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ABSTRACT

This paper examines the effect of stringent environmental regulations on firms' environmental practices, economic performance, and environmental innovation. Reducing COD levels by 10% relative to 2005 levels is an aim of the Chinese 11th Five-Year Plan. Using a difference-in-differences framework based on a comprehensive firm-level dataset, we find that more stringent environmental regulations faced by firms are positively associated with a greater probability of reducing COD emissions; also, there exists an evident heterogeneous effect across industries with different pollution intensities. Stricter environmental regulations also account for the sharp decline in firms' profits, capital, and labor. After executing a complete chain of tests of the underlying mechanisms, we find that firms rely more on recycling and abatement investment than on innovations when meeting environmental requirements.

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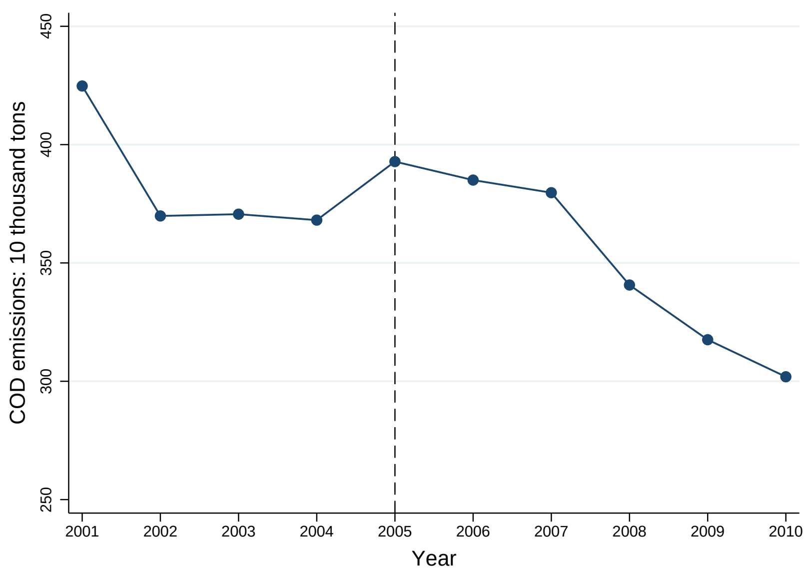
1 Introduction

From 2006 to 2010, emissions of major regulated water pollutants such as chemical oxygen demand (COD) from Chinese manufacturing fell by 23.1% relative to the 2005 level, even as China has boosted its manufacturing output by 137.5%.[1] When looking into the pattern of the cleanup shown in Figure 1, we find the turning point first appearing in 2006, the starting year of China's 11^{th} Five-Year Plan characterized by stringent emissions target control and enforcement. This suggests a link between environmental improvement and environmental regulations. Have stringent environmental regulations contributed to a cleanup? And, if so, to what extent? What are the main driving forces for the effect?

Figure 1: Chemical Oxygen Demand Emissions in Chinese Manufacturing



In this paper, we study the effects of stringent environmental regulations on firms' pollution emissions and their related economic performance, and, more importantly, we also study the driving forces behind firms' responses. Even though historically established from the 9^{th} Five-Year Plan, emissions target control in China was not seriously pursued until the 11^{th} Five-Year Plan. Following a failure to abate during the 9^{th} and 10^{th} Five-Year Plan, China began to strengthen emissions reduction target schemes by subdividing mandatory national emissions targets among all levels of government and in the end, polluters. Legal enforcement was enhanced by imposing comprehensive legal liabilities, making enforcement part of governmental officers' achievement evaluations,

[1] COD is an indicative measure of the amount of oxygen that can be consumed by reactions in a volume of water to reflect water quality. In China, COD emissions have been rigorously regulated since the 1980s.

accountability, and promotion prospects, as well as the introduction of stricter administrative penalties for polluters. The large variation of regulatory stringency among cities due to disparate emissions control targets set from central to local government is helpful in identifying causal effects between environmental regulations and firms' response, and how it varied across industries. Moreover, facilitated by the mandatory COD emissions reduction target scheme substantively reinforced by the 11^{th} Five-Year Plan since 2006, we mainly rely on difference-in-differences (DID) approach to study the effect of environmental regulations before and after 2006.

To begin, we document three stylized facts pertaining to COD emissions from manufacturing in China through a set of analyses. First, faced with different environmental regulation stringency, firms in tightly regulated regions reduce more pollutants than those in loosely regulated regions. Second, the effect of environmental regulation stringency on firms' pollution emissions varied across industries with different polluting intensity. Industrial polluting intensity positively reinforces the effect of environmental regulation stringency on firms' pollution reduction. Third, a "composition effect" adjustment of market share of each industry and "technique effect" lowered pollution intensity brought by technological progress are both responsible for a decline in water pollutants from Chinese manufacturing upon stricter environmental regulations, whereas the "technique effect" is the predominant causal factor accounting for environmental improvement.

We construct a rich firm-level panel dataset drawing from multiple sources: firm-level pollution data from the Annual Environmental Survey of Polluting Firms (AESPF), firm-level economic data from the Annual Survey of Industrial Firms (ASIF), firms' green patent data from the Patent Dataset, maintained by the China National Intellectual Property Administration (CNIPA), firms' environmental penalty data from the Institute of Public and Environmental Affairs (IPEA), and city-level data from statistical yearbooks. This dataset contains rich information on firm-level and city-level variables, including environmental regulation stringency and firms' environment-related activities, economic performance, patent, and legal enforcement.

We then employ a DID strategy to study the effect of environmental regulation stringency. We find that, more stringent environmental regulations faced by firms are positively associated greater probability of reducing COD emissions after 2006. For example, among all the large cities, the COD emissions reduction magnitude in Shanghai, which ranks first in environmental regulation stringency concerning COD emissions reduction target, is nearly 30% larger than that of Kunming, the city with the lowest control target. A with-in firm decomposition further shows that, pertaining to changes in pollution reduction across cities with different environmental regulation stringency after 2006, around 30% of them can be explained by within-firm "scale effect", that is, a drop in firms' total output, whereas 70% of them can be explained by within-firm "technique effect", including but not limited to the adoption of pollution abatement facilities, introduction of cleaner production processes and recycling use of energy inputs. Our baseline results are further proved by a differential time trends test and robustness check on other pollutants.

In order to consider large variation in COD pollution intensity across industries, we study heterogeneous effects to verify whether industrial polluting intensity positively reinforces the effect of environmental regulation stringency on firms' pollution reduction. We find that, firms which belong to heavily polluting industries located in cities with more stringent environmental regulations cut down much more on pollutants, compared with their intra-city counterparts in less-polluting industries. The greater responsiveness of firms in heavily polluting industries to more stringent environmental regulations lends solid evidence to our stylized facts about the inter-industry allocation.

To find out whether more stringent environmental regulations have stimulated firms to become light green or bright green, we execute a broad spectrum of tests about recycling practice (recycling of wastewater), adoption of pollution abatement facilities (waste water treatment), and firms' technological progress (green patents), among others.[2] First, we assess whether the tightened legal enforcement on emissions target controls increased on the probability that firms would be punished after 2006. Second, we employ a finer within-firm decomposition by introducing another pollutant, effluent, which is industrial wastewater discharged into the environment. We find that, the effect of environmental regulation stringency on COD emissions reduction is mostly attributable to decreased discharge of effluent, and the decline is much more distinct for heavily polluting industries. Third, we examine the adjustment of firm's total water consumption and freshwater consumption per unit of output affected by environmental regulations. Fourth, according to our tests, the increasing use of control devices and their treatment capacity is higher for firms in cities with stringent environmental regulations than their counterparts in cities

[2] Despite the origins in Hicks (1963) and Porter (1991) on induced innovation, we still seperate different types of environmentally friendly technologies. When it comes to COD emissions, the first category is end-of-pipe technologies, which directly treat wastewater to reduce COD levels. End-of-pipe technologies are called *treatment technologies*. The second category of technologies adopted in freshwater saving and wastewater recycling objectively reduce COD levels. They are called *recycling technologies*. The last category, called *green innovations*, improves production techniques and processes to reduce COD levels at the source. When faced with various green technologies, firms might adopt *treatment technologies* and *recycling technologies* to reduce pollution. Here, we refer to this approach as "light green". Or they might innovate, especially pertaining to *green innovations*, through green patent applications. This pattern is informative about firms' inherent innovation strength and generally followed by better environmental performance. Here, we refer to this approach as "bright green", following the environmental politics literature. Whether firms are greening lightly or brightly is critical in understanding the whole scenario about driving forces, and this knowledge further affects firms' improved environmental performance.

with weaker environmental regulations after 2006. Relative to firms in cleaner industries, firms in dirtier industries tend to be more progressive in expanding pollution treatment capabilities. Last, we focus on firm's performance in green innovation as a result of stricter environmental regulations. However, there is little evidence that strict environmental regulations lead to an increase in green patents and water-related green patent applications, regardless of what industry firms belong to. Therefore, we are able to infer that, emissions target controls, at least during the 11^{th} Five-Year Plan, failed to stimulate firms to become "bright green" innovators, maybe because other lower-cost "light green" countermeasures, such as pollution abatement facilities, were sufficient to meet the target. How to stimulate firms to shift from adopting end-of-pipe treatment technology (light green) to innovations (bright green) still needs further investigation.

After verifying the positive effect of environmental regulations on firms' pollution reduction, especially for those in heavily polluted industries, we turn to examine their economic impacts on firms. Significantly reduced pollution, output, and pollution per unit are believed to influence firms' economic performance. To this end, we conduct a test to further assess the impact of environmental regulations on firms' economic performance including profits, capital, labor and market share. The empirical results show that these four indicators, without exception, decrease across all industries. Also, for firms belonging to heavily polluting industries located in cities with more stringent environmental regulations, their profits, capital, labor and market share decline more compared with their counterparts in less-polluting industries located in cities with weaker regulations. A decrease in output, input and market share of firms might shed light on potential adjustment of firm relocation. To provide more evidence on somewhat "internal" variant of the pollution havens hypothesis, we therefore further testify the impact of environmental regulation on firm entry.

