The Effect of Environmental Regulation on Firm Emissions and Performance- Evidence from China

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Abstract

This paper examines the effect of environmental regulation on the firm SO2 emissions and firm performance in China. We focus on the Two Control Zone (TCZ) policy which is a national action aiming to solve one of the most serious environmental challenges in China, SO2 pollution. Using difference-in-difference approach we find that this policy induced 28.9% reduction in firm SO2 discharged amount, 29.8% reduction in firm SO2 generated amount, and 35.7% loss in firm total factor productivity (TFP), but no influence on firm profitability outcomes. We proved that firms applied two various methods, increasing pollution abatement devices and improving production technology, to reduce their emissions, and the former one discourages firms' productivity but the later one stimulates firms' productivity. Thus, our results support the theoretical predictions of neoclassical models and the Porter Hypothesis (PH) simultaneously. Finally, we calculated the economic cost brings by the TCZ policy that is 10% reduction on SO2 discharged amount led to 0.42% to 1.2% reduction on firms' TFP; and 10% reduction on firms' SO2 generated amount brought 0.34% decrease on firms' employment. During China's 11th Five-Year Plan, this policy would cause 99.43 to 413.2 billion RMB total output loss based on 2006 industrial output 23893.86 billion RMB.

1 Introduction

The debate about whether environmental regulation hiders firm performance remains controversial. Now, in fast-growing developing countries like China, this discussion attracts from scholars and policymakers. On the one hand, neoclassical theory on environmental economics hold that environmental regulation causes an additional cost for production, including the cost of purchasing desulfurization equipment, cost of operating and maintaining desulfurization equipment, fines for excessive sewage discharge, and so on, which reduce firm competitiveness (Jaffe and Palmer, 1997). So, the implement of environmental regulation will reduce firm emissions accompanied by the decrease in firm performance or employment (Greenstone, 2002; Greenstone et al., 2012; Walker, 2011). Based on the idea of additional cost, the Pollution Haven Hypothesis (PHH) suggests that regulated firms will relocate to a new place with less regulation to avoid the loss (Copeland and Taylor, 2004). On the other hand, proponents of environmental regulation argue that appropriate regulation can stimulate polluters to develop cleaner technologies and take more efficient production methods to reduce firm emissions, which implies that environmental regulation can in turn be beneficial to firm productivity and competitiveness (M. Porter, 1990; M. E. Porter and Linde, 1995).

In this paper we examines the effect of a wide-ranging Chinese national environmental policy, The Two Control Zone (TCZ) policy, on the firm SO2 emissions and firm performance. The TCZ policy aims to solve the SO2 pollution and the acid rain issue which are two serious environmental challenges in China. China's long-term reliance on coal-burning for energy lead to two environmental problems, air pollution and acid rain problems. The acid rain area increased from 1.7 million km^2 in the early 1980s to more than 2.7 million km^2 in the mid-1990s. Until 1993, 62.3% of Chinese cities' annual average ambient SO2 concentration values exceed the national Class II standard, 60 ug/m3 (Cai et al., 2016).

For reducing SO2 pollution and solving the acid rain problem, the TCZ policy was proposed in 1998, which is treated as an important environmental policy improving Chinese air quality. This policy belongs to the "33211 project" of the Ninth Five-Year-Plan which contains a series national environmental protection actions and policies. The project is China's first and largest environmental protection plan in the 21st century, setting the tone for future environmental protection work. As part of the project, TCZ policy is a large-scale regulatory policy including 1.09 million km2 which encompass 380 prefecture-cities and 175 cities and aiming to improve China's air conditions. The whole TCZ area accounts for 11.4% of the nation's territory, 40.6% of the population, 62.4% of GDP, and 58.9% of total SO2 emissions in 1995 (Hao et al., 2001). This huge scope of influence makes research on it even more necessary and meaningful. In 2000, only 102 TCZ cities achieved the national Class II standard for average ambient SO2 concentrations (*China Environment Yearbook 2001*). After TCZ regulation, 94.9% of TCZ cities achieved the national Class II standard in 2010.

