collinearity between the two fees, our regressions only include one measure of fees.

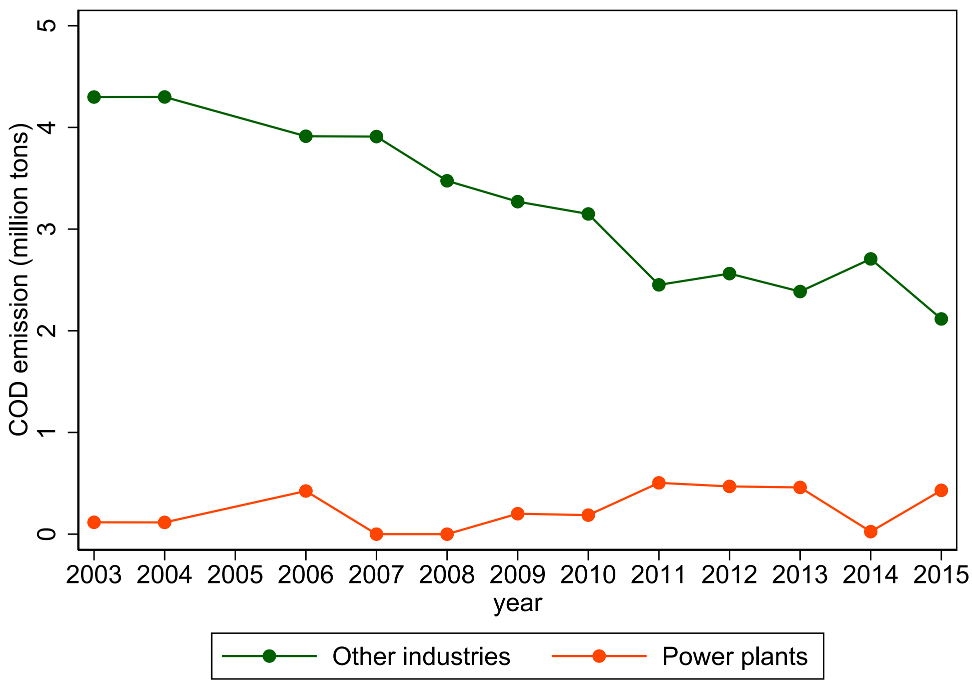
At the same time as provinces implemented air pollution fees, they also implemented water pollution fees. This study does not directly consider water pollution fees for three reasons. First, the water pollution fees may have been less effective because firms often did not pay the fees directly to the government but may instead have paid them to sewage plants, who may not have fully collected them. Second, there were a number of other local water pollution policies for particular regions within provinces, often centered on particular lakes or watersheds (He et al., 2019). Finally, power plants are a relatively small source of water pollution. Figure **??** shows the amount of the major measure of water pollution, chemical oxygen demand, emitted by power plants and other industrial sources. Unlike for our air pollution measures, power plants emit a very small proportion of the chemical oxygen demand pollution.

The difference between water fees and air fees is that not all firms pay the water fees directly. Some firms may pay management fees to sewage plants and then sewage plant pay the water fees. The collection of these fees is indirect and may not reflect their actual pollution during our sample period. Also, China started to control water pollution before air pollution and hence other water pollution standards may affect the level of water pollution. Also, local fees near lakes that we don't observe. Finally, power plants have relatively little water pollution.

Figure 4 provides a map of the $SO_2$ fees at two points in our sample: 2006 and 2013.

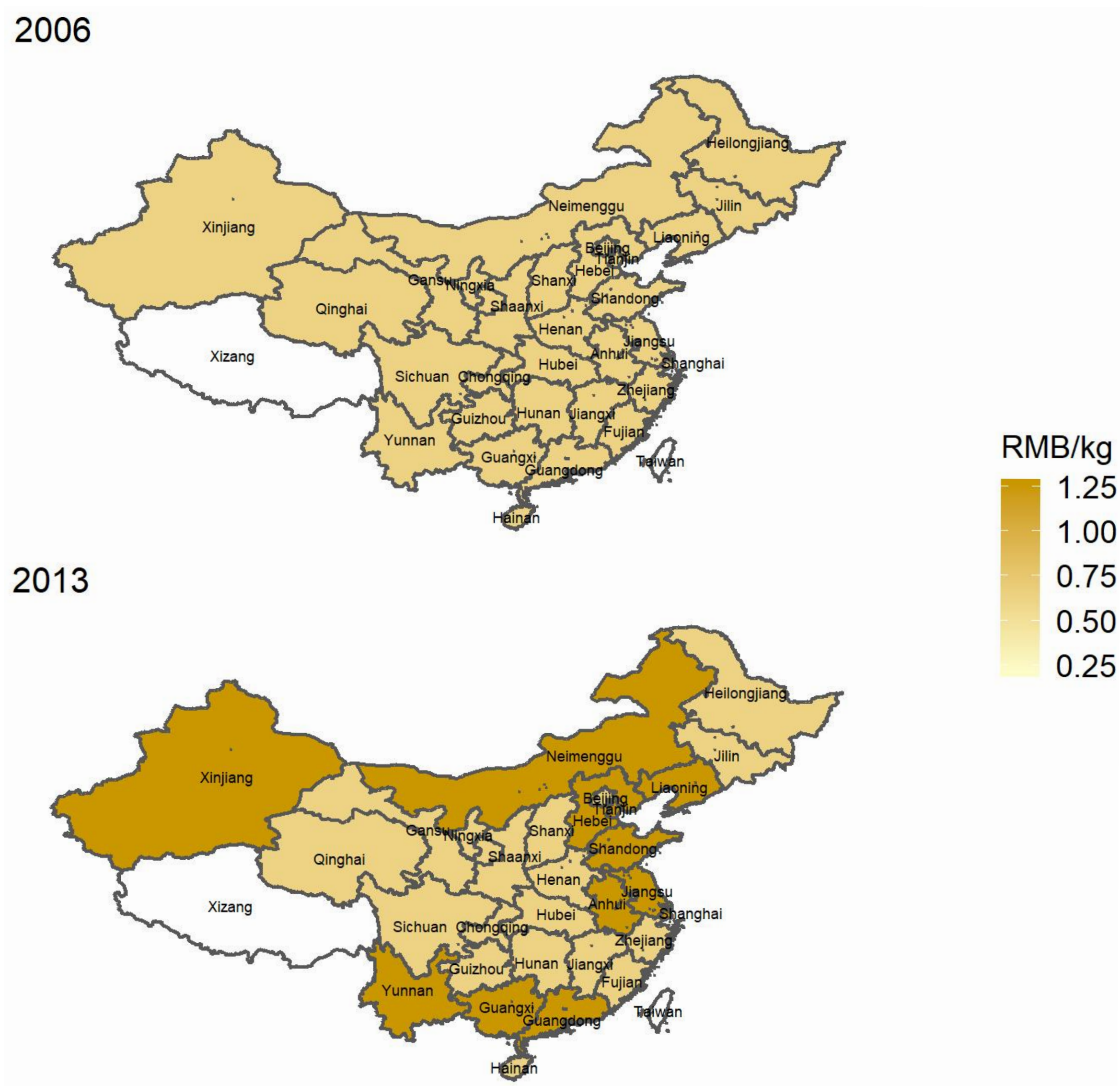
[5]The 10th and earlier Five-Year Plans did not specifically mandate pollution targets but did establish pollution reduction measures such as the Two Control Zone policy (Schreifels et al., 2012).