There already exists an extensive literature on the effects of environmental regulations on emissions reduction in manufacturing activity and environmental quality improvement (Nelson, Tietenberg and Donihue, 1993; Chay and Greenstone, 2005; Greenstone and Hanna, 2014).[3] Researchers are also curious about mechanisms underlying regulation-induced environmental cleanup. As Levinson (2009), we prove that the technique effect plays the predominant role in environmental improvement. The way how

[3]Despite the emerging but still limited research using firm-level pollution data (Martin, 2011; Zhang, Chen and Guo, 2018), most studies rely on macro-level data. We add to the former literature by using comprehensive firm-level pollution and economic data to provide micro-level evidence on whether and to what extent changes in regulatory stringency have contributed to not only firms' emissions reductions but also their economic loss. More importantly, by integrating industrial variance in pollution intensity, we also find notable cross-industry heterogeneity in firms' environmental performance.

technology matters is closely related to the literature on environment-friendly innovation (such as green patents) induced by environmental protection. Some of the researchers find positive effects (Acemoglu, Akcigit, Hanley and Kerr, 2016; Aghion, Dechezleprêtre, Hemous, Martin and Van Reenen, 2016; Gutiérrez and Teshima, 2018; Aghion, Bénabou, Martin and Roulet, 2019), while some others find negative ones (Nelson, Tietenberg and Donihue, 1993; Gray and Shadbegian, 1998; Gans, 2012). As Gutiérrez and Teshima (2018) theoretically proves that tighter climate policy including emissions caps does not necessarily improve innovations, we also find little evidence on firms' green patent applications in reaction to stringent environmental regulations. Instead, in response to stricter emission reduction regulation, firms are more prone to adopt other environment-friendly technologies, such as abatement facilities to reduce COD level in effluent, freshwater saving, and wastewater recycling technologies.

This research is also linked to the literature on the effect of environmental regulations on the microeconomic activities of regulated firms and industries, on their employment (Henderson, 1996; Greenstone, 2002; Walker, 2013), firm productivity (Berman and Bui, 2001; Greenstone, List and Syverson, 2012), industrial location (Henderson, 1996; Becker and Henderson, 2000; Chen, Kahn, Liu and Wang, 2018), trade-environment links (Gutiérrez and Teshima, 2018), and on export and foreign direct investment (Keller and Levinson, 2002; Cai, Lu, Wu and Yu, 2016; Shi and Xu, 2018), among others. Our paper is also related to studies executing decomposition of change of emissions reductions that can be explained by various effects (Levinson, 2009; Martin, 2011; Shapiro and Walker, 2018). We complement the literature by not only implementing intra-industry decomposition to find out the contribution of manufacturing scale, composition of industries and technology, but also decomposing within-firm behaviors to more clearly portray the role of within-firm scale effect and within-firm technique effect.

The rest of the paper is organized as follows: Section 2 discusses relevant institutional background and presents stylized facts based on preliminary data analysis. Section 3 provides the main empirical specification and describes the data. The main empirical results are presented in Section 4, followed by a discussion on the mechanism underlying the effect of environmental regulations in Section 5. In Section 6, we discuss firms' other economic performance upon stricter environmental regulations. Section 7 concludes.

2 Institutional Background and Stylized Facts

2.1 Institutional Background

Among all the regulatory tools for emissions reductions, concentration controls and emissions target controls are two of the fundamental ones. The former one aims to require pollution sources (e.g., industrial facilities) to control for concentrations of contaminants to comply with national pollution control standards, while the latter sets compulsory emissions caps as well as reduction targets of regulated pollutants. These two tools coexist in Chinese environmental regulations, since the nationwide adoption of emissions target controls from the 9^{th} Five-Year Plan between 1996 and 2000. To account for invalidity of concentration control in limiting total scale of pollutants entering environment, emissions target controls in China mainly focus on "critical pollutants" by setting national reduction targets followed by top-down subdivision from the central government to provinces then to cities.

Unfortunately, the emissions reduction goal wasn't accomplished during the 9^{th} Five-Year Plan period or in the term that followed. Among all the targeting indicators set up in the 10^{th} Five-Year Plan, pollution control targets were the only ones unachieved. COD emissions in 2005 were only 2% lower than that of the baseline year 2000. To reverse the failure in accomplishing the emissions control targets, the government substantively strengthened the emissions target control scheme in the 11^{th} Five-Year Plan period from 2006 to 2010. After decomposing the national goal to provinces, the goal statements on emissions reductions were accordingly signed between each provincial government and the national Ministry of Environmental Protection. The performance of government officers in fulfilling their duties relating to the emissions mandates, according to Measures on Accomplishment Evaluation of Critical Pollutants Emissions Control Target, were evaluated and incorporated into their competency assessment, with potential impacts on their accountability and promotion. Moreover, other complementary regulations, such as Statistical Measures on Critical Pollutants Emissions Control Target and Interim Verifying Measures on Critical Pollutants Emissions Control Target, were enacted in 2006. As a result, the 10% reduction target of two "critical pollutants"—COD and SO_2—lower than 2005 level was exceeded achieved.[4] We therefore infer that the 11^{th} Five-Year Plan period was the turning point pertaining to the effectiveness of emissions target controls.

[4]The scope of critical pollutants in each five-year plan varied. The 9^{th} Five-Year Plan defined 12 pollutants as "critical pollutants." The scope was narrowed into 6 pollutants during the 10^{th} Five-Year Plan. COD and SO_2 were the only two focuses of the 11^{th} Five-Year Plan.

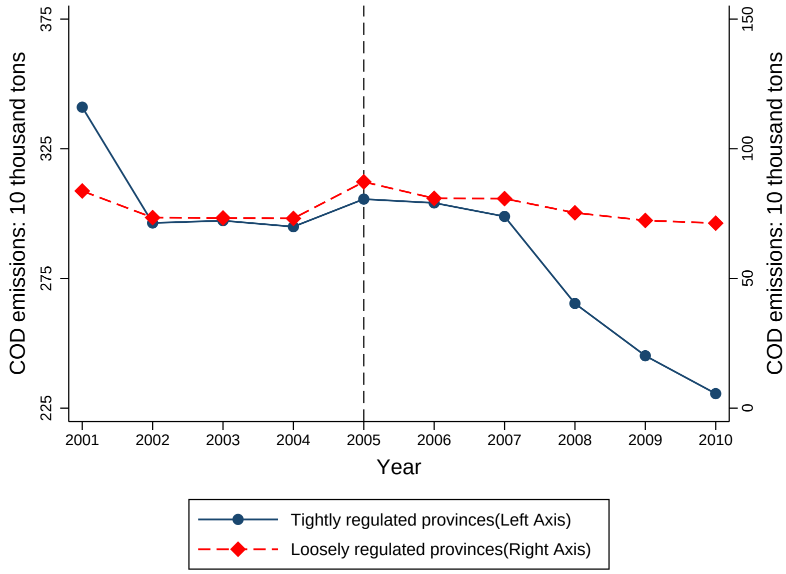
2.2 Stylized Facts

As the core of emissions control target, provinces were assigned with different emissions reduction targets within the 11^{th} Five-Year Plan. For instance, Guangdong with the highest target is obliged to reduce 0.159 million tons of COD during 2006 and 2010, while Xizang, Qinghai, and Xinjiang at the bottom have no target for COD emissions control. With such differing mandatory targets, there prevails a wide discrepancy in the stringency of environmental regulation across provinces. Bearing in mind these regional variations in legal enforcement, we plot COD emissions changes for firms located in different provinces, to provide a hint on whether COD emissions levels are associated with stringency of environmental regulations. Provinces are accordingly divided into two groups—tightly regulated and loosely regulated provinces—based on whether their COD reduction targets is above or below the median target mandated in the 11^{th} Five-Year Plan. We sum the volume of firms' COD emissions in each group, and Figure 2 presents the results. The blue line, associated with the left y-axis, plots the overall COD emissions of tightly regulated provinces, whereas the red dashed line corresponding to the right y-axis is indicative of COD emissions of the loosely regulated group. It is interesting to note that, according to Figure 2, COD emissions in tightly regulated provinces decreased, plunge sharply from 2007, reaching a historically low level in 2010. COD emissions in loosely regulated provinces, quite on the contrary, remained largely stable with slight decline between 2005 and 2010. We summarize the first stylized fact as follows:

Stylized fact 1. In response to different environmental regulation stringency, firms in tightly regulated regions reduce more pollutants than those in loosely regulated regions.

To further explore whether the effect of environmental regulation stringency on firms' pollution reduction depends on pollution intensity difference across industries, we take industrial pollution intensity into consideration. After all, heavily polluting industries contribute most of the pollutants and are often viewed as the main sources of emissions reduction. Apart from separating highly and loosely regulated provinces, we divide all 30 manufacturing industries at CIC-2 (Chinese Industry Classification) level into heavily polluting industries and lightly polluting industries depending on whether their pollution intensity is above or below the median level of all manufacturing industries. As demonstrated by the graph at the top of Figure 3, no matter whether they are located in tightly or loosely regulated provinces, firms belonging to heavily polluting industries both experience declines in COD emissions. The graph at the bottom which plots changes in firms' COD emissions in lightly polluting industries, however, shows that COD emissions of firms located in tightly regulated provinces, surprisingly, increases (the blue-dotted line) during the 11^{th} Five-Year Plan period. Thus, we come to the second stylized

Figure 2: COD Emissions in Manufacturing in Tightly and Loosely Regulated Provinces



fact:

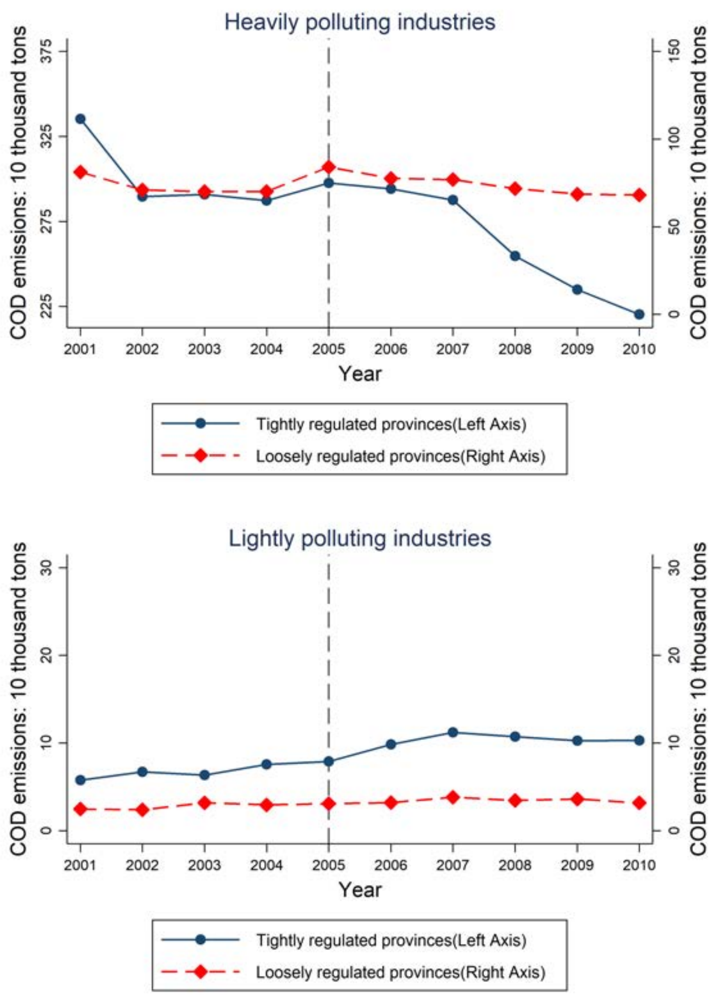
Stylized fact 2. The effect of environmental regulation stringency on firms' COD emissions varied across industries with different polluting intensity. Industrial polluting intensity positively reinforces the effect of environmental regulation stringency on firms' pollution reduction.