To identify the effects of the TCZ policy, we conduct a difference-in-difference (DID) estimation. Specifically, the first difference comes from the comparison of firm emissions, productivity, and performance in TCZ and non-TCZ cities (with the firms in TCZ area facing more stringent environmental regulations); the second difference is due to the policy implementation in 2000, which divides the sample into pre- and post-treatment periods. In specification, firm productivity is denoted by total factor productivity (TFP) as a proxy, and profitability is denoted by return on assests (ROA) and return on sales (ROS) as proxies.

Our result shows that the TCZ policy induced 28.9% reduction in firm SO2 discharged amount, 29.8% reduction in firm SO2 generated amount, and 35.7% loss in firm TFP, but no influence on firm profitability outcomes. The mechanism analysis proved that firms applied two various abatement methods, increasing pollution abatement devices and improving production technology, to reduce their emissions. The former one discourages firms' productivity but the later one stimulates firms' productivity. Thus, this paper finds evidence that support both the theoretical predictions of neoclassical models and the Porter Hypothesis (PH). The economic cost brings by the TCZ policy is also calculated, suggesting a 10% reduction on SO2 discharged amount led to 0.42% to 1.2% reduction in firms' TFP; and a 10% reduction on firms' SO2 generated amount brought 0.29% decrease on firms' employment. During China's 11th Five-Year Plan, 2006-2010, this policy would cause 99.43 to 413.2 billion RMB total output loss based on 2006 industrial output 23893.86 billion RMB.

One challenge of this investigation is the endogenous concern of environmental policy (Millimet and Roy, 2016). First, the criteria of counties regulated by the TCZ policy is determined by local environmental quality, especially the air quality. So, the implement of environmental policy is not influenced by the local economy (Greenstone et al., 2012). Second, as we only have two observe year before policy implement for parallel testing, we use the Propensity Score Matching (PSM) method to do the robustness check. The result is robust after the PSM.

The present paper makes four contributions to the literature. Firstly, this paper is the first study to investigate the effect of the TCZ policy on the firm SO2 emissions and firm performance. This is also the first study to obtain an estimate of the TCZ policy's economic cost. Existing papers have investigated various Chinese environmental regulations' impact on firm behaviour. For example, G. He et al. (2018) find the set of water monitoring station reduce upstream firm productivity, and C. Wang et al. (2018) find that the "three rivers and three lakes basins" (3Rs3Ls) policy has no effect on firm emissions and productivity. Both G. He et al. (2018) and C. Wang et al. (2018) focus on water regulations, leaving a gap in knowledge regarding the economic cost of air regulation on SO2 pollution, which this study intends to fill in. As the most important air pollution control policy in China, the TCZ policy's effect on firm productivity and performance has not been estimated. In this paper, we focus on firm productivity, the efficiency of firms, which uncover that with given inputs whether the TCZ policy change how effectively firms converts inputs into outputs. Thus, a clearer economic interpretation is shown in our result than the finding that the TCZ policy are associated with neonatal mortality (Tanaka, 2015) and foreign direct investment (Cai et al., 2016).

Secondly, most studies to date about the relationship between environmental policies and firm behaviour have focused on developed countries (e.g., Becker and Henderson, 2000; Berman and Bui, 2001; Greenstone, 2002; Greenstone et al., 2012; Jaffe, Peterson, et al., 1995; Kahn and Mansur, 2013; Ryan, 2012; Walker, 2011). This paper investigates China, the largest developing country, and estimates the economic cost of the TCZ policy in the context of a rapid growing economy. Our findings add to the literature on the effect of Chinese environmental regulation on firm emissions and productivity (G. He et al., 2018; C. Wang et al., 2018).

