Toulouse School of Economics

Master 1 economics - International track

Applied econometrics - Group 13 final paper

What is the impact of pollution policies on firms' Total Factor Productivity (TFP) in China?

Abstract: Environmental policies have sparked debate over their effects on firms' Total Factor Productivity (TFP). This study investigates the impact of pollution regulations on TFP using firm-level data from 2015 to 2019 in China and applies a Difference-in-Differences approach with Propensity Score Matching for causal estimation. It is based on The Jing-Jin-Ji collaborative development strategy, implemented in 2017 in the Beijing Hebei Tianjing area and aiming to introduce stricter regulation. Findings reveal that while compliance costs initially lower productivity, firms investing in cleaner technologies gain efficiency in the long run. The average treatment effect on the treated ranges between 1.74 percent and 2.86 percent, with manufacturing firms experiencing a stronger increase (4.7 percent). Beijing and Hebei display significant productivity improvements, whereas Tianjin shows a weaker response, suggesting disparities in enforcement. Compared to previous studies, these results align with the Porter Hypothesis, suggesting that stringent environmental regulations, when well-implemented, can enhance productivity through innovation. Policymakers should consider expanding such regulations while ensuring balanced enforcement across industries and regions. Future research should explore the long-term economic effects of these policies and assess the role of financial incentives in promoting sustainable corporate practices.

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Introduction

Since China started its economic reforms in 1978, the country's fast industrial growth, driven by coal and the creation of special economic zones (SEZs) like Shenzhen and Shanghai, has caused serious environmental problems. The heavy use of coal has led to high levels of air pollution, with dangerous particles (PM2.5) and sulfur dioxide (SO) causing smog and acid rain. At the same time, waste from factories has polluted major rivers like the Yangtze and Yellow Rivers, as well as farmland, with toxic metals such as lead (Pb) and cadmium (Cd), making some land impossible to farm. These environmental problems have also harmed public health, increasing respiratory diseases, lung cancer, and heavy metal poisoning, especially in cities and among industrial workers.

Recent studies have shown that pollution also affects economic productivity. Chang et al. (2016) found that high pollution levels reduce worker efficiency, even in office jobs, because employees take longer breaks. Zivin and Neidell (2012) also showed that long-term exposure to polluted air increases hospital admissions for respiratory infections, proving that pollution is not just an environmental issue but also a serious health and economic problem. Pollution also affects labor markets, creating economic inequalities. Hoffmann and Rud (2022) found that educated workers tend to move to less polluted areas, a trend also noted by Vuong et al. (2022). Similarly, Shen et al. (2023) showed that air pollution discourages people from moving to affected areas.

In response to these growing concerns, China has introduced several policies to reduce pollution and protect natural resources. China first recognized the need for environmental protection in 1972, but it was not until 2015 that the revised Environmental Protection Law made companies more responsible for pollution. In 2013, China launched the Air Pollution Prevention and Control Action Plan to reduce sulfur dioxide and fine particulate emissions, followed by similar policies for water and soil in 2015 and 2016. In 2018, the government introduced the Environmental Protection Tax Law, which fined polluting companies. That same year, the Ministry of Ecology and Environment was created to strengthen environmental policies.

There are two main economic theories about how environmental policies affect businesses. The Pollution Haven Hypothesis, based on trade theory, argues that strict environmental rules increase costs for companies. As a result, some companies move their polluting factories to countries with weaker regulations, leading to "pollution havens" (Levinson and Taylor, 2008). On the other hand, the Porter Hypothesis (Porter and van der Linde, 1995) suggests that stricter environmental rules can actually make companies more competitive. By pushing firms to improve efficiency and invest in innovation, these policies can lower long-term costs and even help companies become global leaders in green technology.

This essay will explore whether environmental regulations have positive or negative effects. It will focus on China's air pollution laws, and their impact on the most polluting industries. It will also analyze how different regions in China are affected by these policies, looking at their impact on total factor productivity (TFP). To do this, a comparison between regions with different levels of regulation over time using the difference-in-differences (DID) method will be carried out, notably thanks to propensity score matching (PSM) and with the use of recent data (2015-2019). This methodology allows for a precise estimation of the effect of environmental policies on firm performance by minimizing selection bias and isolating the specific effects of regulations. Most studies focus on national or individual firms' responses to environmental regulations, rather than regional or multi-sectoral effects, this study instead focus on multiple policies with coordinated enforcement allowing to compare differences in enforcement and outcomes across regions with varied industrial structures. This study provide a robust analysis on a quasi experimental setting.

Literature Review

The effect of environmental policies on business productivity is a major topic in environmental economics. Many believe that such policies create extra costs for companies, but some argue that they can also encourage innovation and increase productivity. This has led to two main views.

The Pollution Haven Hypothesis states that strict environmental policies increase production costs, reduce competitiveness, and push companies to relocate to countries with weaker rules (Jaffe et al., 1995). Greenstone, List, and Syverson (2012) provide evidence for this, showing that environmental rules in the U.S. led to a 2.6 percent drop in total factor productivity (TFP) in the manufacturing sector.
In contrast, the Porter Hypothesis argues that well-designed regulations can boost innovation and competitiveness. Porter (1991) and Porter and van der Linde (1995) suggest that companies forced to follow strict regulations may become more efficient in the long run. Dechezlepretre and Sato (2017) support this idea, showing that while very strict policies may hurt competitiveness by pushing firms abroad, well-designed regulations can drive technological improvements and efficiency.