2.3 A Statistical Decomposition of China's COD Emissions, 2001–2010

Probing for the cause of COD emissions change in a much broader spectrum, we, in this subsection, decompose changes in total manufacturing COD emissions into changes that can be explained by total scale of manufacturing output, the composition of products produced, and the pollution intensity of a given set of products following Levinson (2009). Total pollution P from manufacturing, equals to sum of pollution from each industry p_s, which can be further written as sum of output of each industry, y_s multiplied by e_s, that is pollution intensity of that industry denoted by amount of pollution per unit of output value. Alternatively, we can also write manufacturing pollution as equal to total output Y times each industry's share of total output ($v_s = y_s/Y$), multiplied by e_s. The equation is as follows:

$$P = \sum_s p_s = \sum_s y_s e_s = Y \sum_s v_s e_s. \tag{1}$$

Figure 3: COD Emissions in Manufacturing with Different Pollution Intensities in Tightly and Loosely Regulated Provinces



In vector notation, we have

$$P = Yv'e, \tag{2}$$

where v' and e are vectors representing market share of each of the n industries and their pollution intensity, respectively.

Differentiating Equation 2 totally, we obtain

$$dP = v'edY + Yedv' + Yv'de. \tag{3}$$

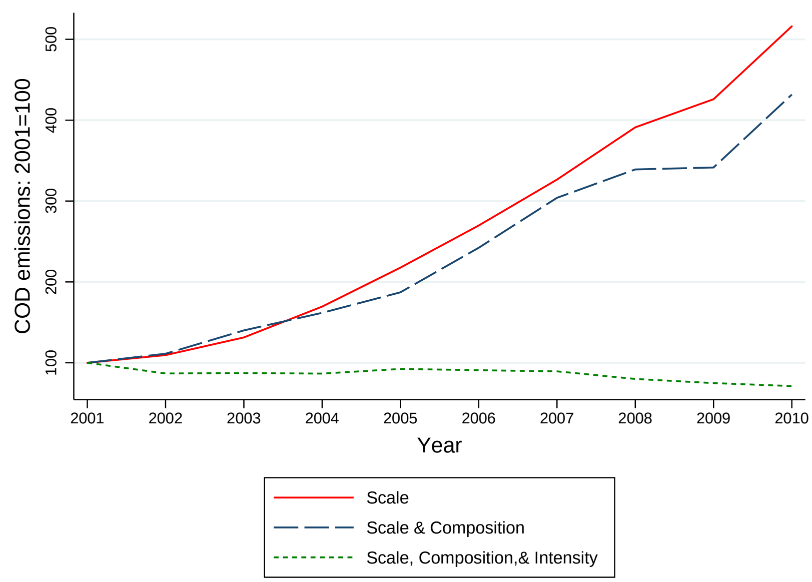
The first term on the right-hand side of Equation 3 is the scale effect, indicating changes of total pollution that can be explained by increase of overall scale of manufacturing, holding the composition of industries and industrial pollution intensity fixed. The second term is composition effect, revealing the change of industries mix, holding manufacturing scale and industrial pollution intensity fixed. The third term is technique effect, which accounts for changes in pollution intensities of each industry, holding scale and composition unchanged.

Figure 4 illustrate the resulting statistical decomposition for COD emissions in China. The top red solid line depicts COD emissions that would have occured if the market share of each industries and its pollution intensity had remained fixed at 2001 level but the overall manufacturing output had equalled obeserved historical values. The middle blue dashed line in Figure 4 plots the change of COD emissions if we keep the amount of pollution per unit of output value, that is the pollution intensity of each industry as in 2001 level, but the overall manufacturing output and market share of each industry equal to its obeserved historical values. It reflects the comprehensive impact of overall manufacturing scale and composition of industries on COD emissions. The bottom green dashed line plots actual COD emissions from manufacturing, explaining the overall impact from manufacturing scale, composition of industries and technology.

Figure 4 carries rich information on the driving force of firms' COD emissions. First, the gap between the red solid line and the blue dashed line shows the change of COD emissions that can be explained by the change in composition of industries in manufacturing. The increased gap between the two provide clear evidence that composition between manufacturing products that require high and low amounts of pollution emissions for production has changed over time. The change, implicit though it is, shows the reduction of dirtier industries but the expansion of cleaner industries in Chinese manufacturing. Second, the gap between the blue-dashed line and green-dashed line shows how much a decline in pollution intensity at industrial level is accounted for COD emissions reduction from manufacturing in China. Combined with the gap between the solid-red line and the blue-dashed line, we can conclude that around 18.97% of COD emissions change can be explained by "composition effect," whereas the "technique effect" accounts for 82.03% of COD emissions change. Thus, our third stylized fact is as follows.

Stylized Fact 3. "Composition effect" (adjustment of market share of each industry) and "technique effect" (lowered pollution intensity brought by technological progress) are both responsible for a decline of COD emissions from Chinese manufacturing upon stricter environmental regulations. The environmental improvement is, however, mostly brought about by "technique effect".

Figure 4: Decomposition of the Three Main Effects Causing COD Emissions in Chinese Manufacturing



3 Empirical Specification and Data Description

3.1 Empirical Specification

The three previous stylized facts provide intuitive evidence that strengthening emissions reduction control enforcement and greater controls on industrial pollution intensity have positive effects on firms' pollution control. The large variation in regulatory stringency among cities due to the disparate emissions control targets set from central to local government is useful in helping identify the causal effects between environmental regulations and firms' responses, and how it varied across industries. We therefore adopt a DID strategy facilitated by a mandatory COD emissions reduction target scheme that were substantively strengthened by the 11^{th} Five-Year Plan from 2006. Given the potential legal liabilities and the enhanced accountability to government, cities assigned with high reduction targets have accordingly shifted into a stricter environmental regulation pattern. We compare firms' pollution in cities with more stringent environmental regulations before and after 2006 with the equivalent changes in cities with less stringent environmental regulations based on the following specification:

$$y_{it} = \beta_1 \mathrm{R}_c \times \mathrm{Post}_t + \gamma \mathrm{Z}_{c,t-1} + \varphi_i + \varphi_t + \epsilon_{it}, \tag{4}$$

where the dependent variable, y_{it}, refers to firm i's pollution-related activities, including log value of COD, output, and pollution intensity at year t.[5] R_c is a measure of environmental regulation stringency denoted by the total COD reduction target mandated by the 11^{th} Five-Year Plan for city c from 2006 to 2010. $Post_t$ is a dummy variable equals to 0 for all years before 2006, and to 1 from 2006 and onward. $Z_{c,t-1}$is a vector of city-level characteristics including log gross domestic product (GDP) per capita and log population at year $t-1$. φ_i is firm fixed effects accounting for unobserved time-invariant differences across firms that may affect firms' polluting activities. In other words, we focus on the within-firm variation arising from changes in environmental regulation stringency faced by the firm. φ_t is year fixed effects capturing common economic factors affecting all the cities. ϵ_{it} is the standard errors clustered at city level capturing all unobserved factors that influence y_{it}.

Intangible though it is, environmental regulation stringency could reasonably be proxied by the differing COD emissions reduction targets mandated by the 11^{th} Five-Year Plan. Considering that open-accessed official documents only provide emissions reduction targets at provincial level, we follow Chen, Kahn, Liu and Wang (2018) to construct emissions reduction targets at the city level, that is, R_c, in Equation 4, as follows:

$$\Delta COD_{c,05-10} = \Delta COD_{p,05-10} \times \sum_{i=1}^{39} u_i \frac{\text{output value of industry } i \text{ in city } c}{\text{output value of industry } i \text{ in province } p}, \tag{5}$$

where $\Delta COD_{c,05-10}$ is COD emissions reduction targets in the 11_{th} Five-Year commitment period for city c. The second term on the right-hand side of the equation is a measure of a city's proportion to its province's total output value across all the 39 two-digit industries, weighted by each industry's proportion of COD emissions to total COD emissions from

[5]Firms could possibly respond to stricter mandated emissions targets by producing less or lowering the pollution intensity of emissions per output through, for example, using less polluting input, recycling usage of inputs, adopting pollution abatement devices or green innovation.

manufacturers, u_i.[6] Even though a city's emissions target could also be measured by proportion of a city's actual COD emissions that accounts for total emissions of its province, we still use the strategy denoted by Equation 5 in our main empirical analyses due to endogeneity concerns. However, as a robustness test, we rely on the other measurement of R_c specified as follows,

$$\Delta COD_{c,05-10} = \Delta COD_{p,05-10} \times \frac{P_{c,2005}}{\sum_{j=1}^{J} P_{j,2005}} \tag{6}$$

where the second term on the right-hand side of the equation is a measure of the city's proportion of the province's total emissions volume in 2005 based on firm-level emissions data provided by AESPF. Table A3 in the appendix presents the results. Figure 5 provides a map of China in which we depict the level of R_c of all 285 cities in our sample. The darker the color is, the higher the emissions reduction targets are and the stricter the environmental regulations and legal enforcement.

There are large variations in pollution intensity across industries of China's manufacturing. Extreme examples are paper production (CIC code 22) as the most heavily polluting industry responsible for 35.16% of the total COD emissions and recycling and manufacturing of articles for cultural, educational, and sporting activities (CIC code 43 and 24) as the least polluted industry accounting for only 0.013% of the total COD emissions. Along with the compulsory targets, industries such as paper production, textiles, chemical materials and products, beverage production are identified as "key" target industries for lowering pollution in China's 11^{th} Five-Year Plan. The response of firms in industries with discrete pollution intensity to stricter environmental regulations is not necessarily the same considering different enforcement pressures that might be exerted.