Figure 3: Chemical oxygen demand emissions by power plants and other industrial sources




Source: authors' calculations based on CES data.

Figure 4: Sulfur dioxide emissions fees in 2006 and 2013



In 2006, the fees were very similar across provinces while in 2013, there was substantial variation in fees across provinces. Despite the variation in fees in 2013, the map shows that the variation is not random across regions. In particular, the coastal regions of China had the highest increase in fees. These regions are the ones that experienced the highest economic growth over this period and thus the likely highest increase in pollution. A difference-in-difference comparison between provinces that raised fees and other provinces would miss the fact that the provinces with increases in fees are likely the ones where pollution would have increased the most in the absence of fees. Thus, our main analyses identify the impact of fees from a difference-in-difference in local border areas on the sides of borders.

## 2.2 Ambient Pollution Monitor Data

For the ambient pollution analysis, we use a monitor-year panel dataset comprised of readings from air pollution monitors spread throughout China. We obtain the data from Ebenstein et al. (2017). In that study, the authors compile pollutant measures using information from various sources including *Chinas EPA*, *China Environmental Yearbooks*, and *China Environmental Quality Annual Reports*. See Ebenstein et al. (2017) Supplemental Appendix for more details on this dataset construction.

Our analysis on ambient pollution considers three pollutants for which we have available data: Sulfur Dioxide ($SO_2$), Nitrogen Dioxide ($NO_2$), and Particulate Matter of 10 micrometers or less in diameter (PM10). We restrict our analysis to the years 2003-2012. As noted above, meaningful pollution fees started in 2003 and hence our analysis for these data starts in this period as well. This dataset ends in 2012.

Figure 5 presents a map with the plotted locations of each monitor in our dataset. Note that there are monitors located throughout China. However, not all monitors reported data in all years.

Table 1 presents the summary statistics for each pollutant of interest. The unit of measurement is Micrograms per Cubic meter of Air ($\mu g/m^3$). The mean, standard deviation, and total number of observations are reported for both the full sample and the border only

Figure 5: Ambient pollution monitor data used in our estimation

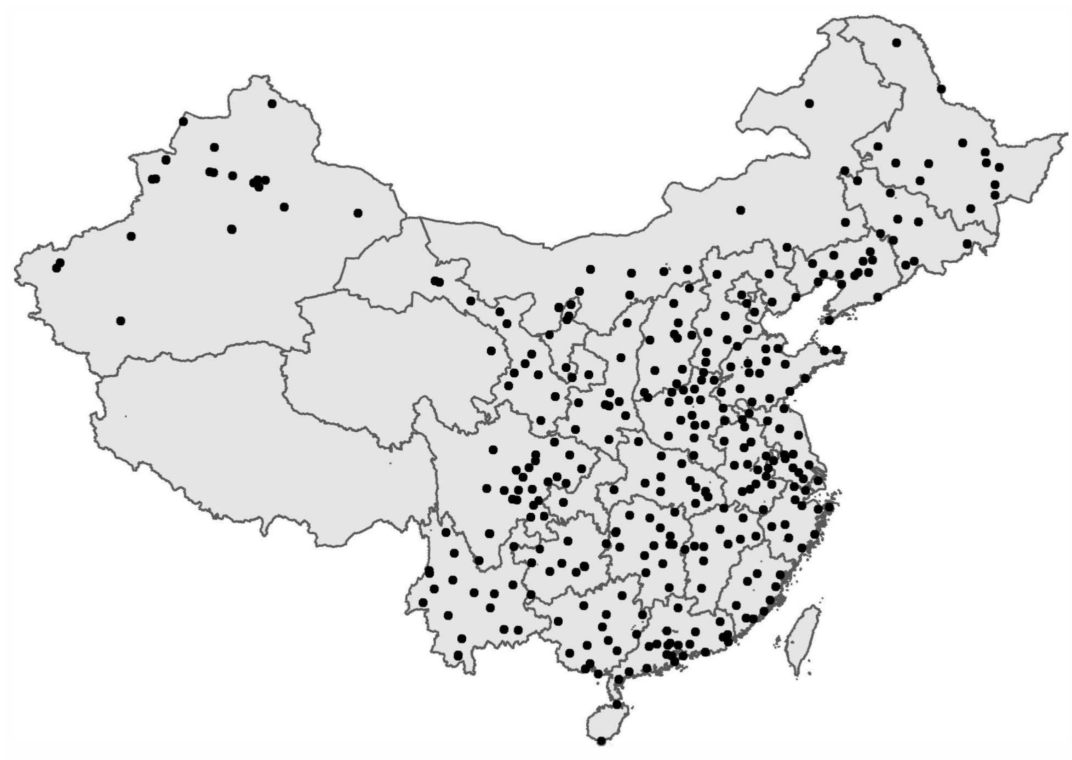


Table 1: Summary Statistics on Ambient Air Pollution

| | All Sample | | | Borders Only | | |
|---|---|---|---|---|---|---|
| Pollutant | Mean | Std.Dev. | N | Mean | Std.Dev. | N |
| Sulfur Dioxide ($SO_2$) | 42.167 | 25.068 | 1971 | 45.799 | 28.417 | 625 |
| Nitrogen Dioxide ($NO_2$) | 30.525 | 12.060 | 1970 | 30.585 | 11.087 | 624 |
| Particulate Matter (PM10) | 86.305 | 31.576 | 1961 | 88.871 | 28.340 | 622 |

sample, which includes only monitors within 50km of each provincial border.

## 2.3 Chinese Environmental Survey Data

Our next data source is the Chinese Environmental Survey (CES). We observe these data from 2004-15. Our CES data report environmental discharges for power generation firms at the firm/year level. Each firm is assigned a unique ID that we use to link to the databases noted below. The dataset is derived from information collected by the Chinese Ministry of Environmental Protection (MEP). It is the most comprehensive environmental dataset in China and only recently became accessible to researchers. It is supposed to record 85% of air pollution from the power generation sector (Liu et al., 2017).[6] We observe three main main measures from this data base. First, we observe $SO_2$, which is a major source of smog. Second, we observe $NO_X$, which is another major source of smog. Finally, we observe fuel consumptions including coal consumption, oil consumption, and natural gas consumption. Most of our data are at the firm (legal entity) level and are recorded annually. A firm in China is much more similar to a plant in the U.S. Even though our data are at the firm level, researchers typically treat these data as being analogous to U.S. plant-level data.[7]

These data are the most comprehensive national pollution data collected by the Chinese government. Moreover, they are more comprehensive than data in the U.S. For instance, in the U.S., $SO_2$ and $NO_X$ discharges are collected for power generation firms but typically not for industrial firms. While the data are comprehensive, they do not include some pollutants of interest, such as small particulates (PM2.5s), CO, and $CO_2$.