Empirical studies give mixed results on the impact of environmental policies on productivity. Some research finds positive effects, especially in encouraging innovation. For example, Albrizio (2017) found that environmental policies encourage investment in innovation, which improves firm productivity. Similarly, Huang and Lio (2019) found that while regulations hurt Chinese firms in the short run, they promote technological progress and improve productivity in the long run. Johnstone, Hascic, and Popp (2010) also found that strict environmental policies in OECD countries led to more green patents, showing that policies can encourage innovation.

However, other studies highlight short-term negative effects. Greenstone, List, and Syverson (2012) found that U.S. manufacturing industries subject to strict air quality rules saw an average 2.6 percent drop in TFP. Lanoie, Patry, and Lajeunesse (2008) noted that while productivity declines at first, firms eventually adjust and recover. Barbera and McConnell (1990) also found that environmental regulations initially create high costs for companies, leading to a drop in productivity before any long-term benefits appear.

Beyond these general findings, the impact of environmental policies depends on the type of regulation and the industry. Kosluk and Zipperer (2014) argue that flexible policies—such as incentives rather than strict limits—allow companies to adapt more easily. Cohen and Tubb (2018) found that large firms with more money to invest in green technology can handle regulations better than small firms. Additionally, Alpay et al. (2002) compared different countries and concluded that in wealthier economies, regulations encourage innovation rather than reduce production. Similarly, Nesta, Vona, and Nicolli (2014) found that how well renewable energy policies encourage innovation depends on market competition. Cross-country comparisons show that the impact of environmental policies varies. In China, Huang and Lio (2019) found that regulations initially slow productivity but later boost innovation. In contrast, in the U.S. and Europe, the effects are more industry-specific (Greenstone et al., 2012; Dechezlepretre and Sato, 2017).

Overall, research suggests that the effect of environmental policies on productivity is not clear-cut. Some studies highlight short-term losses, while others show long-term benefits through innovation and efficiency.

Institutional Context

China's environmental polies aim to improve business practices, but their impact depends on the region because of the country's decentralized system. The central government, led by the CCP, sets national policies, but local governments are responsible for applying them. This means that richer cities like Beijing and Shenzhen, which have stronger regulations, enforce environmental rules more strictly than poorer areas, where economic growth is often the priority.

The Ministry of Ecology and Environment (MEE) was created in 2018 to improve oversight, but problems remain. Complicated bureaucracy and the power of state-owned companies, which focus on economic growth, slow things down. In recent years, China has introduced stronger environmental policies. Key measures include the Revised Environmental Protection Law (2015) and action plans to reduce air, water, and soil pollution. In 2018, the government introduced an environmental tax, forcing polluting companies to pay fines. However, enforcement is still inconsistent, as local governments struggle to balance economic and environmental goals.

One of China's main environmental focus areas is the Beijing-Tianjin-Hebei (Jing-Jin-Ji) region, home to major industries but also some of the country's worst pollution. Hebei province, in particular, has the world's biggest steel production sites, making it a major source of air pollution. Because of its importance, the government is using this region as a testing ground for new environmental policies. According to the Paulson Institute (2023), Jing-Jin-Ji could become a leader in cutting emissions and developing renewable energy.

However, environmental rules are not applied equally everywhere. Wealthy cities have well-funded agencies and stricter controls, while poorer provinces like Gansu and Chongqing have fewer resources and weaker enforcement. This difference affects both the environment and businesses, since companies in stricter areas face higher costs to follow regulations.

In Hebei province, a major government program focuses on reducing air pollution from the steel industry. It includes strict rules, factory inspections, and heavy fines for non-compliance. While it has led to lower PM2.5 levels, enforcement has been difficult due to opposition from businesses and inconsistent local regulation.

China is making efforts to strengthen environmental policies, showing a growing focus on sustainability. However, regional inequalities, bureaucratic obstacles, and resistance from industries remain challenges. The success of the Jing-Jin-Ji region as a testing ground for reforms could influence future policies across the country. The real challenge is finding a balance between economic growth and long-term environmental protection.

Hence, this study builds on the air pollution control policies strengthened in 2017 under the Jing-Jin-Ji collaborative development strategy, which aims to reduce pollution in this region. Examples of these policies include the Hebei Air Pollution Prevention and Control Program, or also, the Beijing-Tianjin-Hebei Air Pollution Prevention and Control Work Plan, both of which aim to limit PM2.5 emissions, thus constraining companies. The Jing-Jin-Ji region includes Hebei, Beijing, and Tianjing as administrative divisions.

Data Presentation

The data come from the study "How air pollution affects corporate total factor productivity?" conducted by Jialiang Yang and Wen Yin. This study includes two databases mainly derived from the China Stock Market and Accounting Research (CSMAR) database of Guotaian, macroeconomic data from the China Urban Statistical Yearbook, and patent data from the State Intellectual Property Office on the technical complexity of cities. The data are collected from corporate financial reports and Air Quality Index (AQI) reports published by the government.