The third contribution is that this paper uses the principal instruments of the TCZ policy, the SO2 emission-specific, county-level TCZ area designations, as its measures of regulation. We accurate the smallest unit of the policy implementation area to county. Previous studies rely on measures of regulation that are aggregated (e.g., city-level measures), see Cai et al. (2016). But, the 1998 Reply listed the name of cities and counties under regulated. It will bring selection bias if we target a regulated city who has counties out of the policy. For accuracy, we set firms in the treatment group as the one who located in counties listed in the 1998 Reply.

Finally, through mechanism analysis, this paper proves that firms under environmental regulation would take two different pollution abatement methods. One is adding up pollution abatement devices after production to reduce emissions, which is an additional cost for firms. The other one is applying cleaner technologies during production, which can reduce the pollutant generated during production. Our research proved that both methods have been applied under the TCZ policy, and the total effect of the TCZ policy on firms' emissions and performance is the superposition of the effects caused by the two methods. This finding add to the literature on discuss about the environmental regulation promote (Ambec et al., 2013; Costantini and Mazzanti, 2012; Jaffe and Palmer, 1997; M. Porter, 1990; M. E. Porter and Linde, 1995; Stavropoulos et al., 2018) or hider (Berman and Bui, 2001; Gollop and Roberts, 1983; Gray, 1987; Greenstone, 2002; Walker, 2011) the economy.

The remainder of our study is organized as follows. Section 2 introduces the literature review from both theoretical and empirical perspectives. Section 3 describes the background of Chinese environmental regulation. Section 4 presents the data description, summary statistics, and baseline specification. Section 5 reports the baseline empirical results and heterogeneity analysis. Section 6 presents our robustness test. Section 7 is the conclusion.

2 Literature Review

The stringency of environmental regulation keeps increasing in the US since 1970s (Berman and Bui, 2001; Jaffe, Peterson, et al., 1995). As firm abatement costs have continued to increase, researchers began focusing on the economic costs of environmental regulations. But the debate about whether environmental regulation hiders firms' performance remains controversial. On the one hand, neoclassical theories hold that environmental regulation impose additional costs for production, slow productivity growth, and thereby reduce firm competitiveness. These costs include purchasing desulfurization equipment, operating and maintaining desulfurization equipment, fines for excessive sewage discharge, and so on. The implement of environmental regulation will reduce both firms' emissions and firm performance (Greenstone, 2002; Greenstone et al., 2012). Haveman and Christiansen (1981) go as far as implicating environmental regulations as contributors to the US productivity reduction in the 1970s. Based on this additional cost idea, The Pollution Haven Hypothesis (Copeland and Taylor, 1994) also suggests that firms will relocate to a new place with less regulation. On the other hand, proponents of the environmental regulations argue that appropriate regulation can stimulate polluters to develop cleaner technologies and take more efficient production methods to reduce firms' emission (Jaffe and Palmer, 1997; M. Porter, 1990;

M. E. Porter and Linde, 1995). So, basing the idea of the Porter Hypothesis, environmental regulation can in turn be beneficial for firm competitiveness (M. Porter, 1990; M. E. Porter and Linde, 1995).

2.1 Neo-classical Theory on Environmental Economics

Conventional wisdom and Neo-classical theory surmise that firms will suffer deleterious effects from stricter environmental regulations. Neo-classical analysis starts from the assumption that all firms are perfect profit-maximizers who can choose a production method to minimize their production costs. Environmental regulations would force firms away from their optimal production process as the regulation constrains firm choices.