An important issue regarding the plausibility of the results of our proposed study is the reliability of this dataset. We would expect that there would be an incentive to underreport pollution, to the extent that this may be used in the long run to tax or shut down a firm. We propose to understand the reliability of the data by comparing the aggregate levels reported in these data to national levels of pollution. We will also investigate whether there is a

[6] It also records information on water pollution and for manufacturing sectors.

[7] For instance, Hsieh and Klenow (2009) also use Chinese firm data and then explicitly treat firms as plants.

presence of immediate changes following fee increases that might prove suspicious. Finally, the combination of observed pollution discharge and productivity impacts would be helpful as we do not believe that firms would have an incentive to understate revenues following increases in environmental fees.

As a check of our data, we compared the $SO_2$ discharges reported in our data to those reported in the Chinese Statistical Yearbook on Environment 2016, which are generally considered accurate. For 2015, our data report 8,002,169 tons of $SO_2$ discharged for power plants and manufacturing firms, while the Statistical Yearbook (which reports data for 2015) reports 8,711,762 tons discharged for all such firms in China.[8] Thus, in this year, our data appear to capture 91% of the total $SO_2$ emissions, which is higher than the 85% goal.

Table 2 provides summary statistics information on our environmental discharge data. We have 55,160 firm/year observations for power plants throughout China. We observe 12,504 unique power plants. Firms are in this data for about 4-5 years on average. The mean $SO_2$ emissions are 2,223 tons per year; the mean $NO_X$ emissions are 1,693 tons per year; coal consumption is 239,366 tons per year; oil consumption is 914 tons per year; natural gas consumption is 914,000 cubic meters per year.

Table 2: Summary statistics on environmental data for power plants

| Variable | Value |
|---|---|
| Number of firm/year observations: | 55,160 |
| Number of unique firms: | 12,504 |
| Mean $SO_2$ emissions (tons): | 2,223 (11,227) |
| Mean $NO_X$ emissions (tons): | 1,693 (26,793) |
| Mean coal consumption (tons): | 239,366 (830,469) |
| Mean oil consumption (tons): | 914 (830,469) |
| Mean gas consumption (1000 cubic meters): | 914 (90,811) |

Note: standard deviations are included in parentheses.

[8]See http://www.stats.gov.cn/tjsj./tjcbw/201706/t20170621_1505831.html.

## 2.4 Annual Survey of Industrial Production Data

Our final main data source is firm production data from the Chinese Annual Survey of Industrial Production (ASIP), 2004-13. These data derive from annual surveys conducted by National Bureau of Statistics and includes all non-state-owned firms with sales above CNY 5 million, or about USD 700,000, per year, and all state-owned firms. For our purposes, these data contain information from firms in the manufacturing sector—with 2-digit industrial sector codes from 13 to 43—and power generation firms—with a 2-digit code of 44. We standardize industrial codes to the 2013 definition. Besides the industrial sector, the main variables that we use are the number of workers, capital, output, whether the firm is state-owned, and whether it is an exporter. We follow Brandt et al. (2012) in our variable choice and deflation measures.

There are some known issues with these data. The data after 2007 lack variables of interest such as intermediate inputs. In addition, Brandt et al. (2017b) exclude 2010 data for data quality concerns. Our own investigation confirms that the data in 2010 look suspiciously close to the data from 2009. In addition, the 2012 data appear to not correctly report the number of workers, because the reported numbers are almost always exactly the same as in 2011, unlike between other pairs of subsequent years.[9] For these reasons, we exclude the data from 2010 and 2012. Our ASIP analysis data currently include information from 2004-2009, 2011, and 2013.

Table 3: Summary Statistics on production data for power plants

| Variable | Value |
|---|---|
| Number of firm/year observations: | 60,601 |
| Number of unique firms: | 10,914 |
| Mean output (1000 CNY): | 473,563 (3,901,136) |
| Mean labor (number of workers): | 497 (2,186) |
| Mean capital (1000 CNY): | 593,962 (3,830,152) |

Note: standard deviations are included in parentheses.

Table 3 provides summary statistics for the production data for manufacturing firms. We have 60,601 power plant observations. The mean output is about CNY 473 million. The

[9] We thank Yifan Zhang for pointing out this data problem to us.

mean of the number of workers is 497 and the mean of capital of a firm is about CNY 594.

There are 10,914 power plants in our sample. Each firm lasts about 6 years in the data, similarly to the environmental data. This is less than what one would expect in U.S. data. However, Brandt et al. (2012) also find relatively short, but slightly higher, tenure of firms.

We have linked the CES and ASIP datasets using the unique firm ID, firm name, firm address, and phone number. Table 4 provides summary statistics for the merged CES/ASIP data for power plants and manufacturing firms. We merge approximately 35% of the observations in the CES data for the common years. Our merged data include 15,087 power plant firm/year observations. We observe 3,567 unique power plants, so firms are in the matched data for about 4-5 years on average.

The mean output of the matched sample is about CNY 539 million which is similar to that of the ASIP. The larger mean size can be explained by the fact that the CES concentrates only on relatively highly polluting firms. In this sample, the mean number of workers is 586 and the mean capital is CNY 730 million. The mean $SO_2$ emissions is 3478 tons per year; the mean $NO_X$ emissions are 836 tons per year; the mean coal consumptions are 332,301 tons per year; the mean oil consumptions are 351 tons per year; the mean natural gas consumption are 440,000 cubic meters per year.

Table 4: Summary statistics on merged power plant data

| Variable | Value |
|---|---|
| Number of firm/year observations: | 15,087 |
| Number of unique firms: | 3,567 |
| Mean output (CNY 1000): | 538,579 (3,488,970) |
| Mean labor (number of workers): | 586 (2,005) |
| Mean capital (CNY 1000): | 729739 (2,939,184) |
| Mean $SO_2$ emissions (tons): | 3478 (9,571) |
| Mean $NO_X$ emissions (tons): | 836 (4,624) |
| Mean coal consumption (tons): | 332,301 (838,354) |
| Mean oil consumption (tons): | 351 (6,418) |
| Mean gas consumption (1000 cubic meters): | 440 (7,842) |

Note: standard deviations are included in parentheses.