The nature of the data is panel data, covering the period from 2015 to 2019. An observation corresponds to a company listed on the Shanghai and Shenzhen stock exchanges (A-shares) for a given year. Initially, the sample is composed of 13,738 observations and 29 variables covering the period from 2015 to 2019. On this sample, a sorting is carried out. This consists of merging the two databases from the Yang and Yin study and keeping only the industries that are relevant according to their pollution level. Then a Propensity Score Matching (PSM) method is carried out. This method is explained in the *Econometric model and estimation* section. Thus, after selection, the sample is composed of 877 observations on 180 companies and 26 variables covering the same period (2015-2019).

For this work, four variables are created and added to the database. These are administrative division (”admin_div”), ”Treated”, ”Post” and ”ATT”. ”admin_div” represents the administrative division where the firm is located. ”Treated” is a binary variable and is equal to 1 if the firm is located in Hebei, Beijing or Tianjing (the Jing-Jin-Ji region), 0 otherwise (509 control observations, 368 treated observations). ”Post” is also a binary variable equal to 1 (527 observations) after 2017 (introduction of the policy) and 0 for 2015-2016 (350 observations). “ATT” is described just below. Their description is also given in Table 12, in the *Appendix* section.

The main explanatory variable is ”ATT” which refers to Average Treatment effect on the Treated. This variable is the interaction between the variable ”Post” and ”Treated”. It takes the value 1 if the firm is treated and the year is strictly after 2016 (220 observations), 0 otherwise (657 observations). Concretely, it represents the firms subject to environmental policies fighting against air pollution from 2017. The firms concerned are all those located in the Jing-Jin-Ji region.

The dependent variable is total factor productivity (TFP). This variable is determined using the Levinsohn and Petrin (LP) method. It is an index that measures the efficiency with which capital and labor are used to produce goods and services. In the econometric study, TFP is log transformed. Descriptive statistics for this variable are presented in the *Appendix, Graphs and tables* section, in the Table 1,2 and 3.

Model construction and estimation

Construction

To estimate the impact of these policies on firm’s TFP, a **Difference-in-Difference (DiD)** model is used. The treated group consists of regulated companies. To compare properly treated and control firms, a **propensity score (PS) matching** was used. PS was computed using the maximum number of variables available, to obtain the best value in terms of accuracy. Equation 5 describes PSM estimation. The matching is then executed using pre-treamtent data only, with nearest neighbor method, and a 0.2 caliper, meaning that two firms having a PSM difference superior to 0.2 cannot be matched. In addition, a 2-times replacement was authorized, meaning that a treatment firm can be matched to at most two control firms. It was also ensured that no firm was matched with itself, as years 2015 and 2016 were both used to get the maximum data in the end.

Once the matching done, pre and post treatment datasets are merged. The dataset contains 877 observations: 509 control and 368 treated. 180 unique firms, **105 control, 75 treatment**, meaning that 30 treated firms were matched twice. Post-match descriptive statistics are in Table 3.

To check for matching quality, T tests (Table 4) were used, and no significant mean difference was found between control and treatment groups (p-values > 0.05). In addition, Figure 1 shows TFP along time for treatment and control groups. With treatment applied in 2017, the assumption that **trends are parallel before treatment** seems reasonable. Figure 2 represents distribution of key variables with treatment. Distributions look generally similar, except for Log(GDP), so heteroskedasticity might be an issue with this variable.

Overall, this is a great matching, as the number of observations is decent, there are no significant mean differences, and parallel trends assumptions seem respected.

Four main regressions were estimated, adding controls progressively to get a better isolation of the effect of the policy. First, a basic OLS model is run, then fixed effects of year and industry are successively added. Finally, firm fixed effects are controlled.

$$\text{Basic Model:} \quad \log(TFP)_{it} = \beta_0 + \beta_1 \text{ATT}_{it} + X_{it}\beta + \varepsilon_{it} \tag{1}$$

$$\text{Year Fixed Effects:} \quad \log(TFP)_{it} = \beta_0 + \beta_1 \text{ATT}_{it} + X_{it}\beta + \sum_t \gamma_t \text{Year}_t + \varepsilon_{it} \tag{2}$$

$$\text{Year \& Industry FE:} \quad \log(TFP)_{it} = \beta_0 + \beta_1 \text{ATT}_{it} + X_{it}\beta + \sum_t \gamma_t \text{Year}_t + \sum_j \delta_j \text{Industry}_j + \varepsilon_{it} \tag{3}$$

$$\text{Firm Fixed Effects:} \quad \log(TFP)_{it} = \beta_0 + \beta_1 \text{ATT}_{it} + X_{it}\beta + \sum_i \alpha_i \text{Firm}_i + \varepsilon_{it} \tag{4}$$

The matrix X contains the control variables for each model, results are available in Table 6. ATT is the main variable of interest, as it reflects the effect of the policy on firm's TFP. Since firms are regulated on pollution emitted by each unit produced, their environmental impact is included in production cost. In order to maximize their profits, they have to become more efficient, so we expect a positive ATT. Also, successive fixed-effects addition allows to discern what also impacts policy's effect on TFP. For example, if ATT decreases when controlling for year FE, it means that the believed impact was in fact overestimated, and caused by a general growing trend in TFP for all firms.