2.1.1 Theoretical literature on proving the neo-classical theory on environmental economics

From the 1970s, some studies theoretically proved the negative relationship between environmental regulation and firm competitiveness (international trade). Pethig (1976) tested the impact of the environmental policies on international trade using a two-sector general equilibrium model. He derived several versions of the theorem of comparative advantage under the restriction of environmental policies, a theorem about welfare losses from trade with environmental regulations, and an emission charge equalization theorem. In this two-sector general equilibrium model, two goods, good 1 and good 2, are produced by one single resource, labour, and a by-product emission. The work make several assumptions on producers: the good and the by-product are generated in fixed proportions $q_i = f_i(a_i, e_i)$, where a_i and e_i represents good i's labour input and emission respectively; good 1 is environment intensive and good 2 is labour intensive; these two goods are produced by two industries who are profit maximizers; and the total emission in the economy is $e = e_1 + e_2$. For consumers, this study assume that the environment quality is a public consumption good determined by the amount of emission, where environmental quality $Q = Q(e) = (s(\bar{e}) - s(e))/s(\bar{e})$. The welfare in this economy is $W = min(q_1, q_2, Q)$. Under these assumptions the paper proved that, after environmental regulation, countries specialize on environment-intensive good would suffer a welfare loss from international trade because of the reduction of exports in environment-intensive industries. Environment-intensive industries will face reduction in production and labour.

Siebert (1977) also studied the effect of environmental regulation on environment-intensive goods export using a two-sector economy model where pollutants also treated as a by-product of production. Siebert (1977) has a plenty of similar assumptions as Pethig (1976), such as one commodity is a pollution-intensively good, firms maximize their profits, and the country specializes pollution-intensively goods would implement regulatory policies to increase environmental quality. The differences are that Siebert (1977) assumed the quantity of pollutants rises proportionally with output, i.e., $e_i^p = H_i(Q_i)$; and the resources used in production would also be used for pollution abatement purposes, which indicates the quantity of pollutants reduced in Sector i is $e_i^r = H_i^r(R_i^r)$. Then the net emissions are the difference between emissions generated and emissions reduced, $e = e_i^p - e_i^r$. In Siebert (1977)'s theoretical model, inputs can be used for both production and pollution abatement. After deducting the trade-off between environmental quality and the gains from trade, Siebert (1977) find that for a country exports pollution-intensively goods, its gains from trade are accompanied by environmental degradation. With the implementation of environmental policy in this country, pollution-intensively industries will suffer a reduction in production and trade, which is a similar result as Pethig (1976).

Yohe (1979) also shows the backward incidence of pollution controls using a two sectors model. While, in this model, the author treat pollution behaves as an input rather than a by-product of production. Polluters pay for their use of the environment resources, just, as they pay for labour at the expense of an employee's leisure. Capital, labour, and pollution are three input factors in this linearly homogeneous production functions. McGuire (1982) develops an approach which can incorporate regulation into the theory of production, distribution, and trade. In its analysis of production function, they conclude that the effect of regulation on other cooperating factors is equivalent to neutral technical regress, i.e. negative progress. They even proved that if production factors are free flow across borders, regulation policies will drive out regulated industries from the regulated economy to the less regulated economy. Cobb-Douglas production function and CES production function are took as an example to clarify the equivalence between regulation and negative neutral technical progress.

2.1.2 Empirical literature on proving the neo-classical theory on environmental economics

Empirical literature supports the neo-classical theory from various lines. Gray (1987) find that US environmental regulation reduce productivity growth in the average manufacturing industry by 0.44% per year. Haveman and Christiansen (1981) hold that the environment regulation contributes to the slowdown in productivity growth in the US economy during the 1970's. Ryan (2012) evaluate the welfare cost of US environment regulation through a dynamic model and two-step estimation. They find that the regulation significantly increased the sunk cost of entry and brought a loss in product market surplus. Besides evaluate the industrial or welfare cost induced by environment regulations, existing literature also find the negative impact of environment regulation on firm competitiveness or behaviour, like employment (Greenstone, 2002; Walker, 2011), industrial output (Greenstone, 2002), firm productivity (Berman and Bui, 2001; Gollop and Roberts, 1983; Gray and Shadbegian, 2003; Greenstone et al., 2012), and firm location choices (Becker and Henderson, 2000; Henderson, 1996). These researches show the deleterious effects of stricter environmental regulations on firms, which are support for the neo-classical theory.