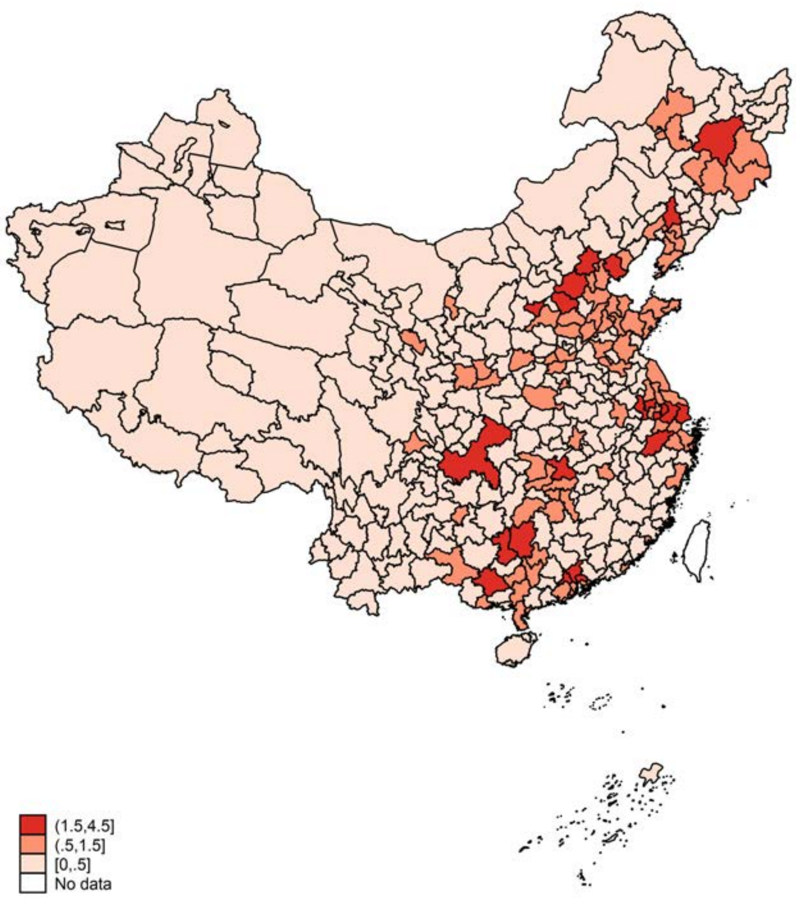
To investigate the varied reaction of firms across industries with different pollution intensity to stricter environmental regulations before and after 2006, we further run a difference-in-difference-in-differences (DDD) regression based on the following model:

$$y_{it} = \beta_1 \mathrm{R}_c \times \mathrm{Post}_t + \beta_2 \mathrm{R}_c \times \mathrm{Post}_t \times \mathrm{Dirty}_s + \beta_3 \mathrm{Dirty}_s \times \mathrm{Post}_t + \gamma \mathrm{Z}_{c,t-1} + \varphi_i + \varphi_t + \epsilon_{it}, \tag{7}$$

where y_{it} is the log value of firm i's COD, output and pollution intensity at year t, respectively. In Equation 7, we incorporate a variable $Dirty_s$, that is industry's polluting

[6] During the commitment period of the 11^{th} Five-Year Plan, COD emissions reduction targets in five cities—Dalian in Liaoning Province, Ningbo in Zhejiang Province, Xiamen in Fujian Province, Qingdao in Shandong Province and Shenzhen in Guangdong Province—are separately listed paralleling to 30 provinces in Mainland China (Xizang is excluded, because it is uncovered by AESPF). We directly use the targets for these five cities in our analysis.

Figure 5: City-Level Regulation Stringency of COD (10 Thousand Tons)



intensity indicated by each industry's proportion of total COD emissions in all industries in 2005. Table A2 in the appendix reports the summary statistics of pollution intensity for all 2-digit manufacturing industries. Definition of other variables assembles those in equation (1). We are interested in co-efficient β_2, which estimated the heterogeneous effects of environmental regulations on firms' pollution activities across highly polluting industries and cleaner industries. Facilitated by this, we are able to grasp the differential effect of environmental regulation stringency on firms' polluting and economic activities across industries with varied polluting levels.

As well as the impact of environmental regulations on firms' environmental performances, we are also interested in how firms react to strengthening environmental enforcement, and more importantly, in the underlying forces driving firms to adjust their environmental and economic performance. To achieve these aims, we firstly re-define our estimated coefficient y_{it} as the legal punishment firms faced, their effluent, water consumption, adoption of pollution control devices, and application for green patents to observe the role of government's enhanced legal enforcement on firms' recycling practice, pollution abatement facilities, and technological progress. We then replace firm i's pollution-related activities with economic indicators including its profits, capital, and labor, as denoted by y_{it}. Accordingly, we rely on firms' pollution data and other firm-level data.

3.2 Data Description

3.2.1 Firms' Pollution Data

The data on firms' pollution emissions come from *Annual Environmental Survey of Polluting Firms* (AESPF) of China.[7] Established by the Ministry of Ecology and Environment (formerly known as the Ministry of Environmental Protection) in the 1980s in a bid to document the state of environmental pollution and abatement in China, AESPF covers rich information on firms' environmenal performance, including emissions of main pollutants (industrial effluent, waste air, COD, NH_3, NO_x, SO_2, smoke and dust, solid waste, noise, etc.), pollution abatement equipment, and energy consumption (usage of freshwater, recycle water, coal, fuel, clean gas, etc.), among others. Even though gradually normalized during the past 40 years, the scope, frequency, main indicators and reporting method of the environmental survey become largely stable from the starting year of the 10^{th} Five-

[7] Because of the lack of an official name, the dataset was also named the China Environmental Statistics dataset (CESD) (Zhang, Chen and Guo, 2018), Environmental Statistics Data (ESD) (Wu, Guo, Zhang and Bu, 2017), or the Environmental Survey and Reporting Database (ESRD) (He, Wang and Zhang, 2018).

Year Plan in 2001. For example, a firm is surveyed when one of its pollutants fall into the top 85% of the total emissions volume of that pollutant at county level.[8] Those firms are included in a key-point environmental survey list. Once listed, they are obliged to complete uniform statistical statements sent by the environmental authorities to report a wide range of environmental information in the last year. Scrutinized and verified by all upper levels of administrative authorities, the data will be confirmed and included in the database.

Like the broadly used Annual Survey of Industrial Firms (ASIF) which provides the basis for macro economy indicators, AESPF is also the sourcing database for calculating macro-level environmental indicators in, for example, China Statistical Yearbook on Environment. In Figure 6, we compare the COD emissions volume/industrial effluent aggregated by firm-level data from AESPF and the total volume of industrial COD/industrial effluent from China Statistical Yearbook on Environment. The coincidence between the blue/red dotted line and the 100% level provides us with more confidence about the reliability of AESPF data in our empirical analysis. Figure A2 in the appendix compares main air pollutants and pollution abatement facilities between the micro-data and the macro-data. Similar coincidence can be found as for air pollutants and facilities.

To investigate the effect of environmental regulations pertaining to COD emissions control in the 11^{th} Five-Year Plan from 2006 to 2010, we mainly rely on AESPF data from 2001 to 2010. The cleaned dataset includes 437,253 observations, containing information on 96,378 unique firms.[9]

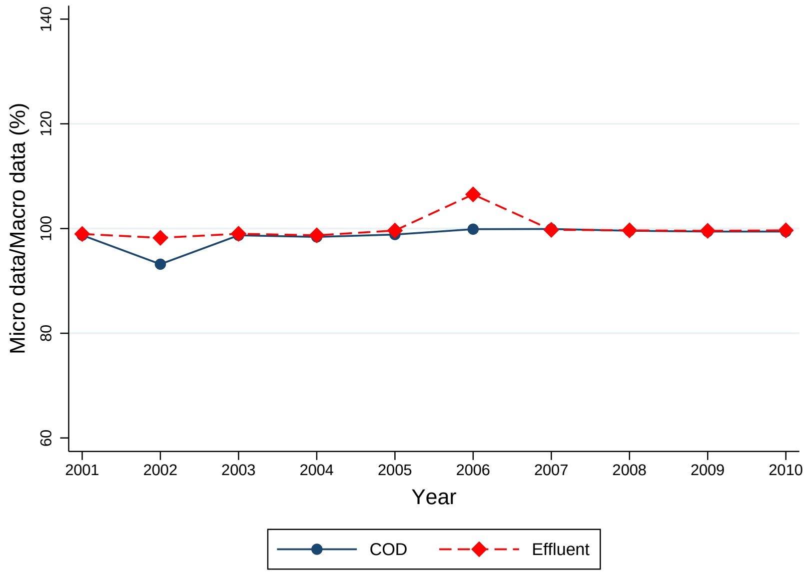
3.2.2 Other Firm-Level Data

As one of the most comprehensive and widely used Chinese firm-level datasets, the *Annual Survey of Industrial Firms* (ASIF) maintained by the National Bureau of Statistics of China (NBSC) provides the basis for our analysis on firms' economic performance affected by environmental regulations. This data panel covers all state-owned industrial firms and non-state-owned industrial firms with annual sales above 5 million RMB. It contains detailed information on each of those Chinese firms, including basic information (name, identification number, registration type, etc.) and information on a firms' accounting statement (balance sheet, profit and loss account, and cash flow information).

[8] During the 9^{th} Five-Year Plan period, industrial polluting sources covered by the survey were limited to state-owned enterprises above the county level and township industrial plants. Even though the scope gradually expanded during the Five-Year Plan periods after the 10^{th} Five-Year Plan period, the basic 85% selection principle of industrial polluting sources remains unchanged.

[9] When cleaning the data, we only keep information on manufacturing; we exclude firms with missing or zero values for COD and total output in our cleaned dataset.

Figure 6: Comparison between Micro-Data and Macro-Data on COD and Effluent



Notes: The macro-data come from China Statistical Yearbook on Environment, and the micro-data come from Annual Environmental Survey of Polluting Firms (AESPF) of China.

Grounded in a firms' name, and then registration number, the merged ASIF and AESPF data contain information for 222,780 observations from 2001 to 2009.[10] As well as investigating firms' response of production to stricter pollution abatement requirements, we also use the merged dataset to construct robustness checks.

In an effort to find out the innovative effect of stricter environmental regulation, the green patent data we use comes from the Chinese Patent Dataset, maintained by the China National Intellectual Property Administration (CNIPA). The dataset records detailed information on each patent applied for through CNIPA since 1985, including year, name of the applicants, description of the patent, etc.[11] Firms' performance in green technology induced by stricter environmental regulations is at the core of our analysis. We, therefore, follow the IPC classification of environmental-related technologies in Haščič and Migotto (2015) to identify all the green patents, or more precisely innovation patents and utility models aimed to reduce pollution emissions during production, from the

[10] Although the AESPF data we used are from 2001 to 2010, ASIF data from 2010 include some misreported information and have been generally abandoned by researchers, such as Fan, Lin and Tang (2018) and König, Storesletten, Song and Zilibotti (2018). Therefore, the duration of time in the merged dataset is from 2001 to 2009.