Before any interpretation, heteroskedasticity was checked, and it is assumed to be present in the first three models. Figure 3 depicts residuals vs. fitted values. The red line is curved for these models, indicating heteroskedasticity. Thus, these models were estimated with robust standard errors. ”Basic model” suppose independent errors with different variances. The other two models use year-clustered standard errors. Supposing that the errors are correlated within the same year, but not between years.

Estimation and interpretation

Table 6 displays the results for each main regression. R-squared is not available because it is based on the variance of the uncorrected residuals, and it doesn’t hold under heteroskedasticity.

The main variable to interpret is the **ATT**. As expected, it is positive for every model, and significant. The policy encouraged firms to be more efficient. The basic OLS gives an ATT of 0.0236*, but its effects decreases when ”year” is controlled. Thus, the overestimated impact of the policy was in fact caused by an unobserved general growing trend in TFP for all firms. This difference in coefficients also suggests that the effect is different for each year. The interpretation for the ”Year FE” model is that **on average, *ceteris paribus*, implementation of the policy increased TFP by 1.74% in the sample, when controlling for year.**

When adding control for industry, ATT increases ($\beta_1 = 0.0206^{***}$), meaning that the impact of the policy is also influenced by unobserved industry-specific characteristics. In less competitive industries, it is easier to adjust price in reaction to policies, so price increases can absorb the cost increase caused by the policy. The policy would be less effective in these cases. It also depends on physical capital dependence, some industries (such as manufacturing) can adapt more easily with massive investments in R&D to get cleaner technologies, whereas in less capitalistic industries such as services, it is harder to adapt.

Adding firm fixed-effects yields a higher ATT ($\beta_1 = 0.0286^{*}$): the impact of the policy is also influenced by unobserved firm-level characteristics. If parallel trends assumption was not respected, this great difference with others coefficients could indicate that there were differences between control and treated firms before treatment, so selection bias. But it is respected, so these initial differences, if they exist, did not influence TFP’s dynamics before treatment. Thus, there is a causal effect of the policy on treated firms: they increased their productivity to respond to the policy.

The other covariates also have expected signs, growing the number of employees increases TFP: bigger companies can create increasing return to scale by reducing average cost with larger infrastructures, and increasing the overall outcome for the same input. It is the same for R&D: investments in cleaner and more efficient technologies logically increase productivity. GDP has no statically significant impact on TFP, surely because its impact on TFP travels via other variables (R&D or number of employees).

In conclusion for estimation, **the policy had an impact on treated firms productivity:** the ATT is positive and varies between **1.74% and 2.86%** depending on the controls. This effect is suspected to be different for years, and industry. These divergences will be analyzed in the next part.

Additional results

To get an idea of the variable influencing the impact, three regressions were run. The model belived to be the more precise (Firm FE) was used, with an interaction between ATT and Administrative division, Industry and Year separately.

Table 7 desribes the differenciated impact of the policy for each region. Several policies were applied on three regions, the impact is similar and significative on Beijing and Hebei: TFP for fimrs located in these areas increased by **5%**, on average. Surprisingly, the interaction is not significant for Tianjin. The three regions have no clear structural differences, the sample size is correct (approx. 160 observations for each region). Maybe the level of controls to ensure the policy's application was not sufficient, or Tianjin compensated the effects of the policy with local measures. There is not enough information to answer clearly. We can nonetheless conclude that **the impact is differentiated depending on the administrative division.**

The differentiated impact of the policy for each industry is summarized in Table 8, as well as the industry codes. The policy had a significant impact on manufacturing (C), energy (D), water supply (E) and accommodation (I). These results should be interpreted with caution, as except for manufacturing, the subsamples are small (676 C vs. less than 50 observations by other sector). After the policy, manufacturing firm's TFP increased by 4.7% in average, which is higher than the other results. Again, this is one of the most polluting sectors, so the adjustment was bigger for them. The issue this approach points out is that the general results stated before can be in fact dominated by the effect on manufacturing firms. It is sure that the policy had an impact on manufacturing firms, but the other subsamples are too small to say that the impact is the same for the other industries, more data on other sectors is needed to provide stronger results.

A model with a "ATT*year" interaction was used to determine if the policy had a durable impact. Table 9 summarizes the results. The coefficients are significant for each post-treatment year, and fluctuate between 3.6 and

4.5%. The interpretation here is that treated firms increased they TFP by 3.6% in 2017 compared to pre-treatment years. In 2018, TFP increased by 4.5%, compared to 2015-2016, not 2017. Consequently, the impact of the policy was durable along time, but again, additional data on post treatment years could help to provide a better estimation of long term effects of the policy.

Robustness checks

An additional regression (Table 10) controlling for sub-sector fixed-effects was used, to get information about the robustness of the results. The ATT is still in the same range ($\beta_1 = 2.3\%$), positive and statically significant, this is a good indication of robustness for the models.

Finally, the same main models were run with a different matching. It is a 1:1 matching on year 2015 observations only, with a caliper on GDP's standard errors, because it was hard to get no mean difference in GDP. The second matching was less strict than the first, because if the results hold with less restrictions, they are robust. The outcome is 462 firms (231 control and treated), 2258 observations (1126 control and 1132 treated), this difference might be caused by the exit of control firms from the market. Table 11 contains the results. The second matching reduces selection bias, but increases variability. The att is still in the same range, positive and statically significant. For "Year FE" and "Year + Indus. FE", the ATT is really similar to the first matching models. ATT for "Firm FE" decreases a lot more. With this more smooth matching, the effect captured is more general, but also smaller. This also suggests that the impact is focused on particular specific firms (manufacturing), and that the stricter first matching capted the firms that reacted the most.