2.2 Pollution Haven Hypothesis (PHH)

The pollution Haven Hypothesis (PHH) is based on the idea of neo-classical theory that regulated firms will be forced away from their optimal production choice. To achieve a new optimal production condition, existing firms would relocate to a new place with less regulation to reduce their abatement cost; and new firms would also choose a place without environmental regulation to product. The debate among policymakers and economist about whether stricter environmental regulation will drive out existing firms started from the 1970's when developed countries, like US, took more national environmental policies while less regulation in developing countries. PHH, the most commonly used theory in papers related to firm location decisions under environmental regulations, was first proposed by Copeland and Taylor (1994) whose research is about North-South trade under the North American Free Trade Agreement (NAFTA). They predicted that NAFTA would cause Mexico's environmental degradation and the USA's job loss.

Copeland and Taylor (1994) defined the Pollution Haven Hypothesis (Competitiveness Hypothesis) in two ways. One is that for given levels of environmental policy, liberalizing trade or foreign investment rules causes polluting industry (or firms/production facilities) to relocate to countries with weaker environmental policy. And the other is that tightening pollution policy in one country causes the production of polluting industry (or firms/production facilities) to relocate to other countries with weaker environmental policy (Copeland and Taylor, 2004). Brunnermeier and Levinson (2004) also provide three definitions of PHH for later study: economic activity shifts to jurisdictions with less strict environmental regulations; trade liberalization encourages an inefficient race to the bottom (Environmental regulation); or trade liberalization shifts polluting economic activity toward countries that have less strict environmental standards.

2.2.1 Theoretical literature on proving the PHH

Theoretically explaining of firm location decisions under environmental regulation proves the PHH from the market decision view and game theory. Ulph and Valentini (1997) theoretically analyse the relationship between strategic environmental policy and plant location decisions by testing different sectors' firm location choices. Those various sectors are linked by an input-output structure of intermediate production. They considered inter-sectoral linkages between different industries to analyse the incentives for agglomeration of industry and reflect the economy's input-output structure. The model of this paper contains two countries (or markets) and two industries (an upstream sector and a downstream sector) with two firms in each industry. The model reflects a three-stage game. In the first stage, each country's government sets their environmental policies, like emission taxes and profit taxes; in the second stage, all firms make their decisions on which country and how many plants to locate; in the third stage, each firm chooses their output levels, while upstream firms demand is determined endogenously by downstream firms. The purpose of the paper is to find out a sub-game Nash equilibrium for firm location decisions.

Chao and Yu (2007) theoretically examine the effect of trade liberalization on firm ownership, home or foreign, with pollution by-product in a small open economy. On the supply side, they considered a small open economy with two trade goods and two inputs, labour, and capital. The production in this economy will generate pollution emissions as a by-product. To control the emission level, a pollution tax is imposed in the domestic country. On the demand side, consumers' utility is determined by two goods and emission levels. To analysis the inward FDI, they assume that capital is mobile internationally, while labour is not. After deducing the optimal pollution tax and optimal policies, they conclude that after tariff reduction, trade liberalization can induce firm ownership change from domestic to foreign where have lower pollution tax.

Levinson and Taylor (2008) employ both theoretical and empirical methods to analyse and estimate the Pollution Haven Effect. They developed a multi-sector (partial equilibrium) model and re-examined the link between firm abatement costs (commonly used as a proxy for environment regulation stringency in research about the USA) and trade flows from theory and empiric perspective. They find that some important econometric and data issues existing in environmental economic research are responsible for the mixed results produced in those articles. They also criticized that previous research is suffered from both inadequate accounting for unobserved heterogeneity and the endogeneity of pollution abatement cost (PAC) measures.

Kheder and Zugravu (2008) confirm the PHH through a geographic economy model on French firm-level data for a global sample. The geographic economy model has the advantage on dealing with the complexity of FDI determinants, such as production factor endowments (labour, capital, etc.); distance between trade partners, local market size and access to other important markets (market potential of the host country); and cultural, historic, or linguistic connections. Another advantage of this model is that it can help to introduce environmental regulation as a determinant of the location decision. This paper not only considers labour and capital as production factors but also consider pollution as a production factor whose cost is pollution tax established exogenously by the government. This paper's model is based on the classic hypotheses of "the new geographic economy".