[11] Patent data in China include three categories: invention patents, utility models, and designs. We exclude the third category, "designs", from our patent data, because the common view is that designs lack relevant information about technological innovation.

patent dataset of CNIPA. We further identify firms' green patents specifically on water pollution abatement based on the comparison table in Haščič and Migotto (2015). Recognizing that the number of firms owning green patents is limited, patent-related variables are measured by the logarithm of 1 plus the initial number of firms' green patents. We merge the patent data with AESPF on the ground of firms' names.

Where they contravene the law, firms might be given warnings, fines, compliance orders, or some combination thereof by the government to enforce compliance with regulatory legislation. To construct measures on legal enforcement, we use data on environmental administrative penalties, collected by the Institute of Public and Environmental Affairs (IPEA), a well-known Chinese environmental NGO. Administrative authorities are obliged to disclose information on environmental penalties they levy on firms, persons or other organizations through many channels including the internet. The database provides detailed information, from 2004 onwards, on environmental penalties, including illegal facts, types of penalties, the amount of monetary fines, and data on the implementation of the penalties, faced by firms because of their illegal polluting activities. We merge the environmental penalty data from 2004 to 2010 with the AESPF data based on firms' names in our Section 5.

In order to see whether firms will relocate to jurisdictions with less stringent environmental regulations, we utilize the State Administration of Industry and Commerce (SAIC) database in China. The SAIC provides complete records of name and domicile of firms, their representatives, registered capital, business scope, shareholders, and what concern us most, their establishment year. Therefore, we are able to trace firm's entrancce in different cities by adding the number of firms firstly established at city level.

We also take advantage of various statistical books, such as the China City Statistical Yearbook and the China Statistical Yearbook on Environment, and many official documents, for instance, Approval of National Emissions Control Targets of Main Pollutants during the 11^{th} Five-Year Plan by the State Council, to obtain the city-level data and industrial COD emissions as well as emissions reduction targets. Table A1 in the appendix reports summary statistics for all the variables.

4 Main Results

4.1 Baseline Results

To more precisely capture the underlying forces that drive firms' environmental performance in response to more stringent environmental regulations, we follow Martin (2011) to decompose the within-firm sample as follows:

$$e_{i,t} = y_{i,t} \times \frac{e_{i,t}}{y_{i,t}} \tag{8}$$

$e_{i,t}$ is firm i's total pollution at year t, which equals to firms' output $y_{i,t}$ multiplied by pollution per unit of output $e_{i,t}/y_{i,t}$. Taking the log of both sides of equation 8, we have:

$$\Delta log(e_{i,t}) = \Delta log(y_{i,t}) + \Delta log(\frac{e_{i,t}}{y_{i,t}}) \tag{9}$$

where $\Delta log(e_{i,t})$ refers to changes in firm i's total COD emissions at year t. The first term on the right-hand side of Equation 9 is the "within-firm scale effect", which explains changes of total pollution as firms' overall output increase or decrease. The second term is "within-firm technique effect", accounting for pollution changes brought by changes in firm level pollution intensity, through, for instance, adoption of pollution abatement facilities, introduction of cleaner production process, and recycling usage of inputs, among others. We can find that changes of the total emissions can be explained by a within-firm "scale effect" and a "technique effect". The finer within-firm disaggregation is, the more likely we could accurately evaluate the role of different underlying forces in abating water pollution.

Table 1 presents the estimation results of Equation 4. All columns include firm fixed effects and year fixed effects. We control for log GDP per capita and log population in all odd columns rather than the odd columns. Columns (1) and (2) present the estimated coefficient for COD; Columns (3) and (4) are the results for output; while the last two columns indicate the results for firms' pollution intensity, that is, COD/output. In Column (1), the estimated coefficient is -0.063, which is statistically significant at the 1% level. This finding suggests that, with the advent of stricter environmental regulations, manufacturing in China is becoming cleaner overall. The extent of emissions reduction, however, varies for cities faced with different environmental regulation stringency denoted by mandatory COD emissions targets set in the 11^{th} five-year plan period starting from 2006. Compared with cities with lenient environmental regulations, cities with tight regulation account for larger pollution reductions. Taking Shanghai and Kunming in Yunan Province as an example, the former ranks first in R_c, that is COD emissions reduction (45 thousand tons) among all large cities, whereas the latter ranks bottom among all large cities in COD emissions reduction target (4.2 thousand tons). Taking Column (2) as our preferred baseline result, in response to stricter emissions control under 11^{th} Five-year Plan, the extent of the COD emissions fall in Shanghai is nearly 30% larger than that in

Kunming.[12]

An important assumption of our DID identification strategy is that the different over-time changes in pollution activities across firms at cities with different levels of environmental regulation stringency are solely caused by the laying out of reduction targets set in the 11^{th} Five-Year Plan, rather than by any pre-existing differential time trends across firms. To test this assumption, we replace the interaction between environmental regulation stringency and the post dummy in Equation 4 with the sum of the interaction terms between environmental regulation stringency and all the year dummies. Figure A1 in the appendix plots the estimated yearly effects of environmental regulation stringency R_c on firms' COD emissions. We observe no significant pre-trend before 2005 but a break in 2005.

When looking at Columns (4) and (6) of Table 1, we perceive that, among 7.3% of the variation in pollution reduction across cities with different environmental regulation stringency after 2006, 2.2% of them can be explained by within-firm "scale effect", that is, a drop in firms' total output, whereas 5.1% of those can be explained by within-firm "technique effect", including but not limited to the adoption of pollution abatement facilities, the introduction of cleaner production processes and recycling inputs. A back-of-the-envelope calculation reveals that, within-firm "technique effect" is the predominant determinant, contributing up to 70% (-0.051/-0.073) to the effect of environmental regulation stringency on firms' pollution reduction, whereas the within-firm "scale effect" accounts for the other 30% (-0.022/-0.073).[13] Our benchmark results imply that, when stringent environmental regulations comes into force, firms located in cities with more stringent environmental regulations are stimulated to reduce more pollutants largely through technological progress, compared with their counterparts in cities with lenient environmental regulations. In addition, Table A3 in the appendix shows that our baseline results are robust to alternative methods of calculating environmental regulation stringency.

We further test the impact of environmental regulation stringency on other pollutants in Table 2. All columns include firm fixed effects and year fixed effects. We control for log GDP per capita and log population in all even columns rather than the odd columns. First, we execute a test for the effect of environmental regulation stringency on firms' SO_2 emissions, another one of the two pollutants regulated by top-down mandatory reduc-

[12]The discrepancy in the percentage of emissions reduction between these two cities brought on by stricter emissions control from 2006 is calculated as $-0.073 * (45 - 4.2) = -0.29784$.

[13]It is noteworthy that the weight of the "technique effect" in accounting for overall changes in manufacturing emissions in our cross-industry decomposition in 2.3 is larger than it is here. This finding implies that, from the viewpoint of individual firms, adjustments in output will be an easier way to trade off between an output of production and costs in meeting stricter emissions control requirements. From the viewpoint of industries, however, shifts among industries happen more.

Table 1: Baseline Results

	COD		Output		$\frac{COD}{Output}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$R_c \times Post_t$	-0.063***	-0.073***	-0.021*	-0.022*	-0.043*	-0.051**
	(0.022)	(0.018)	(0.012)	(0.012)	(0.025)	(0.021)
Log GDP per capita		0.386		0.042		0.345
		(0.305)		(0.064)		(0.349)
Log Population		-0.099		0.043		-0.142
		(0.116)		(0.058)		(0.131)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	437,253	437,253	437,253	437,253	437,253	437,253
Adj R-Square	0.800	0.801	0.885	0.885	0.782	0.782

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. All dependent variables are logarithmic.

tion targets in the 11^{th} Five-Year Plan. In Columns (1) and (2) of Table 2, we also find that, upon the advent of the pollution reduction commitment period from 2006, firms' SO_2 emissions decrease, and the negative effect with similar magnitude with those in the baseline is, more notably, declared for cities with more stringent environmental regulations. Second, we study the effects of environmental regulations on two other pollutants NH_3-N and smoke and dust before and after 2006. Since these two pollutants are not "critical pollutants" in the 11^{th} Five-Year Plan, the strictness in environmental regulations should have little effect on emissions if our results in Table 1 are not driven by confounding factors. In contrast, if the results were entirely driven by confounding factors, the confounding factors should also apply to pollutants not regulated by obligatory emissions reduction targets. As can be told from Columns (3) to (6), we do not find emissions of NH_3-N and smoke and dust to be significantly affected by environmental regulation stringency. Therefore, Columns (3) to (6), which provide a placebo test, rule out strong confounding factors as being responsible for the relationship between environmental regulation stringency and pollution emissions.

4.2 Heterogeneous Effects by Industry

As our third stylized fact in Section 2.2 reveals, the effect of environmental regulation stringency on firms' COD emissions varied across industries with different polluting intensity. Industrial polluting intensity may positively reinforce the effect of environmental

Table 2: Other Pollutant Results

	SO_2		NH3-N		Smoke and Dust	
	(1)	(2)	(3)	(4)	(5)	(6)
$R_c \times Post_t$	-0.103***	-0.099***	0.013	0.014	-0.002	-0.008
	(0.028)	(0.028)	(0.040)	(0.041)	(0.045)	(0.042)
City-level Controls	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	301,439	301,439	232,430	232,430	169,432	169,432
Adj R-Square	0.818	0.818	0.777	0.777	0.842	0.842

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. All dependent variables are logarithmic. City-level controls include log per capita city GDP and log city population.

regulation stringency on firms' pollution reduction. To test the heterogeneous effect, we estimate Equation 7, and Table 3 presents the results.