Overall, the results are robust, as the ATT doesn't lose significance, or changes sign across different specifications.

Conclusion

This paper studies the impact of pollution policies on firms' Total Factor Productivity (TFP) in China using a difference-in-differences (DID) approach. It is based on the air pollution control policies strengthened in 2017 under the Jing-Jin-Ji collaborative development strategy. A panel dataset (2015-2019) of firms listed on the Shanghai and Shenzhen stock exchanges (A-shares) from multiple sources is used, with key variables such that total factor productivity (TFP), R&D investment (CRD), and number of employees (NumbEmp), among others. Propensity score matching (PSM) is used to ensure similarity between companies in the control group and the treated group in order to reduce selection bias.

Air pollution control policies thus significantly increased firm productivity. ATT estimates range from 1.74%

to 2.86%. The manufacturing sector experienced the strongest impact (4.7%), followed by energy, water supply, and accommodation. For other sectors, the subsamples limit their conclusion. In the Jing-Jin-Ji region, the effect is significant for Beijing and Hebei (around 5%), but not for Tianjin, likely due to differences in local measures between these three areas. Over time, the impact of these policies was maintained, with ATT estimates of 3.6% in 2017 and 4.5% in 2018, indicating a lasting effect. Robustness tests, however, confirm the results for all models and alternative matching strategies, strengthening the causal effect of the policies on productivity.

The study's results suggest that environmental regulations can improve firms' total factor productivity (TFP). This is consistent with Porter's hypothesis, which states that more stringent environmental policies will lead to innovations to reduce inefficiencies, which, in turn, will eventually reduce costs, according to Ambec, Cohen, Elgie, and Lanoie. This result can therefore serve as an example for other polluting countries, particularly developing ones, which is one of the indirect objectives of the Jing-Jin-Ji collaborative development strategy. Thus, knowing this result, policymakers could consider extending similar policies to other regions of China, while ensuring that these stricter regulations do not disproportionately affect certain sectors or geographical areas. Moreover, extending similar policies to other types of pollution beyond air quality, such as waste management or industrial water pollution, could also be relevant, as well as providing financial incentives to companies to invest in cleaner technologies, which could thus amplify these positive effects for the environment, the health of all, and the competitiveness of companies.

However, this article has some limitations that should be taken into account. Indeed, the dataset only covers 2015-2019, which means that trends prior to 2015 are not available for a more robust comparison, whereas having data for years prior to 2015 could provide a more meaningful matching and thus further reduce selection bias. Moreover, having a clearer idea of how policies are implemented could help identify which firms are most constrained by the implementation of these policies, thus allowing for the identification of even more precise effects of the impact of these policies on firms' TFP, notably via a Difference-in-Difference-in-Differences approach.

In addition to this work, it seems interesting to extend the analysis to other types of policies targeting other types of pollution besides air pollution. For example, an extension of this study could examine and compare the impact of several environmental policies. These could be, for example, carbon taxes, emission quotas, water and soil pollution controls, subsidies for green technologies and energy efficiency standards, among others. Thus, by comparing the impact of these different policies, it could help to identify the regulations with the greatest positive effect on business productivity and determine whether certain policies are more effective in certain sectors. This would, therefore, provide information to policymakers to develop the most effective environmental regulations, combining sustainable development and economic efficiency.

Appendix

Graphs and tables

Table 1: **Descriptive Statistics: Whole Sample**

Variable	Mean	Median	SD	Min	Max
TFP	7.922	7.853	1.304	1.033	12.301
GDP	13412.288	10503.02	10338.583	212.652	38155.32
NumbEmp	6041.898	1965.5	21133.474	2	521566
CRD	2219.488	551.251	9318.61	0	218717.83
FCF	0.342	0.309	0.385	0	28.548
AQI	82.158	82.016	19.425	0.082	247.348
Polluter	0.141	0	0.348	0	1

Table 2: **Descriptive Statistics: Pre-Match Pertinent Industries**

Variable	Mean	Median	SD	Min	Max
TFP	7.934	7.851	1.265	2.138	12.301
GDP	13164.554	10050.208	10294.622	212.652	38155.32
NumbEmp	6211.961	1981	21904.954	2	521566
R&D	2359.832	585	9696.246	0	218717.83
FCF	0.338	0.304	0.392	0	28.548
AQI	82.218	81.995	19.587	0.082	247.348
Polluter	0.151	0	0.358	0	1

Table 3: **Descriptive Statistics: Post-Match**

Variable	Mean	Median	SD	Min	Max
TFP	8.104	8.112	1.387	2.262	12.301
GDP	14250.417	11912.61	10042.931	660.061	38155.32
NumbEmp	5981.413	2400	9714.324	50	71617
R&D	2496.92	779.462	6644.677	0	88640
FCF	0.328	0.312	0.203	0	1.188
AQI	103.684	104.216	21.816	53.586	247.348
Polluter	0.152	0	0.359	0	1