2.2.2 Empirical literature on proving the PHH

Empirical studies testing the relationship between firm location choice and environmental policies can be classified into direct measurement and indirect measurement. To test this relationship directly, existing literature use the conditional logit framework of McFadden (1973) to test firms' plant location decisions. A common characteristic of those papers is that their research focuses on the location choice of new plants and factors affecting those location decisions. The advantage of using new plant data is that they are not constrained by sunk cost when making choice and are sensitive to regulations of different regions.

citeauthorHenderson1996 (1996) examines the effect of grand level ozone regulation on 5 polluting industries' economic activity. This research uses the Tobit and conditional Possison model with panel data to estimate U.S. plant location decisions. The dependent variable is the number of plants of different counties from 5 polluting industries from 1977 to 1987. The independent variable used is the attainment status of counties where attainment counties have loss environmental regulation, while nonattainment counties have more stringent regulations.. The result shows that stringent regulation, i.e., a switch from attainment to nonattainment status, lead to improved air quality but also result in polluting industries' exit. As polluting industries in nonattainment countries spread out, fewer plants located in nonattainment areas. This effect is more obvious in dirtier industries.

Becker and Henderson (2000) test the effects of the U.S. Clean Air Act on polluting industries' firm decision including plant locations, births, sizes, and investment patterns. The Clean Air Act divides countries into attainment and nonattainment ones (Becker and Henderson, 2000; Greenstone, 2002). Becker and Henderson (2000) use plant data from 1963 to 1992 and panel conditional Poisson approach for estimation. The dependent variable is the birth of plants from 4 polluting industries. The independent variable used is the ambient ozone attainment status of countries. They conclude that nonattainment countries have fewer plant births in polluting industries, and the reducing birth in nonattainment areas is 26% to 45%. Industries and sectors that have bigger plants are mostly affected.

Another way to empirically test firms' relocation decisions under environmental policies is the indirect estimation of firms' output and input flow (Brunnermeier and Levinson, 2004).

On the one hand, firm production, net export, and emissions are investigated for testing the effect of environmental policies on firm output flow (Brunnermeier and Levinson, 2004). From the PHH standpoint, stringent environmental regulation policies in developed countries pushed their polluting industries plants to relocate to developing countries who own loose policies, which causes raised pollution in developing countries (Gill et al., 2018). Thus, some studies use dirty goods trade, such as steel, iron, non-ferrous metals, paper, pulp, chemical products, and chemical industry, between developed and developing countries to test the PHH, i.e., testing the change of output flow after environmental regulation. Because of developing countries had a comparative advantage in pollution-intensive goods as loose regulation (Greenstone et al., 2012), they are expected to export more dirty goods after the implementation of environmental policies in developed countries.

On the other hand, some literature focus on the effects of environmental policy on inputs for production. They test whether firm inputs movement, such as capital and labour movement across regions, is affected by environmental policies. Testing the foreign direct investment (FDI) flow is a quiet popular measurement among papers focus on capital movement. Using a two-country model of international factor movements, Rauscher (1997) theoretically predicts that the country adopts stringent environmental regulations will drive capital out of it. According to the PHH, dirty industries in developed countries may "relocate" to developing countries in the form of FDI.

Kneller and Manderson (2009) investigate whether pollution intensive FDI prefer to move from countries with stringent environmental regulations to countries with weak environmental regulations. They estimate this issue by using conditional logit model estimation on outward FDI by UK firms. They find that environmental regulation is a significant determinant of pollution-intensive multinational enterprise's FDI location decision, while it is not significant for internationalisation decision.