In Table 3, the dependent variables are COD (see Columns (1) and (2)), output (see Columns (3) and (4)) and firms' pollution intensity (see Columns (5) and (6)), respectively. We control for firm fixed effect and year fixed effect in all columns. By adding city-level variables in Columns (2), (4), and (6), the results are not substantively different from those in the odd columns. Combining the estimates of $R_c \times Post_t \times Dirty_s$ as well as $R_c \times Post_t$ which are both negative in all columns, we find that, firms' pollution emissions decrease in all industries. The extent of emissions reduction, however, varies across industries. Firms that belong to heavily polluting industries located in cities with more stringent environmental regulations cut down much more on pollutant use after 2006, compared with their intra-city counterparts in less-polluting industries. Here is a back-of-the-envelope calculation on the base of Column (2). Let's take the two noticeable industries—manufacturing of paper and paper products and manufacturing of articles for cultural, educational, and sporting activities—in Shanghai and Kunming again as examples.[14] Compared with paper industry firms in Kunming, firms in the same industry in Shanghai reduced 69.4% more COD emissions in response to stronger emissions reduction enforcement ((-0.339×0.35164-0.051)×(4.5-0.42)=-0.694). Firms in the latter industry in Shanghai reduce, however, only 20.8% more COD in relation to their counterparts in Kunming ((-0.339×0.00013-0.051)×(4.5-0.42)=-0.208). The greater sensibility of firms in

[14] Among all two-digit industries, the paper and paper products industry reports the highest pollution intensity with a $Dirty_s$ of 0.35164, whereas the manufacturing of articles for culture, education, and sport activities has the smallest industrial pollution intensity at 0.00013.

heavily polluting industries to environmental regulations after 2006 lends solid evidence to our stylized facts about the inter-industry allocation.

As a robustness check, we further use a dummy variable to measure industrial pollution intensity. The variable equals to one for heavily polluting industries, and equals to zero for lightly polluting industries. As shown in Table A4, the results remain similar. We also conduct robustness checks by using information on above-scale firms from ASIF data. Our results are robust to the sample adjustment, as shown in Table A6 in the appendix.

Table 3: Heterogeneous Results

	COD		Output		$\frac{\text{COD}}{\text{Output}}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$R_c \times Post_t \times Dirty_s$	-0.343***	-0.339***	-0.133*	-0.136*	-0.210*	-0.203*
	(0.123)	(0.130)	(0.072)	(0.073)	(0.120)	(0.123)
$R_c \times Post_t$	-0.041*	-0.051**	-0.010	-0.012	-0.031	-0.039*
	(0.025)	(0.020)	(0.012)	(0.012)	(0.026)	(0.020)
$Post_t \times Dirty_s$	0.280	0.288	0.525***	0.531***	-0.245	-0.243
	(0.183)	(0.187)	(0.098)	(0.098)	(0.187)	(0.191)
City-level Controls	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	437,253	437,253	437,253	437,253	437,253	437,253
Adj R-Square	0.800	0.801	0.885	0.885	0.782	0.782

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. All dependent variables are logarithmic. City-level controls include log per capita city GDP and log city population.

5 Mechanism

Manufacturers in China are "greening", as observed in the previous analysis. It thus becomes natural to ask: which inherent mechanisms play a role when firms adapt to a new era of stringent environmental regulation? When answering this question, it is necessary to examine activities at firm level. With various firm-level data, we are able to execute a broad spectrum of tests on roles of recycling practice (recycling of wastewater), adoption of pollution abatement facilities (wastewater treatment), and firms' technology progress (green patents), among others.

5.1 Environmental Penalties

Despite the fact that targets assigned to each level of government and polluters are obligatory, the effectiveness of target control heavily relies on the strength of daily legal enforcement, such as environmental penalties levied by authorities on firms, which is also the most frequently used regulatory tool in China. As an important prerequisite, we need to be sure that legal enforcement on emissions target control has been tightened, which could be explained by changes in the probability that firms might be punished before and after 2006.

To do so, we construct two variables, *Polluter Penalty Dum* and *Polluter Penalty Num*. The former one is a dummy variable denoting whether a firm was punished for violations of emissions limitations and other legal obligations. To be specific, *Polluter Penalty Dum* equals to 1 in the year when the firm was penalized and otherwise equals 0. The latter one, nevertheless, refers to frequency with which the firm was penalized in a certain year. *Polluter Penalty Num* was numerated with the sequence of 1,2,3...according to the number of times the firm was punished.

As shown in Table 4, after the start of the 11^{th} Five-Year Plan in 2006, the strengthened environmental regulations significantly increased the probability firms might be punished. The increased probability is much more notable for firms located in cities with stricter environmental regulations and in industries with higher pollution intensity.

Table 4: Polluter Penalty Results

	Polluter Penalty Dum		Polluter Penalty Num	
	(1)	(2)	(3)	(4)
$R_c \times Post_t$	0.016**	0.013*	0.016**	0.013*
	(0.007)	(0.007)	(0.007)	(0.007)
$R_c \times Post_t \times Dirty_s$		0.048***		0.049***
		(0.017)		(0.018)
$Post_t \times Dirty_s$		0.083***		0.097***
		(0.029)		(0.030)
City-level Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	437,253	437,253	437,253	437,253
Adj R-Square	0.124	0.124	0.119	0.120

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. City-level controls include log per capita city GDP and log city population.

5.2 Further Decomposing Within-Firm Pollution Activities

First, we execute a finer within-firm decomposition based on Section 4.1 by introducing another pollutant—effluent. Effluent is an important water pollution parameter, because it not only reflects the total volume of industrial water entering into the natural environment, but also provides us means by which we may assess the real determinants of firms' environmental performance. Therefore, firms' effluent discharge can be further decomposed into

$$\Delta log(f_{i,t}) = \Delta log(y_{i,t}) + \Delta log(\frac{f_{i,t}}{y_{i,t}}), \tag{10}$$

where $\Delta log(f_{i,t})$ is change of effluent discharge of firm i at year t. Changes in firms' output is expressed by $\Delta log(y_{i,t})$. The second term on the right-hand side of the equation refers to changes of firm i's pollution intensity, that is effluent discharge per unit of output.

We repeat the regression of our preferred baseline specification and the triple interaction with industrial polluting intensity for each of above two components. Columns (1) and (2) of Table 5 present the results for firms' effluent discharge. Columns (3) and (4) report the results for firms' pollution intensities. In all columns, we add city-level controls, firm fixed effect, and year fixed effect. As shown in Column (1) of Table 5, the coefficient on firms' effluent is negative and statistically significant, which implies that firms' discharge of effluent declines adhering to similar patterns as COD emissions after 2006. In other words, the extent of effluent discharge is negatively associated with stringency of environmental regulations. After including the triple interaction, the point estimates of $R_c \times Post_t$ and $R_c \times Post_t \times Dirty_s$ in Column (2) are both negative. It indicates that firms' effluent declines in all industries after strengthening the environmental regulations on target pollution reduction in 2006. The effect is, however, much stronger for heavily polluting industries. We find similar effects on firms' effluent discharge per unit of output as shown in Columns (3) and (4). That is to say, decreased industrial wastewater discharge (effluent) is the main reason for firms' emissions reduction.

5.3 Water-Related Energy Consumption

We now turn to examine the adjustment of firms' total water consumption (industrial water) and freshwater consumption (freshwater) per unit of output affected by environmental regulations. Recycling use of industrial water is a feasible approach to "kill two birds with one stone" with lower costs for firms to save energy while also reducing pollution emissions. We thus expect that the beneficial effect of environmental regulations

Table 5: Effluent Results

	Effluent		$\frac{\text{Effluent}}{\text{Output}}$	
	(1)	(2)	(3)	(4)
$R_c \times Post_t$	-0.059***	-0.027	-0.035**	-0.013
	(0.014)	(0.018)	(0.017)	(0.017)
$R_c \times Post_t \times Dirty_s$		-0.471**		-0.348*
		(0.191)		(0.207)
$Post_t \times Dirty_s$		0.847***		0.325*
		(0.174)		(0.190)
City-level Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	435,555	435,555	427,583	427,583
Adj R-Square	0.852	0.852	0.799	0.799

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. All dependent variables are logarithmic. City-level controls include log per capita city GDP and log city population.

on firms' emissions reduction through water recycle should be stronger for firms in cities with stricter environmental regulations and those in industries with higher levels of pollution intensity. The negative coefficients in Columns (1) and (3) of Table 6 prove our speculation that, relative to cities where regulations are weaker, firms in cities where environmental regulations are more stringent consume less industrial water and freshwater after 2006. As we can tell from Columns (2) and (4) of Table 6, for firms in more heavily polluting industries, the decline of water consumption is much sharper, among which the fall of freshwater consumption is especially notable.

5.4 Adoption of Pollution Control Devices

The adoption of pollution control devices refers to devices installed and operated to eliminate emissions of pollutants in effluent entering natural waterways. To meet mandatory emissions caps and reduction targets on COD, firms may choose to install more pollution control devices and to expand their treatment capabilities. We examine the effect of environmental regulation stringency on firms' pollution abatement. Column (1) of Table 7 shows the estimation results for adoption of pollution control devices divided by firms' volume of effluents. We find that the interaction effects between environmental regulation stringency and devices per unit of effluent after 2006 is positive at 1% significant

Table 6: Energy Results

	Industrial Water Output		Fresh Water Output	
	(1)	(2)	(3)	(4)
$R_c \times Post_t$	-0.033**	-0.023	-0.033*	-0.011
	(0.016)	(0.019)	(0.018)	(0.020)
$R_c \times Post_t \times Dirty_s$		-0.150		-0.340*
		(0.107)		(0.192)
$Post_t \times Dirty_s$		0.189		0.297*
		(0.134)		(0.178)
City-level Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	437,123	437,123	437,090	437,090
Adj R-Square	0.808	0.808	0.797	0.797

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. All dependent variables are logarithmic. City-level controls include log per capita city GDP and log city population.

level. By summing up the triple interaction among environmental regulation stringency, post 2006 dummy, and industrial pollution intensity, we observe positive and statistically significant results in Column (2) Table 7. The estimates on the ability of firms' pollution control devices per unit of effluent reveals similar positive results in Columns (3) and (4) with those in Columns (1) and (2). After introducing stringent environmental regulations in 2006, firms adopted more environmental abatement devices and expanded their treatment capacity. The increasing use of control devices and their treatment capacity is more notable for firms in cities with stringent environmental regulations than their counterparts in cities with weaker environmental regulations after 2006. Relative to firms in cleaner industries, firms in dirtier industries tend to be more progressive in expanding their pollution treatment abilities.

5.5 Patents

Even though pollution abatement devices always involve technological innovation, it is actually somewhat end-of-pipe solutions because the devices are usually purchased from the market, and thus firms barely need to do their own R&D. In this subsection, we turn to examine firms' performance in terms of "bright green" induced by stricter environmental regulations by using disaggregated firm patent data provided by National Intellectual

Table 7: Facilities Results

	Facilities Effluent		Facility Capacity Effluent	
	(1)	(2)	(3)	(4)
$R_c \times Post_t$	0.067***	0.030*	0.036**	0.022
	(0.015)	(0.016)	(0.015)	(0.018)
$R_c \times Post_t \times Dirty_s$		0.525***		0.192
		(0.191)		(0.140)
$Post_t \times Dirty_s$		-0.688***		-0.370**
		(0.184)		(0.164)
City-level Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	291,735	291,735	283,386	283,386
Adj R-Square	0.826	0.826	0.530	0.530

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. All dependent variables are logarithmic. City-level controls include log per capita city GDP and log city population.