Matching

Propsentiy score estimation

$$
\begin{aligned}
P(Treated_i = 1) = \text{logit}^{-1}(&\beta_0 + \beta_1 \text{CRD}_i + \beta_2 \text{AQI}_i + \beta_3 \text{State}_i + \beta_4 \text{Size}_i \\
&+ \beta_5 \text{FCF}_i + \beta_6 \text{Pollute}_i + \beta_7 \text{Cash}_i + \beta_8 \text{GDP}_i + \beta_9 \text{ALE}_i \\
&+ \beta_{10} \text{GS}_i + \beta_{11} \text{TFP}_i + \beta_{12} \text{TCD}_i + \beta_{13} \text{CPemp}_i + \beta_{14} \text{NumbEmp}_i \\
&+ \sum_j \gamma_j \text{letter}_{ij})
\end{aligned} \tag{5}
$$

Table 4: **T tests results**

Variable	Mean (Control)	Mean (Treatment)	T Statistic	P Value
R&D	1594.2	1519.448	0.15	0.88
GDP	12344.94	12579.93	-0.22	0.83
AQI	107.42	108.78	-0.56	0.58
Size	98567.56	102359.169	-0.13	0.89
FCF	0.32	0.33	-0.65	0.52
Pollute	0.17	0.14	0.74	0.46
Cash	44.78	46.13	-0.37	0.71
GS	429.71	962.54	-1.31	0.19
TFP	7.93	7.96	-0.18	0.86
NumbEmp	5886.80	5202.68	0.57	0.57
TCD	-0.07	-0.00	-1.58	0.12

Figure 1: **TFP trends: treated vs control**

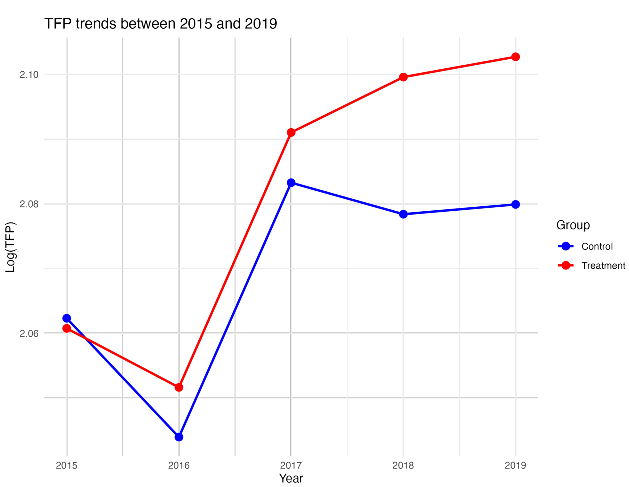
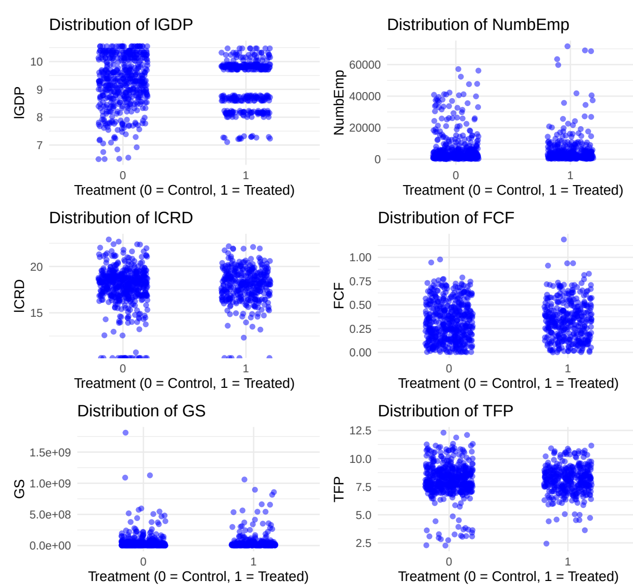