Rezza (2013) separates FDI into efficiency-seeking (vertical) or market-seeking (horizontal) FDI in Norwegian multinationals' affiliates from 1999 to 2005. They found a significant negative effect of environmental stringency of a host country and its enforcement on multinationals with vertical motives. Efficiency-seeking affiliates located in countries with stringent regulation receive less investment from their parent companies compare to affiliates located in countries with lenient regulation. They also find that as the environmental regulation becomes loose in host countries, the total exports from affiliates to parent companies in Norway have decreased.

In addition to testing the capital movement, some researches pay attention to the effect of environmental regulation policies on the labour movement. Greenstone (2002) use a firm-level panel data analysis to research the effect of federal Clean Air Act regulations on polluting manufacture firms, and the result shows that compared to attainment counties, nonattainment counties lost about 590,000 jobs and $37 billion in capital stock between 1972 and 1987. Walker (2011) estimate the dynamic effects of the Clean Air Act on sector-level and plant-level job employment using a generalized triple-difference (DDD) approach. From sector level and plant level estimation, they proved that the regulation has resulted in significant employment decline.

2.3 Porter Hypothesis (PH)

Contrary to neo-classical theory and the PHH, some studies suggest that environmental regulation is of favourable impacts on the firm performance and competitiveness. They hold that properly designed environmental regulations (especially, market-based policies such as taxes or cap and trade emissions allowances) can 'trigger innovation (broadly defined) that may partially or fully offset the costs of complying with them in some instances (M. Porter, 1990; M. E. Porter and Linde, 1995). Following this Porter Hypothesis (PH), if properly designed, environmental regulations can lead to "innovation offsets" that can not only improve environmental performance, but also partially and sometimes more than fully offset the additional cost of regulation (Ambec et al., 2013). In other words, there may be a "free lunch" for firms under regulated, and also a "win win" scenario for government and corporations.

2.3.1 Theoretical support on the PH

The PH is theoretically proved by the Acemoglu et al. (2012) who build a growth model with environmental constraints to analyses the response of dirty sectors' and clean sectors' technological change to various environmental policies. So, the technical change in their model is endogenously and directly. They hold that temporary emission tax or technology subsidies can bring innovation to clean sectors, which leads to sustainable growth in the long run. They also emphasize the combination of "carbon taxes" and research subsidies and government intervention.

Simon (1947) builds an alternative model about the R&D process. "In this "evolutionary" model, firms use "rules of thumb" and "routines" to determine how much to invest in R&D, and how to search for new technologies (Jaffe et al., 2003)." Because they assume that firms are not always optimizing, the evolutionary model uncovers the consequence that a new external policy constraint, such as a new environmental rule, may fail to reduce firm profits. So environmental regulations can lead to "innovation offsets" that will not only improve environmental performance but also partially and sometimes more than fully offset the additional cost of regulation (Ambec et al., 2013).

2.3.2 Empirical works on weak version of PH

The empirical evidence of proving the Porter Hypothesis can be divided into three strands, the weak version, the strong version, and the narrow version of PH (Jaffe and Palmer, 1997). The weak version contends that environmental regulation only brings firm innovation but has no effect on firm competitiveness and productivity. For reducing additional costs brought by environmental regulation, firms would search for new technology to improve production. But it is unnecessary for firms to increase their overall innovation capacity and productivity (Jaffe and Palmer, 1997). The strong version posits that firms operate in imperfect markets, so they are not always catching the maximal profit conditions, and not always detecting profitable opportunities. Thus, in addition to searching new ways, new products, and new production processes for complying with environmental regulation, firms are also forced to develop new technological opportunities which can increase their profits and productivity. Under such scenario, the regulation becomes a "free lunch" for firms. Environmental regulation spurs firms' innovation that further results in higher productivity, which means an increased competitiveness for firms (D'Agostino, 2015). Finally, the narrow version notes that only certain regulation policies spur innovation (Jaffe and Palmer, 1997). Especially, flexible and market based regulatory policies are more likely to stimulate firms to innovate, rather than command and control policies that sets technological or performance-based standards, such as the "end of pipe" pollution control (D'Agostino, 2015).