Property Administration of China.

However, we find little evidence that the severity of environmental regulations is associated with an increase in green patent and water-related green patent applications, regardless of what industry firms belong to. The weak negative results in Columns (1) to (4) are even indicative of the possibility that environmental regulations impede firms' environment-related innovation. Thus, we are able to infer that emissions target controls during the 11^{th} Five-Year plan failed to stimulate firms to adopt much more effective technology to eliminate more pollutants from the production process, maybe because other lower-cost and end-of-pipe countermeasures, such as pollution abatement facilities, were sufficient to meet the targets. Moreover, we further divide the two variables in Table 8 into green innovation patents, green utility models, water-related green innovation patents, and water-related utility models according to the general classification of patents in China. The results in Table A5 in the appendix are similar to those in Table 8.

6 Firms' Other Economic Performance

The preceding Section 4 verifies the positive effect of environmental regulations on firms' pollution reduction, especially for those in heavily polluted industries. The significantly

Table 8: Green Patent Results

	Green Patent		Water Patent	
	(1)	(2)	(3)	(4)
$R_c \times Post_t$	-0.0002	-0.0003	-0.0002	-0.0001
	(0.0003)	(0.0005)	(0.0003)	(0.0004)
$R_c \times Post_t \times Dirty_s$		0.0013		-0.0005
		(0.0036)		(0.0024)
$Post_t \times Dirty_s$		-0.0155***		0.0007
		(0.0057)		(0.0035)
City-level Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	437,253	437,253	437,253	437,253
Adj R-Square	0.232	0.232	0.147	0.147

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. All dependent variables are logarithmic after adding 1. City-level controls include log per capita city GDP and log city population.

reduced pollution, output and pollution per unit are thought to influence firms' economic performance. To this end, we accordingly conduct a test in this section to further assess the impact of environmental regulations on firms' economic performance, including profits, capital, labor, and market share.

Basically, Columns (1), (3), (5) and (7) of Table 9 show that, with firm fixed effect, year fixed effect and city-level variables controlled for, more severe environmental regulations are associated with a sharp decline in firms' profits, capital, labor and market share. The extent of firms' poorer economic performance, nevertheless, is different for firms located in cities with varied environmental regulation stringency. Compared with firms in cities with lenient environmental regulations, firms in highly regulated cities experience larger decreases in profits, capital, labor and market share as a result of environmental regulations. By incorporating the triple interaction among environmental regulation stringency, industrial polluting intensity and post year dummy, the consistently negative estimates of $R_c \times Post_t$ and $R_c \times Post_t \times Dirty_s$ in Columns (2), (4), (6) and (7) of Table 9 is indicative of decreases in firms' profits, capital, labor and market share in all industries. Also, as for firms located in tightly and loosely regulated cities respectively, heavily polluting industry firms experienced much more decline in profits, capital, labor and market share, compared with their counterparts in cleaner industry. For example, regardless of the discrepancy in industrial polluting intensity, the average fall in firms' profits, capital, labor and market share in Shanghai is 67.9%, 23.5%, 3.9% and 1.2% larger than those in Kunming of Yunan Province, respectively; When taking into account of industrial pollution intensity, compared with firms in paper industry in Kunming, profits, capital, labor and market share of firms in the same industry in Shanghai experienced a fall of 101.6%, 51.4%, 21% and 1.5%; firms manufacturing articles for cultural, educational, and sporting activities, the cleanest industry when it comes to COD emissions, in Shanghai encountered a fall of only 60.2%, 17.1%, 0.2% and 1.1% in their profits, capital, labor and market share.

Table 9: Performance Results

	Profit		Capital		Labor		Market Share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$R_c \times Post_t$	-0.1664***	-0.1474***	-0.0577***	-0.0418***	-0.0100*	-0.0004	-0.0029***	-0.0027**
	(0.0222)	(0.0228)	(0.0094)	(0.0116)	(0.0051)	(0.0071)	(0.0009)	(0.0011)
$R_c \times Post_t \times Dirty_s$		-0.2889**		-0.2394***		-0.1450**		-0.0025
		(0.1173)		(0.0889)		(0.0602)		(0.0055)
$Post_t \times Dirty_s$		0.6034***		0.6814***		0.2072***		0.0296***
		(0.2033)		(0.1195)		(0.0724)		(0.0076)
City-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	169,311	169,311	222,149	222,149	220,575	220,575	222,780	222,780
Adj R-Squared	0.753	0.753	0.907	0.907	0.917	0.917	0.870	0.870

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. All dependent variables are logarithmic. City-level controls include log per capita city GDP and log city population.

A decrease in output, input and market share among firms might shed light on firms' relocation, we therefore further test the impact of environmental regulation on firm entry into new regions. Two variables *Entry Num* and *Entry Capital*, which denote log value of the number of firms' newly registered in a city and log value of their total registered capital, respectively, are introduced here.[15] The significantly negative estimates in Columns (1) and (2) in Table 10 show that, the relocation of firms to cities with stringent environmental regulation plunged sharply compared with those in loosely regulated cities after 2006. The shrinkage of overall registered capital in highly regulated cities presents a similar pattern, as shown in Columns (3) to (4). Their escape signifies, to a certain extent, an "internal" variant of the pollution havens hypothesis.

[15] In the absence of information on industries of registered firms in SAIC, we only include the interaction term $R_c \times \text{Post}_t$ in our regression.

Table 10: Entry Results

	Entry Number		Entry Capital	
	(1)	(2)	(3)	(4)
$R_c \times Post_t$	-0.097***	-0.096***	-0.193***	-0.194***
	(0.033)	(0.033)	(0.038)	(0.039)
City-level Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,860	2,860	2,860	2,860
Adj R-Squared	0.959	0.959	0.828	0.828

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. All dependent variables are logarithmic. City-level controls include log per capita city GDP and log city population.

7 Conclusion

This paper examines the effect of environmental regulations on firms' COD emissions reductions. We find that with the advent of stricter environmental regulations, represented by the differential emissions reduction targets set up in the Chinese 11^{th} Five-Year Plan after 2006, manufacturers have emitted less COD. More stringent environmental regulations faced by firms is positively associated with a greater probability of reducing COD emissions after 2006. Also, firms belonging to heavily polluting industries have since cut down their pollutant use by much more when compared with their counterparts in less-polluting industries. We find no such effects of the policy on other non-targeted pollutants, such as NH_3 and smoke and dust. Our analyses suggest that stricter environmental regulations have induced firms to pay more efforts to COD emissions-related issues. By constructing a comprehensive dataset, we execute a series of tests to determine the underlying mechanisms affecting firms' reactions to stringent environmental regulations. With the stricter target control system in place, firms face a higher probability of receiving administrative penalties and are more likely to discharge less effluent, to consume less industrial water by recycling water, and to adopt devices that control pollution as well as expand their current pollution treatment abilities. However, we find no evidence of an increase in green patents and water-related green patent applications, leading us to believe that firms are, nevertheless, reluctant to increase environment-related innovation.

Our research has three important implications. First, as environmental regulations become tighter, firms' emissions fall. Tasked with meeting concrete emissions reduction targets, firms are consciously trading off between production arrangements and COD emissions. Overall, manufacturing firms in China are becoming green. Second, the industrial infrastructure in China is becoming cleaner due to the expansion of cleaner industries, while polluting industries are shrinking. As firms in heavily polluting industries are more responsive to environmental regulations, their sharply declining output and the pollution intensities of their production provide more evidence of the "composition effect". Third, although clear reduction targets set during the 11^{th} Five-Year Plan were effective, they still failed to stimulate firms to adopt effective technology to eliminate more pollutants from the production process, perhaps because other lower-cost countermeasures, such as adoption of pollution abatement facilities, was sufficient to meet the target. Regulators still face the fundamental challenge of indentifying an appropriate regulatory path that will stimulate firms to shift from the adoption of end-of-pipe treatment technology to "bright green" innovations.

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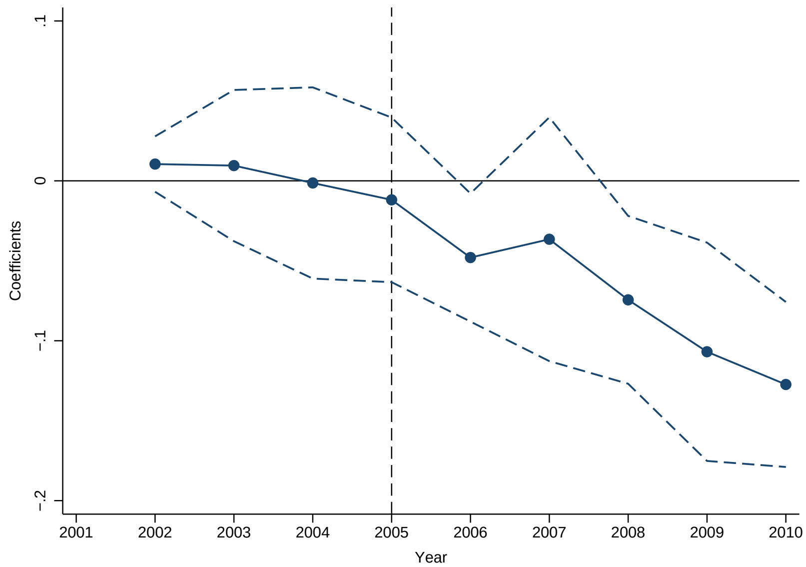
Appendix