# 3 Analytic Framework

## 3.1 Model

We develop a simple conceptual model and use it to motivate our estimating equations. The basic idea of our model is that power plants and other manufacturing firms produce an output good but also discharge air pollution as a byproduct of the output good. The pollutants then enter into the atmosphere where they may increase ambient pollution. This ambient pollution can be detected by pollution monitors.

Index firms $i = 1, \ldots, I$ and the time periods in our sample by $t = 1, \ldots T$. We assume that firms use a number $J$ of inputs that are observable to the econometrician, $k^1, \ldots k^J$, and a total factor productivity (TFP) term to produce two outputs, a production good and pollution discharges. The observable inputs include capital, labor, and materials. Denote the log of these terms $k^1_{it}$, $\ldots$, $k^J_{it}$, $\omega_{it}$, $y^*_{it}$, and $d_{it}$, respectively.

We assume that observed output is $y_{it} = y^*_{it} + \varepsilon_{it}$ where $\varepsilon_{it}$ is a shock to logged output net of logged weighted pollution. The shock might be due to random variation in the amount of pollution discharged or to other factors. With a Cobb-Douglas specification, we can write:

$$\begin{aligned} y_{it} - \beta^d d_{it} &= \beta^{k1} k^1_{it} + \ldots + \beta^{kJ} k^J_{it} + \omega_{it} + \varepsilon_{it} \\ \Rightarrow y_{it} &= \beta^{k1} k^1_{it} + \ldots + \beta^{kJ} k^J_{it} + \beta^d d_{it} + \omega_{it} + \varepsilon_{it}. \end{aligned} \tag{1}$$

We expect that it is costly for firms to mitigate pollution. Hence, $\beta^d$ is likely negative, implying that more observable inputs and TFP are required to produce *less* pollution.

The goal of the paper is to analyze the impact of pollution fees in reducing pollutant discharges and ambient pollution and the side effects that these fees may have on reducing production of the output good. Our identifying variation is from changes in fees across provinces. In particular, different provinces raised pollution fees at different times during our sample period, which provides variation in the level of pollution fees. Denote Chinese provinces by $p = 1, \ldots P$. Fees vary at the province and time period (year) level. Denote logged fees for province $p$ and time period $t$ as $f_{pt}$.

The production function in (1) has a general TFP term, that is indexed by both firm $i$ and time $t$. Variation in TFP across firm and time can potentially confound an estimation of the impact of fees or pollution on outcomes. In particular, during our sample period, China had been growing rapidly and unevenly across different regions. This implies that there are potential changes over time in the production function across different parts of China.

As an example, areas with high TFP growth were likely to have seen the construction of many new power plants and manufacturing facilities, which would increase ambient air pollution. The increase in TFP in these areas also likely increased incomes, which would likely increase the demand for air quality. Both of these factors would increase the demand for air pollution mitigation, and thereby lead to increases in fees. A difference-in-difference research design that examined the impact of pollution fees on outcomes such as ambient pollution or emitted pollution using province and year dummies may provide inconsistent results due to this source of endogeneity. For instance, regressions with this design might implausibly conclude that pollution fees led to higher ambient pollution, but the causality might be the reverse, that higher ambient pollution levels led to a demand for higher pollution fees. As we discuss below, our model of firm production and pollution takes this variation in TFP into account through a research design that identifies the impact of fees and pollution on outcomes using differences-in-differences in local areas.

We now discuss the impact of firm production on ambient pollution. We observe annual data from a set of ambient pollution monitors. These monitors record ambient levels of $NO_2$, $SO_X$, and PM10. Denote monitors by $j = 1, \ldots, J$ and logged ambient pollution at time $t$ as $a_{jt}$. We assume that expected ambient pollution at each monitor is a function of the discharges from firms that are located near the monitor.

## 3.2 Estimation and Identification

We estimate a series of specifications based on our model developed in Section 3.1. The dependent variables include ambient pollution $a_{jt}$, pollutants discharged $d_{it}$, and production $y_{it}$. The majority of our specifications are reduced forms of the model in (1). In these specifications, the main regressor of interest is fees, $f_{pt}$. These specifications seek to understand the impact of fees on the different dependent variables.

Our regressions need to control for the fact that there is variation across time in TFP growth across different parts of China. To do this, we employ a research design of differences-in-differences in local areas. Specifically, we define a *border region* as the geographic area that is within 50 KM of the border of any given set of Chinese provinces and no other province. We further define an *interior region* as the part of any province that is not in a border region. Most of our specifications assume that the production processes are the same at any time period in each region.

Figure 6 illustrates our border region concept graphically. This figure shows the provinces of Guangdong (to the south), Fujian (to the northeast), and Jiangxi (to the northwest). Focusing on these three provinces, there are four border regions: the Fujian-Guangdong border ($B_{12}$ and $B_{21}$), the Fujian-Jiangxi border ($B_{23}$ and $B_{32}$), the Guangdong-Jiangxi border ($B_{13}$ and $B_{31}$), and the Fujian-Guangdong-Jiangxi border ($B_{123}$, $B_{213}$, and $B_{312}$), and three interior regions: the interiors of Guangdong ($I_1$), Fujian ($I_2$), and Jiangxi ($I_3$). Together, our sample would include 7 regions (4 border regions and 3 interior regions) if China included only the three provinces in the figure.[10]