Figure 2: **Distribution of key variables with treatment**



Heteroskedasticity checks

Figure 3: **Residuals vs. fitted value**

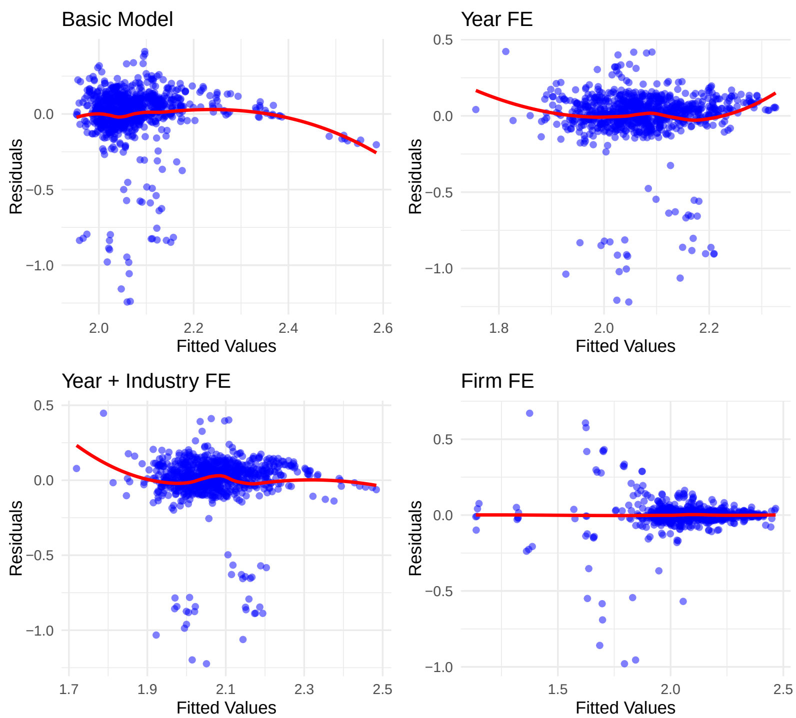


Table 5: **Breusch-Pagan Test Results**

Model	**BP Statistic**	**p-value**
Basic Model	18.033	0.00291
Year FE	20.860	0.00753
Y + I FE	28.284	0.02924
Firm FE	7.8624	0.04894

Regressions results

Table 6: **Regression Results with Robust Standard Errors**

	Basic Model	**Year FE**	**Year + Industry FE**	**Firm FE**
ATT	0.0236*	0.0174***	0.0206***	0.02864*
	(0.0120)	(0.0019)	(0.0014)	(0.0126)
Log(NumbEmp)	0.0495***	0.0495***	0.0418***	0.0240*
	(0.0072)	(0.0053)	(0.0063)	(0.0108)
Log(R&D)	0.0182**	0.0181**	0.0214***	0.0188**
	(0.0062)	(0.0059)	(0.0047)	(0.0062)
Log(GDP)	0.0140	0.0138+	0.0034	-0.0201
	(0.0091)	(0.0073)	(0.0071)	(0.0356)
(Intercept)	1.2177***	1.2262***	1.2991***	1.9454***
	(0.0947)	(0.0804)	(0.1057)	(0.3123)
Num.Obs.	877	877	877	877
F-statistic	-	-	-	12.038

Additional results

Table 7: **DiD with Firm FE and Interaction between Administrative Division and Post*Policy**

	Frim FE
ATT × Beijing	0.051***
	(0.015)
ATT × Hebei	0.053*
	(0.022)
ATT × Tianjin	0.022
	(0.015)

Table 8: **Interaction with NACE code**

	Firm FE
att × B	0.054
	(0.051)
att × C	0.047***
	(0.013)
att × D	0.025***
	(0.001)
att × E	0.038***
	(0.008)
att × F	0.004
	(0.024)
att × G	-0.073
	(0.106)
att × I	0.043**
	(0.016)
Num. Obs.	877
R^2	0.758

Legend: Industry Codes

- **B** - Mining and Quarrying
- **C** - Manufacturing
- **D** - Electricity, Gas, Steam, and Air Conditioning Supply
- **E** - Water Supply, Sewerage, Waste Management
- **F** - Construction
- **G** - Wholesale and Retail Trade, Repair of Motor Vehicles
- **I** - Accommodation and Food Service Activities

Table 9: **DiD with Firm FE and Interaction between Year and ATT**

	Firm FE
ATT × 2017	0.036**
	(0.012)
ATT × 2018	0.045***
	(0.013)
ATT × 2019	0.038**
	(0.012)
Num. Obs.	877
R^2	0.756
R^2 Adj.	0.693

Robustness checks

Table 10: **Regression with Subsectors Fixed Effect**

	Subsector FE
ATT	0.023***
	(0.006)
Log(NumbEmp)	0.033***
	(0.006)
Log(R&D)	0.032***
	(0.006)
Log(GDP)	0.009
	(0.007)
Intercept	1.128***
	(0.144)
Num. Obs.	877

Table 11: **Regression Results with 2015 1:1 matching**

	Year FE	**Year + Industry FE**	**Firm FE**
ATT	0.0201***	0.0206***	0.0158*
	(0.0048)	(0.0044)	(0.0075)
Log(NumbEmp)	0.0539***	0.0524***	0.0425***
	(0.0017)	(0.0020)	(0.0077)
Log(R&D)	0.0151***	0.0145***	-
	(0.0043)	(0.0037)	
Log(GDP)	-0.0065	-0.0101+	-0.0166
	(0.0054)	(0.0058)	(0.0197)
(Intercept)	1.4419***	1.5611***	1.9287***
	(0.0634)	(0.0669)	(0.2069)
Num. Obs.	2258	2258	2258

Variables descriptions

Some scale adjustments are inferred from data distribution and logical assumptions. However, these adjustments are not from official sources and should be interpreted with caution. An asterisk (*) is placed in the scale column for the affected variables.