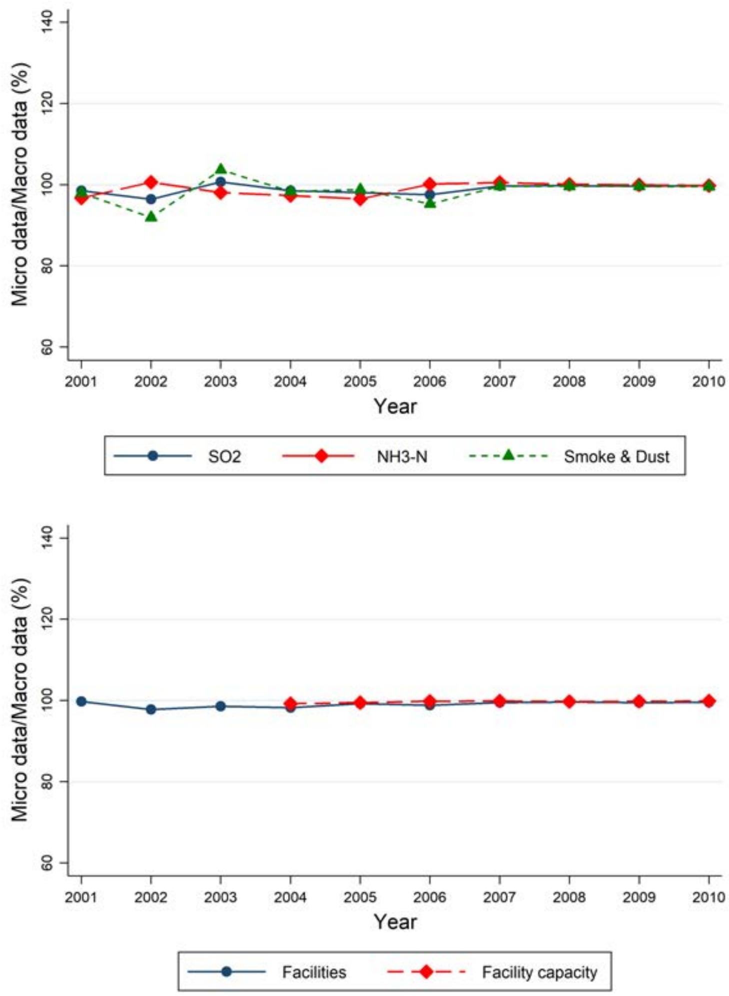
Appendix A Dynamic Trend

Figure A1: Dynamics of Chemical Oxygen Demand Emissions



Notes: This figure plots the estimated coefficients of environmental regulation stringency and year dummy variables (controlling for the log per capita city GDP and log city population, and year and firm fixed effects) and their 90% confidence intervals. The reference year is 2001.

Figure A2: Comparison between Macro- and Micro- Data on Main Air Pollutants and Control Facilities



Notes: The macro-data come from China Statistical Yearbook on Environment, and the micro-data come from Annual Environmental Survey of Polluting Firms (AESPF) of China.

Appendix B Summary Statistics

Table A1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	P10	P50	P90
Dependent Variables (logarithmic)						
COD	437,253	8.297	2.511	5.109	8.312	11.420
Output	437,253	7.725	2.057	5.193	7.696	10.310
$\frac{\text{COD}}{\text{Output}}$	437,253	0.572	2.635	-2.708	0.543	3.895
SO_2	301,439	9.596	2.080	7.021	9.643	12.130
NH3-N	232,430	5.897	2.586	2.625	5.937	9.083
Smoke and Dust	169,432	9.180	2.425	6.258	9.056	12.430
Effluent	435,555	10.440	2.255	7.518	10.490	13.250
$\frac{\text{Effluent}}{\text{Output}}$	427,583	2.719	2.170	-0.086	2.768	5.448
$\frac{\text{Industrial Water}}{\text{Output}}$	437,123	3.407	2.146	0.652	3.433	6.131
$\frac{\text{Fresh Water}}{\text{Output}}$	437,090	3.008	2.110	0.303	3.046	5.655
$\frac{\text{Facilities}}{\text{Effluent}}$	291,735	-10.690	1.967	-13.170	-10.810	-8.033
$\frac{\text{Facility Capacity}}{\text{Effluent}}$	283,386	-5.169	1.196	-6.502	-5.257	-3.689
Green Patent	437,253	0.0048	0.0772	0	0	0
Water Patent	437,253	0.0020	0.0456	0	0	0
Profit	169,311	7.688	2.246	4.836	7.711	10.52
Capital	222,149	9.824	1.780	7.673	9.772	12.08
Labor	220,575	5.555	1.150	4.111	5.481	7.115
Market Share	222,780	0.0349	0.173	0.00102	0.00657	0.0590
Entry Number	2,860	5.903	1.260	4.369	5.798	7.694
Entry Capital	2,860	12.15	1.364	10.51	12.12	13.90
Dependent Variables						
Polluter Penalty Dum	437,253	0.042	0.200	0	0	0
Polluter Penalty Num	437,253	0.044	0.213	0	0	0
Independent Variables						
R_c	437,253	1.080	1.089	0.163	0.677	2.981
$Post_t$	437,253	0.619	0.486	0	1	1
$Dirty_s$	437,253	0.073	0.098	0.003	0.030	0.144
Control Variables (logarithmic)						
Log GDP per capita	437,253	9.964	0.903	8.841	9.921	11.140
Log Population	437,253	6.201	0.634	5.430	6.272	6.887

Appendix C Summary of Pollution Intensity

Table A2: Summary Statistics of Dirty

Code	Industry	Dirty_s
13	Processing of food	0.14403
14	Manufacture of foods	0.02482
15	Manufacture of beverages	0.04471
16	Manufacture of tobacco	0.00106
17	Manufacture of textile	0.06406
18	Manufacture of textile, clothing, and apparel	0.00298
19	Manufacture of leather, fur, and feather	0.01555
20	Processing of timber, manufacture of wood, bamboo, rattan, palm, and straw products	0.00542
21	Manufacture of furniture	0.00110
22	Manufacture of paper and paper products	0.35164
23	Printing, reproduction of recording media	0.00035
24	Manufacture of articles for culture, education, and sport activities	0.00013
25	Processing of petroleum, coking, processing of nuclear fuel	0.02002
26	Manufacture of raw chemical materials and chemical products	0.11802
27	Manufacture of medicines	0.02956
28	Manufacture of chemical fibres	0.01880
29	Manufacture of rubber	0.00138
30	Manufacture of plastics	0.00074
31	Manufacture of nonmetallic mineral products	0.01121
32	Smelting and pressing of ferrous metals	0.04087
33	Smelting and pressing of nonferrous metals	0.00641
34	Manufacture of metal products	0.00396
35	Manufacture of general-purpose machinery	0.00328
36	Manufacture of special-purpose machinery	0.00272
37	Manufacture of transport equipment	0.00922
39	Electrical machinery and equipment	0.00191
40	Manufacture of communication equipment, computers, and other electronic equipment	0.00374
41	Manufacture of measuring instruments and machinery for cultural activity and office work	0.00137
42	Manufacture of artwork	0.00076
43	Recycling and disposal of waste	0.00013
6-11,44-46	Non-manufacturing	0.07002

Notes: The variable $Dirty_s$ is industry's polluting intensity indicated by each industry's proportion of total COD emissions in all industries in 2005. 6-11 are mining sectors and 44-46 are utilities sectors.

Appendix D Using Different Measure of COD Regulation

Table A3: Results by Using Different Measure of COD Regulation

	COD		Output		$\frac{\text{COD}}{\text{Output}}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$R_{c2} \times Post_t$	-0.069***	-0.044	-0.015	-0.005	-0.054*	-0.040
	(0.024)	(0.028)	(0.011)	(0.011)	(0.029)	(0.030)
$R_{c2} \times Post_t \times Dirty_s$		-0.355***		-0.137**		-0.218*
		(0.116)		(0.059)		(0.122)
$Post_t \times Dirty_s$		0.315*		0.534***		-0.220
		(0.183)		(0.099)		(0.190)
City-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	437,253	437,253	437,253	437,253	437,253	437,253
Adj R-Square	0.801	0.801	0.885	0.885	0.782	0.782

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. All dependent variables are logarithmic. City-level controls include log per capita city GDP and log city population.

Appendix E Using Different Measure of Industry-Level COD Intensity

Table A4: Results by Using Different Industry-Level COD Intensity

	COD		Output		$\frac{\text{COD}}{\text{Output}}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$R_c \times Post_t \times Dirty_{s2}$	-0.074**	-0.069**	-0.007	-0.006	-0.067*	-0.062*
	(0.031)	(0.030)	(0.014)	(0.014)	(0.035)	(0.032)
$R_c \times Post_t$	-0.045*	-0.056***	-0.017	-0.019	-0.028	-0.037
	(0.026)	(0.021)	(0.012)	(0.012)	(0.029)	(0.023)
$Post_t \times Dirty_{s2}$	0.078*	0.073*	0.086***	0.086***	-0.008	-0.013
	(0.040)	(0.041)	(0.022)	(0.022)	(0.042)	(0.042)
City-level Controls	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	437,253	437,253	437,253	437,253	437,253	437,253
Adj R-Squared	0.800	0.801	0.885	0.885	0.782	0.782

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. All dependent variables are logarithmic. City-level controls include log per capita city GDP and log city population.

Appendix F Patent Classification

Table A5: Results by Patent Classification

	Green Invention		Green Utility		Water Invention		Water Utility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$R_c \times Post_t$	-0.00024	-0.00047	-0.00004	0.00002	-0.00017	-0.00022	0.00000	0.00006
	(0.00024)	(0.00035)	(0.00027)	(0.00038)	(0.00017)	(0.00018)	(0.00019)	(0.00027)
$R_c \times Post_t \times Dirty_s$		0.00349		-0.00182		0.00095		-0.00102
		(0.00295)		(0.00230)		(0.00197)		(0.00150)
$Post_t \times Dirty_s$		-0.00537		-0.01543***		0.00198		-0.00210
		(0.00447)		(0.00353)		(0.00304)		(0.00162)
City-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	437,253	437,253	437,253	437,253	437,253	437,253	437,253	437,253
Adj R-Square	0.190	0.190	0.223	0.223	0.117	0.117	0.132	0.132

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. All dependent variables are logarithmic after adding 1. City-level controls include log per capita city GDP and log city population.

Appendix G Using ASIF data

Table A6: Results by ASIF Data

	COD		Output		$\frac{\text{COD}}{\text{Output}}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$R_c \times Post_t$	-0.064***	-0.045***	-0.023**	-0.016	-0.041**	-0.029*
	(0.015)	(0.016)	(0.011)	(0.012)	(0.016)	(0.015)
$R_c \times Post_t \times Dirty_s$		-0.292***		-0.102		-0.191**
		(0.077)		(0.062)		(0.085)
$Post_t \times Dirty_s$		0.135		0.311***		-0.177
		(0.200)		(0.109)		(0.204)
City-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	222,780	222,780	222,780	222,780	222,780	222,780
Adj R-Squared	0.797	0.797	0.841	0.841	0.755	0.755

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. All dependent variables are logarithmic. City-level controls include log per capita city GDP and log city population. Results are robust when we control the firm-level controls include log size, log capital-labor ratio and log age.