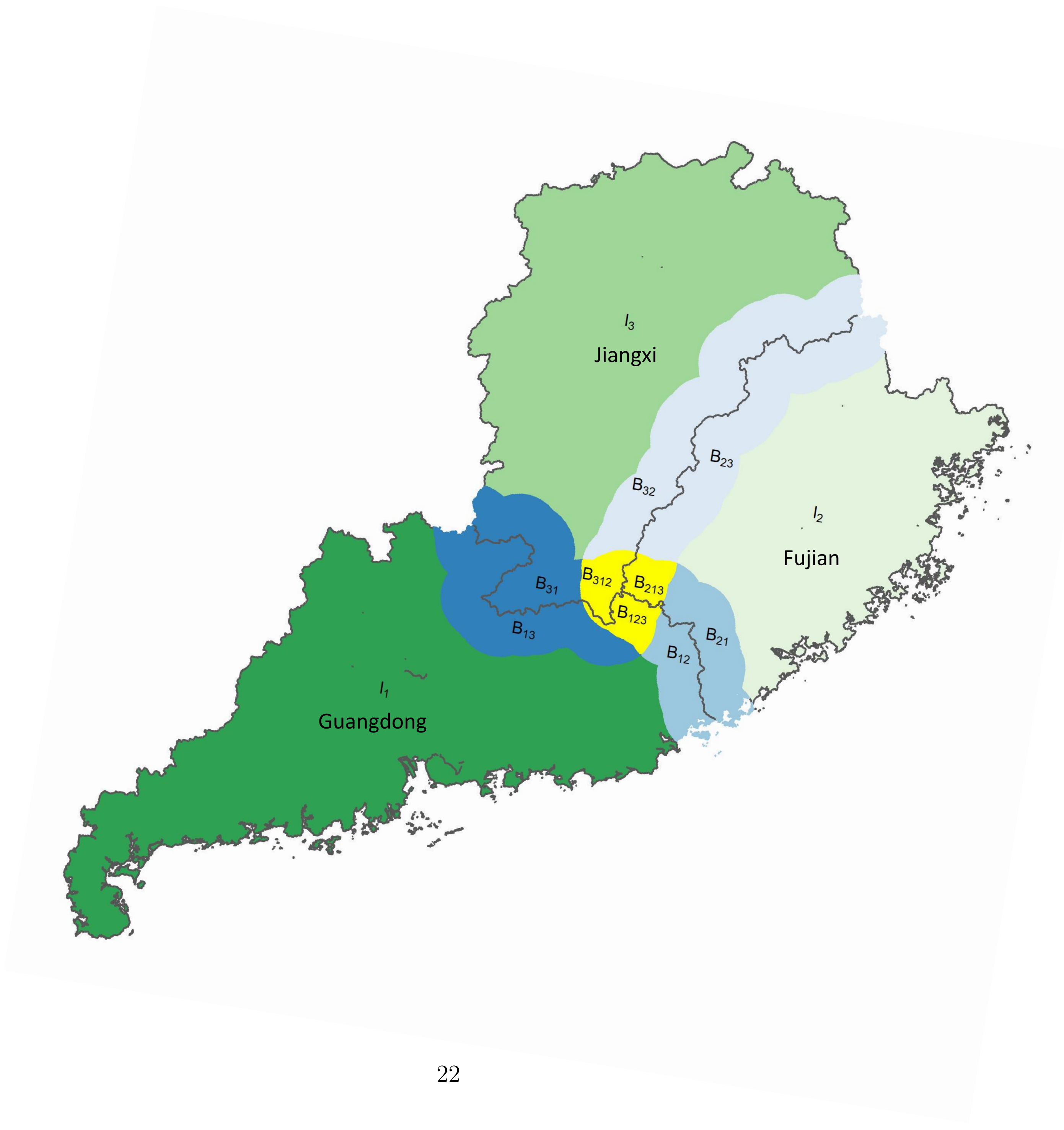
Let $r = 1 \ldots, R$ denote the set of regions in China, $r(i)$ denote the region for firm $i$, and $R(j)$ denote the region for ambient pollution monitor $j$. We estimate models with fixed effects at a number of different levels. One focal estimation specifies that

$$\omega_{it} = \beta^i + \beta^R_{r(i)t}, \tag{2}$$

where $\beta^i$ are firm fixed effects and $\beta^R_{r(i)t}$ are region $\times$ year interactions. Thus, these specifications allow for the baseline TFP and the growth in TFP to vary in each of the many regions of China.

[10] For simplicity, Figure 6 does not show other provinces besides these three. Because of these other provinces, the Guangdong-Jiangxi and Fujian-Jiangxi border regions and the Fujian, Guangdong, and Jiangxi interior regions in our estimation do not include all the area that the figure indicates, since parts of them are in other border regions.

Figure 6: Example of regions from Fujian, Guangdong, and Jiangxi provinces



Using the definition of TFP in (2), we estimate a number of reduced-form specifications. First, we estimate specifications of ambient pollution on discharge fees and fixed effects, at the monitor / year level:

$$a_{jt} = \gamma^f f_{R(j)t} + \gamma^{R(j)t} + \gamma^j + \varepsilon^a_{jt}. \tag{3}$$

In (3), we let logged ambient pollution be a function the logged pollution fees, fixed effects for monitors, and interactions of region and time.

We estimate similar specifications that are at the firm / year level with pollutant discharges as the dependent variable:

$$d_{it} = \alpha^f f_{r(i)t} + \alpha^{r(i)t} + \alpha^i + \varepsilon^d_{it}, \tag{4}$$

and with production as the dependent variable:

$$y_{it} = \delta^f f_{r(i)t} + \delta^l l_{it} + \delta^k k_{it} + \delta^{r(i)t} + \delta^i + \varepsilon^y_{it}. \tag{5}$$

For specifications based on (5), we include $l_{it}$ and $k_{it}$ as regressors, as these specifications are reduced forms of the production function (1) and capital and labor are important predictors of the output good $y_{it}$.

We could also potentially estimate the structural production function in (1):

$$y_{it} = \beta^k k_{it} + \beta^l l_{it} + \beta^d d_{it} + \beta^k k_{it} + \beta^{r(i)t} + \varepsilon_{it}. \tag{6}$$

Under our model, $d_{it}$ will be endogenous as it is an output of the firm and hence not mean independent from $\varepsilon_{it}$. Thus, the instrumental variables specifications allow us to evaluate the causal impact of pollution on output, using the changes in fees within border regions as the source of exogenous variation. We found that the first stage results here were not strong enough to estimate meaningful structural production function results and hence we do not estimate specification based on 6.

Because the specifications based on (3), (4), and (5), include both monitor/firm fixed effects and region × year interactions, identification in these models is based on changes in the dependent variable within a border region-year across monitors/firms faced with changes in fees. As an example, consider a border region with two provinces. Suppose that the fees are different across the two provinces but are the same across time within a province. Then, the impact of fees cannot be identified from these provinces because of the monitor/firm fixed effects.

Now consider two provinces in their entirety for which the fees change in one province but not in the other. The change in the dependent variable in one province versus the other at the time of the change in fees will identify the impact of fees. Note that data from the interior regions will not identify the parameters on fees since there is no variation in fees for an interior region and year. Thus, the identification of the impact of fees will essentially come from data from the border regions only. However, the interior regions will help identify the impact of $l$ and $k$ in (5) and (6).

Thus, we can think of our estimation as being identified by a series of differences-in-differences in border regions. As an example, if China consisted only of the three provinces in Figure 6, this would imply four differences-in-differences. The advantage of this identification strategy is that the assumption that we need is that the trends in $\omega$ in these regions do not vary from one side of the border to the other. This is a much milder assumption than assuming that the trends in $\omega$ do not vary for China as a whole, since the border regions are geographically small and hence it might be reasonable to think that TFP growth rates are similar within a border region. An estimation that included province and year fixed effects would effectively make this latter assumption.

We also estimate other specifications with different levels of fixed effects. First, we estimate specifications where the sample is just on the border region. For the specifications with ambient pollution or pollution discharges as the dependent variables, (3) and (4) respectively, these specifications will give the same coefficient estimates on fees, but different standard errors, since the interior of the provinces do not identify fees. For the regressions with the output good as the dependent variable, (5) and (6), the regression coefficients on fees and pollution may be different since the interior regions help identify $l$ and $k$.