Table 12: **Codebook of the variables**

Full variable name	**Code**	**Definition and construction**	**Scale (unit)**
Total Factor Productivity of Enterprises	TFP	Computed using the Levinsohn-Petrin method	Index
R&D Investment of Listed Companies	CRD	Annual R&D expenses	Chinese Yuan (CNY)
Air Quality Index	AQI	Annual average of the daily air quality index	Index
Government Subsidies	GS	Total annual government subsidies received by the company	Chinese Yuan (CNY)
Gearing Ratio	ALE	Total liabilities divided by total assets. **Note: Some values are negative, which may indicate accounting adjustments or data errors.**	Ratio
Business Size	Size	Total assets at the end of the period	*Million Chinese Yuan (CNY)
Cash Holdings	Cash	Cash and short-term investments divided by total assets	*Percentage (%)
Free Cash Flow	FCF	Cash flow from operating activities divided by total assets	Ratio
Technological Complexity	TCD	Comparison of different regional innovation systems	Index
City Population	CYP	Total population at the end of the year in the respective city. **Note: Some entries are 0, likely due to missing data.**	*Number of inhabitants (10,000s)
Gross Domestic Product	GDP	Total annual GDP of the local city	*Million Chinese Yuan (CNY)

Full variable name	Code	Definition and construction	Scale (unit)
State-Owned Enterprise	State	1 for state-owned enterprises, 0 otherwise	Dummy (0 or 1)
Polluting Enterprise	Polluter	1 for polluting enterprises, 0 otherwise	Dummy (0 or 1)
Regulation Treatment	Treated	1 if the company is subject to environmental regulation, 0 otherwise	Dummy (0 or 1)
Industry Code Letter	Letter	Letter code representing the industry of the enterprise	Alphanumeric code
Post-Policy Implementation	Post	1 if after 2016, 0 otherwise	Dummy (0 or 1)
Average Treatment effect on the Treated	ATT	1 if the firm is treated and the year is after 2016, 0 otherwise	Dummy (0 or 1)
Cash Paid to Employees	CPemp	Total payroll expenses paid to employees	Chinese Yuan (CNY)
Administrative Division	Admin_div	Administrative division where the company is located	Name of the administrative division
Air Flow Coefficient	CUR	Product of ten-meter wind speed and boundary layer height	Meters per second (m/s)

References

[1] Lanoie, P., Laurent-Lucchetti, J., Johnstone, N., & Ambec, S. (2011). "Environmental policy, innovation and performance: new insights on the Porter hypothesis." *Journal of Economics & Management Strategy*, 20(3), 803-842. Retrieved from `https://www.tse-fr.eu/fr/publications/porter-hypothesis-20-can-environmental-regulation-enhance-innovation-and-competitiveness`.

[2] World Bank. (2020). "China Hebei Air Pollution Prevention and Control Project." Retrieved from `https://documents1.worldbank.org/curated/en/746591593402580377/pdf/China-Hebei-Air-Pollution-Prevention-and-Control-Project.pdf`.

[3] Zhang, J., & Zhang, Y. (2017). "Industrial restructuring in Hebei: Economic and environmental policies and outcomes." *Environmental Economics and Policy Studies.*

[4] Liu, X., & Zhang, L. (2019). "The role of industrial upgrading in reducing pollution: Evidence from Hebei province, China." *Journal of Cleaner Production.*

[5] Wu, J., & Li, X. (2020). "Impact of the air pollution control policies on industrial output and economic growth: Evidence from Hebei." *Environmental Science & Policy.*

[6] Chang, T., Graff Zivin, J., Gross, T., & Neidell, M. (2016). "The effect of pollution on worker productivity: Evidence from call centers in China." *American Economic Journal: Applied Economics*, 8(4), 41-70. doi:10.1257/app.20130536.

[7] Zivin, J. G., & Neidell, M. (2012). "The impact of pollution on worker productivity." *American Economic Review*, 102(7), 3652-3673. doi:10.1257/aer.102.7.3652.

[8] Hoffmann, B., & Rud, J. P. (2022). "Research Insights: How Do High Levels of Fine Particulate Matter Impact Daily Labor Supply in Mexico City?."

[9] Vuong, Q. H., Le, T. T., Khuc, Q. V., Nguyen, Q. L., & Nguyen, M. H. (2022). "Escaping from air pollution: Exploring the psychological mechanism behind the emergence of internal migration intention among urban residents." *International Journal of Environmental Research and Public Health*, 19(19), 12233. pmid:36231534.

[10] Shen, F., Wang, Q., Zou, J., Yan, H., & Wang, B. (2023). "Air Pollution and Migration Decision of Migrants in Low-Carbon Society." *International Journal of Environmental Research and Public Health*, 20(1), 870. pmid:36613190.

[11] Levinson, A., & Taylor, M. (2008). "Unmasking the pollution haven effect." *International Economic Review*, 49(1), 223–54.

[12] Porter, M. E., & van der Linde, C. (1995). "Toward a new conception of the environment–competitiveness relationship." *Journal of Economic Perspectives*, 9(4), 97–118.

[13] Jaffe, A. B., Peterson, S. R., Portney, P. R., & Stavins, R. N. (1995). "Environmental regulation and the competitiveness of US manufacturing: What does the evidence tell us?" *Journal of Economic Literature*, 33(1), 132–63.

[14] Greenstone, M., List, J., & Syverson, C. (2012). "The effects of environmental regulation on the competitiveness of U.S. manufacturing." Working Paper 2012-013. MIT Centre for Energy and Environmental Policy Research.

[15] Dechezleprêtre, A., & Sato, M. (2017). "The Impacts of Environmental Regulations on Competitiveness."

[16] Albrizio, S., Kozluk, T., & Zipperer, V. (2017). "Environmental policies and productivity growth: Evidence across industries and firms." *Journal of Environmental Economics and Management.*

[17] Huang, X., & Liu, X. (2019). "The Impact of Environmental Regulation on Productivity and Exports: A Firm-Level Evidence from China." *Emerging Markets Finance & Trade.*