Second, we estimate specifications without firm fixed effects. In these specifications, we include province × region interactions. Thus, as an example, for the Fujian-Guangdong-Jiangxi border region, we would include an interaction for this border region with being in Fujian province and an interaction for this border region with being in Guangdong province (with the Jiangxi interaction being collinear). These terms ensure that the identification comes from changes in fees across provinces in a border region, rather than level differences in fees. These specifications will estimate the impact of fees by comparing outcomes on one province in a border region to the other province. Unlike with firm fixed effects, this will occur even if the outcomes occur through the exit of some firms and the entry of other firms. Thus, for instance, if an increase in fees caused high-polluting firms to exit and low-polluting firms to enter, this specification would capture this, while the specification with firm fixed effects would not.

Finally, we estimate specifications with just firm and year fixed effects and specifications with just region and time fixed effects and province × region interactions, but no region × time fixed effects. These specifications identify the effect of fees by comparing provinces that raised fees to provinces that do not raise fees. We view the identification from these specifications as less plausible than from the other specifications, because of the different TFP growth rates across provinces.

# 4 Results

## 4.1 Ambient Pollution Results

Table 5 presents ambient air pollution results. Columns (1), (3), and (5) present results without monitor fixed effects while columns (2), (4), and (6) present results with monitor fixed effects. Columns (1) and (2) present results that include year and monitor or area (region × province) fixed effects, but do not control for the differential growth rates in TFP across regions in China. Columns (3) and (4) are our main results and present specifications that include region × year interactions. Columns (5) and (6) are analogous to columns (3)

Table 5: Effect of pollution fees on ambient air pollution

| | (1) All Sample | (2) All Sample | (3) All Sample | (4) All Sample | (5) Borders Only | (6) Borders Only |
|---|---|---|---|---|---|---|
| *Panel A: $SO_2$* | | | | | | |
| log($SO_2$ fee) | 0.129 | 0.163* | -0.134 | -0.146 | -0.134 | -0.146 |
| | (0.0837) | (0.0797) | (0.208) | (0.206) | (0.217) | (0.206) |
| $R^2$ | 0.540 | 0.859 | 0.565 | 0.910 | 0.759 | 0.905 |
| Observations | 1971 | 1962 | 1677 | 1669 | 375 | 374 |
| *Panel B: $NO_2$* | | | | | | |
| log($NO_X$ fee) | 0.384*** | 0.190** | -0.0827** | -0.101 | -0.0827** | -0.101 |
| | (0.0875) | (0.0815) | (0.0263) | (0.120) | (0.0338) | (0.121) |
| $R^2$ | 0.378 | 0.834 | 0.389 | 0.871 | 0.649 | 0.889 |
| Observations | 1862 | 1853 | 1589 | 1581 | 356 | 355 |
| *Panel C: PM10* | | | | | | |
| log($SO_2$ fee) | 0.164*** | 0.136** | -0.0310** | -0.0257 | -0.0310* | -0.0257 |
| | (0.0442) | (0.0428) | (0.0126) | (0.0199) | (0.0149) | (0.0203) |
| $R^2$ | 0.571 | 0.873 | 0.605 | 0.930 | 0.811 | 0.938 |
| Observations | 1961 | 1952 | 1669 | 1661 | 375 | 374 |
| Year FE | Yes | Yes | | | | |
| Region×province FE | Yes | | Yes | | Yes | |
| Region×year FE | | | Yes | Yes | Yes | Yes |
| Monitor FE | | Yes | | Yes | | Yes |

Notes: All specifications in this table define border regions as 50km on either side of a provincial border. Standard errors clustered two-way by monitor and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Data Source: Air pollution panel derived from China's EPA, Environmental Yearbooks, and Environmental Annual Quality Reports (see Ebesteina, et al. 2017 for details).

and (4) but they include only the border regions and not the interior of the provinces.

Focusing first on columns (1) and (2), we find that $SO_2$ fees appear to *increase* ambient pollution. In other words, air pollution went up more in provinces that raised these fees more during our sample period, than in provinces that raised these fees less during our sample period. In particular, the results are positive for all three pollutants, and statistically significant at the 10% level for four of the six specifications. The impact of PM10s is the most significant and shows that a 100% increase in fees is associated with a 14–16% increase in ambient pollution.

Our interpretation of these results is that they are likely due to a reverse causality. Provinces with relatively high increases in fees are likely ones where pollution would have been increasing faster in the absence of these fees, due to increases in TFP.

Thus, our main results include region $\times$ year interactions. The effect of fees on ambient pollution is now negative in all of the six specifications and statistically significant for two of these specifications. Columns (5) and (6) limit our sample to the border regions only. In this case, we find identical point estimates for the impact of fees on ambient pollution. However, the clustered standard errors are a little different, and generally larger. We find that a 100% increase in fees is associated with a 9% reduction in ambient $NO_2$ pollution and a 3% reduction in ambient PM10 pollution.

In unreported specifications, we found that the results were not very robust to alternate specifications. In particular, in cases where we used smaller distance boundaries, the results were generally insignificant. This is possibly due to these results being driven by a relatively small number of monitors. Also, because ambient pollution will travel across provincial borders within a border region, it is possible that the lack of significance with a smaller distance boundary is due to higher source pollution on one side of the border region causing higher ambient pollution on the other side. Overall though, we interpret these negative results with caution.

Our main takeaway from the ambient pollution results is that there is a need to control for differential growth rates across areas of China. A study that ignored these differences would find that pollution fees increase ambient pollution.

## 4.2 Pollutant Discharge Results

Table 6 analyzes the impact of fees on discharged pollution by power plants, at the firm-year level. We use the analogous set of six specification as in Table 5. The data here are from the Chinese Environmental Survey (CES) data.

We start by describing the results with year and firm fixed effects, or year and local area fixed effects, in columns (1) and (2). These results show a relatively small impact of pollution fees on decreasing pollution discharges. The effect is not statistically significant in three of the four cases and is statistically significant at the 10% level in one case, for $SO_2$ discharges with firm fixed effects. Thus, this table provides relatively weak evidence that the increase in pollution fees was associated with a decrease in pollution discharged by power plants, particularly when controlling for a stable set of plants.

Focusing next on our main results in columns (3) and (4), we find that with identification coming from changes in fees in the border regions, fees negatively and significantly predict discharged pollution for both $SO_2$ and $NO_X$. In particular, a 100% increase in $SO_2$ fees predicts a 45% drop in $SO_2$ pollution with fixed effects and a 33% drop in $SO_2$ pollution without fixed effects, while a 100% increase in $NO_X$ fees predicts a 35% drop in $NO_X$ pollution with fixed effects and a 22% drop in $NO_X$ pollution without fixed effects. Thus, these results show that there is strong evidence that the pollution fees led to drops in pollution when we allow for changes in TFP growth rates across different parts of China. The point estimate of the results on just the border regions, in columns (5) and (6) are the same, but the clustered standard errors are again somewhat larger, leading to only results with firm fixed effects being statistically significant.

The larger impact of fees on $SO_2$ reductions in the fixed effects estimates suggests that existing power plants are more able to mitigate pollution but that this positive effect on pollution is being compromised by new plants that emit more $SO_2$. For $NO_X$, the relative magnitude of the two coefficients is the opposite, suggesting that some of the reduction of ambient $NO_X$ is for new firms.

To further examine how power plants may be reducing pollution discharges, we look at

Table 6: Effect of pollution fees on power plant pollutant emissions

| | (1) All Sample | (2) All Sample | (3) All Sample | (4) All Sample | (5) Borders Only | (6) Borders Only |
|---|---|---|---|---|---|---|
| *Panel A: Dependent variable:* $\log(SO_2+1)$ *emissions* | | | | | | |
| $\log(\mathrm{SO_2}$ fee) | -0.0948 | -0.345* | -0.328* | -0.445*** | -0.328 | -0.445* |
| | (0.178) | (0.160) | (0.154) | (0.132) | (0.211) | (0.219) |
| $R^2$ | 0.225 | 0.784 | 0.260 | 0.804 | 0.320 | 0.804 |
| Observations | 55,157 | 51,764 | 54,984 | 51,584 | 17,733 | 16,512 |
| *Panel B: Dependent variable:* $\log(NO_X+1)$ *emissions* | | | | | | |
| $\log(\mathrm{NO_X}$ fee) | -0.0785 | -0.0980 | -0.348** | -0.221** | -0.348 | -0.221* |
| | (0.220) | (0.0546) | (0.118) | (0.0764) | (0.191) | (0.0993) |
| $R^2$ | 0.207 | 0.725 | 0.256 | 0.745 | 0.282 | 0.753 |
| Observations | 48,522 | 45,134 | 48,389 | 44,996 | 15,530 | 14,329 |
| Year FE | Yes | Yes | | | | |
| Region×province FE | Yes | | Yes | | Yes | |
| Region×year FE | | | Yes | Yes | Yes | Yes |
| Firm FE | | Yes | | Yes | | Yes |

Notes: All specifications in this table define border regions as 50km on either side of a provincial border. Standard errors clustered two-way by province and year in Columns 1-4 and by region and year in Columns 5-6. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Data Source: CES Sample. Information on $\mathrm{NO_X}$ emissions is missing before 2006.

Table 7: Effect of pollution fees on power plant fuel consumption

| | (1) All Sample | (2) All Sample | (3) All Sample | (4) All Sample | (5) Borders Only | (6) Borders Only |
|---|---|---|---|---|---|---|
| *Panel A: Dependent variable: log(Coal+1)* | | | | | | |
| log($SO_2$ fee) | -0.819*** | -1.015*** | -0.961*** | -0.958*** | -0.961** | -0.958*** |
| | (0.220) | (0.102) | (0.301) | (0.203) | (0.337) | (0.291) |
| $R^2$ | 0.271 | 0.638 | 0.404 | 0.748 | 0.435 | 0.753 |
| Observations | 55,157 | 51,764 | 54,984 | 51,584 | 17,733 | 16,512 |
| *Panel A: Dependent variable: log(Oil+1)* | | | | | | |
| log($SO_2$ fee) | 0.0122 | 0.0378 | 0.196*** | 0.195*** | 0.196 | 0.195 |
| | (0.0714) | (0.0486) | (0.0553) | (0.0639) | (0.115) | (0.115) |
| $R^2$ | 0.227 | 0.729 | 0.267 | 0.750 | 0.277 | 0.746 |
| Observations | 55,157 | 51,764 | 54,984 | 51,584 | 17,733 | 16,512 |
| *Panel A: Dependent variable: log(Natural gas+1)* | | | | | | |
| log($SO_2$ fee) | 0.157 | 0.272* | 0.0826 | 0.203 | 0.0826 | 0.203 |
| | (0.144) | (0.127) | (0.184) | (0.208) | (0.242) | (0.231) |
| $R^2$ | 0.0680 | 0.631 | 0.115 | 0.664 | 0.154 | 0.659 |
| Observations | 50,434 | 46,993 | 50,275 | 46,827 | 16,192 | 14,966 |
| Year FE | Yes | Yes | | | | |
| Region×province FE | Yes | | Yes | | Yes | |
| Region×year FE | | | Yes | Yes | Yes | Yes |
| Firm FE | | Yes | | Yes | | Yes |

Notes: All specifications in this table define border regions as 50km on either side of a provincial border. Standard errors clustered two-way by province and year in Columns 1-4 and by region and year in Columns 5-6. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Data Source: CES Sample.

the impact of fees on fuel usage. We again use the analogous set of six specification as in Table 6 and the data are again from the Chinese Environmental Survey (CES) data. We find very large drops in coal fuel usage for plants, that is similar across the six specifications. Our specifications that control for different TFP growth rates across different parts of China—in columns (3) through (6), also find increase in oil consumption. In other words, power plants in border regions where fees went up relative to the other province in the border region had increases in their oil consumption. Natural gas consumption also increased, though the effect is only significant in column (2).

In the U.S., many power plants have switched from coal to natural gas (**?**). However, plants are unlikely to switch from coal to oil, because it is much more expensive to use oil as a fuel for power plants. These results show that in China, pollution fees appear to have caused power plants to switch from coal to oil. Natural gas may be much cheaper in the U.S. than in other countries due to the shale gas boom caused by hydraulic fracturing (**?**).

## 4.3 Output and Production Function Results

Table 8 presents our results on the effect of fees on power plant output. It uses the matched Chinese Environmental Survey (CES) and Annual Survey of Industrial Production (ASIP) data. We again use the analogous set of six specification as in the previous subsections. However, our results here include a number of controls: for labor, capital, coal, oil, and gas. We use output, labor, and capital from the ASIP data and coal, oil, and gas from the CES data.

Our base results are in Panel A. We find that the coefficients on logged fees are insignificant for Specifications 1, 2, 3, and 5. For Specifications 4 and 6, the impact of logged fees is significantly negative and in both cases, a doubling of fees leads to a 22% decrease in output, after controlling for inputs. Thus, the impact of fees appears to be negative on existing power plants, though this seems to be mitigated when looking at power plants as a whole.

Panel B next tests the interaction of fees with labor and capital, to understand the heterogeneity of effects across plants. Though not displayed in the table due to the space

Table 8: Effect of fees on power plant output

| | (1)<br>All<br>Sample | (2)<br>All<br>Sample | (3)<br>All<br>Sample | (4)<br>All<br>Sample | (5)<br>Borders<br>Only | (6)<br>Borders<br>Only |
|---|---|---|---|---|---|---|
| *Panel A: Base specifications* | | | | | | |
| log($SO_2$ fee) | -0.111 | -0.0799 | -0.0123 | -0.217** | -0.0310 | -0.223* |
| | (0.0840) | (0.0758) | (0.0908) | (0.0774) | (0.122) | (0.100) |
| log(L) | 0.411*** | 0.160** | 0.422*** | 0.164** | 0.435*** | 0.149** |
| | (0.0596) | (0.0592) | (0.0572) | (0.0568) | (0.0640) | (0.0631) |
| log(K) | 0.478*** | 0.317*** | 0.473*** | 0.292*** | 0.455*** | 0.314*** |
| | (0.0328) | (0.0421) | (0.0316) | (0.0389) | (0.0476) | (0.0697) |
| log(Coal+1) | 0.0323*** | 0.0119* | 0.0385*** | 0.0167*** | 0.0238** | 0.0100 |
| | (0.00691) | (0.00572) | (0.00744) | (0.00450) | (0.00980) | (0.00683) |
| log(Oil+1) | 0.0803*** | 0.0232*** | 0.0790*** | 0.0198*** | 0.0879*** | 0.0177* |
| | (0.00719) | (0.00486) | (0.00778) | (0.00442) | (0.0149) | (0.00886) |
| log(Gas+1) | 0.0360*** | -0.00363 | 0.0444*** | 0.00754 | 0.0395** | 0.0132* |
| | (0.0107) | (0.0104) | (0.0122) | (0.00832) | (0.0132) | (0.00581) |
| $R^2$ | 0.797 | 0.944 | 0.805 | 0.950 | 0.807 | 0.953 |
| *Panel B: With fee interactions* | | | | | | |
| log($SO_2$ fee) | -0.314 | 0.0956 | -0.181 | -0.0859 | -0.164 | 0.163 |
| | (0.203) | (0.194) | (0.158) | (0.188) | (0.582) | (0.259) |
| log(L)×log($SO_2$ fee) | -0.0998** | -0.0849** | -0.118** | -0.107*** | -0.0861* | -0.0994** |
| | (0.0381) | (0.0355) | (0.0392) | (0.0314) | (0.0435) | (0.0390) |
| log(K)×log($SO_2$ fee) | 0.0630* | 0.0254 | 0.0701** | 0.0403* | 0.0518 | 0.0154 |
| | (0.0280) | (0.0191) | (0.0269) | (0.0189) | (0.0540) | (0.0218) |
| $R^2$ | 0.798 | 0.944 | 0.805 | 0.950 | 0.808 | 0.953 |
| *Panel C: With fee interactions and translog production function* | | | | | | |
| log($SO_2$ fee) | 0.0503 | -0.0255 | 0.154 | -0.188 | 0.431 | 0.188 |
| | (0.195) | (0.174) | (0.169) | (0.180) | (0.236) | (0.236) |
| log(L)×log($SO_2$ fee) | -0.0677 | -0.0823* | -0.0872* | -0.104** | -0.0418 | -0.0921* |
| | (0.0418) | (0.0385) | (0.0386) | (0.0315) | (0.0494) | (0.0402) |
| log(K)×log($SO_2$ fee) | 0.0174 | 0.0347 | 0.0262 | 0.0487** | -0.0191 | 0.0107 |
| | (0.0284) | (0.0215) | (0.0261) | (0.0197) | (0.0308) | (0.0225) |
| $R^2$ | 0.840 | 0.948 | 0.848 | 0.954 | 0.856 | 0.958 |
| Observations | 14,714 | 14,082 | 14,556 | 13,914 | 4,758 | 4,523 |
| Year FE | Yes | Yes | | | | |
| Region×Province FE | Yes | | Yes | | Yes | |
| Region×Year FE | | | Yes | Yes | Yes | Yes |
| Firm FE | | Yes | | Yes | | Yes |

Notes: All specifications in this table define border regions as 50km on either side of a provincial border. Standard errors clustered two-way by province and year in Columns 1-4 and by region and year in Columns 5-6. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Data Source: Matched CES and ASIP sample.

constraints, it includes all the same regressors as in Panel A plus these two additional regressors. We consistently find a pattern where logged fees interacted with labor imply a negative and significant impact on output, while logged fees interacted with capital implies a positive impact on output, that is significant in Specifications 3 and 4. In other words, plants that add labor when $SO_2$ fees rise see a relative decrease in output while plants that add capital see a relative increase in output.

Panel C repeats Panel B but with a translog production function. Specifically, these specifications add the square of labor, the square of capital, and the interaction of labor and capital and also include all the regressors in Panel B. The purpose of Panel C is to understand whether our results in Panel B could simply be due to size effects, where firms with more capital are more productive. We find that the additional of these non-linear terms does not change the basic message from Panel B, which is that logged fees interacted with labor imply a negative and significant impact on output, while logged fees interacted with capital sometimes imply a positive and significant impact on output.

# 5 Conclusion

The economy of China has experienced a dramatic transformation in recent years but a cost of development has been pollution. Recognizing that pollution is an important concern, the Chinese central government and regional authorities have implemented a number of policies to mitigate pollution. This study considers an important to mitigate pollution. Starting in 2003, firms were assessed fees based on the amount of $SO_2$ and $NO_2$ air pollutants that they emitted. Provinces updated these fees over time and accordingly, these fees varied across provinces and year.

We obtain detailed data on ambient pollution from air pollution monitors, and discharged pollutants, fuel inputs, and firm productivity for power plants, which emit the majority of these air pollutants. We use the data to evaluate the extent to which pollutants reduced pollution. Because the Chinese economy has been growing rapidly and because greater industrial production would lead to more air pollution, it would not be plausible to perform a difference-in-difference on pollution measures based on variation in pollution fees across provinces. Indeed, when consider ambient pollution, we find that this type of specification would imply that pollution fees *increase* pollution for three pollutants.

Accordingly, our identification is based in differences-in-differences in local areas. Specifically, we consider 50 KM border areas that are on both sides of a provincial border where one province raised fees and another province did not. We then examine how pollution and productivity measures changes in the province that raised fees compared to the province that did not raise fees.

Using this identification strategy, we find some evidence that pollution fees caused ambient pollution to drop. We also find that pollution fees led to large reductions in $SO_2$ and $NO_X$ discharges, with elasticities ranging from $-22\%$ to $-45\%$. Power plants reacted to the fees by reducing their coal inputs. There is some evidence that they increased their oil inputs (from a low base) and their natural gas inputs. Even after accounting for these inputs and labor and capital, the fees appear to have led to a drop in productivity, with an elasticity of $-22\%$ with firm fixed effects. Fee increases appear to make labor relatively less productive and capital relatively more productive.

Overall, our results point to environmental discharge fees in China having a major impact on power plants. They appear to have helped lower emitted pollution and ambient pollution. However, they may also have lowered productivity for these firms.

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