To estimate the weak version of PH, R&D and patents (Jaffe and Palmer, 1997) are commonly used as dependent variables or proxies for innovation, while pollution abatement investments and Environmental Regulation Stringency are used as independent variables. Jaffe and Palmer (1997) used R&D and patents as dependent variables respectively to test the effect of environmental regulation on firm innovation. They find that the PH effect lag to environmental regulation for about 4 to 5 years.

Exciting facility level literature find evidence that environment related R&D and technologies is positively affected by the perceived environmental policy stringency (Horbach et al., 2013; Johnstone and Labonne, 2006; Lanoie et al., 2011). Comparing firms in same industry across different countries, Lee et al. (2011) find domestic US firms, under more stringent regulation, are more innovative than foreign firms.

A group of empirical studies using industry level data have also found a positive relation between environmental investments (both R&D and capital) and more stringent environmental regulation (Jaffe and Palmer, 1997; Kneller and Manderson, 2012); while some studies hold inter sectoral spillover as a mechanism to explain why environmental regulation can induce innovation (Corradini et al., 2014; D'Agostino, 2015). However, Kneller and Manderson (2012) found that environmental R&D would crowd out non environmental R&D. As capital is limited, environmental investment may have a crowd out effect on other investments (more profitable innovation).

In firm level research, D. C. Popp (2002, 2001) focuses on energy prices and energy related innovation. In the first paper, he argues that increased energy prices lead to the rise of patenting in energy related fields. This effect mostly occurs within a few days and then fading over time. D. C. Popp (2001) argues that the reason for fading is diminishing returns to R&D. In the second paper, D. Popp (2002), "he attempted to decompose the overall reduction in energy use that is associated with changing energy prices between the substitution effect movements along a given production frontier and the induced innovation effect movements of the production frontier itself induced by the change in energy prices (Jaffe et al., 2003)." He utilized energy related patents as a proxy for energy innovation and uncovered that about one third of the energy use action brought by prices is related to induced innovation, while the other two thirds are related to factor substitution.

2.3.3 Empirical works on strong version of PH

Literature about the estimation of the strong version of PH focus on investigating whether environmental regulations could increase firm competitiveness. The dependent variables used are usually a measurement of competitiveness, such as trade, productivity, and financial performance. The independent variables used are different kinds of proxies of environmental regulations. Direct proxies among them include pollution abatement investments and environmental related tax, and indirect proxies, mediated by innovation, contain innovation and R&D induced by environmental regulation. But this topic is not of a consensus.

On the one hand, positive effects of environmental regulation on productivity growth are found by Hamamoto (2006) and C.-h. Yang et al. (2012) using industrial level data. Stavropoulos et al. (2018) proved a U-shaped relationship between environmental regulations and Industrial competitiveness in China. Only innovation could activate this U-shaped relationship, which can be triggered by stringent regulations and well-designed policies. At the firm level, evidence support the positive effects of environmental regulation on productivity (Vlist et al., 2007) and economic performance (Rennings et al., 2006) were found. Huang and Liu (2019) investigate the impact of environmental policies on firm performance denoted by firm productivity and firm exports. They proved that environmental policies promote firm productivity but with a lag effect. And there is a U-shaped relationship between environmental regulation and firm export.

On the other hand, however, Lanoie et al. (2008) found a negative impact of regulations on industry productivity. They also found that less polluting industries are more likely to support the Porter Hypothesis, rather than high polluting industries. Gollop and Roberts (1983), Kolstad and Turnovsky (1998) and Yaisawarng and Klein (1994) focus on the influence of firm productivity and investment affected by environmental regulation. They find the connection between inhibiting investment and productivity growth, which could be seen as evidence about induced innovation effects are either small or are outweighed by other costs of regulation. Greenstone (2002) found that air pollution regulation policy has a statistically significant but limited impact on overall costs, which shows a small negative productivity influence.

By combining both weak version and strong version, Lanoie et al. (2011) first proposed the Porter Hypothesis causality chain using "two stage least squares" method using OECD firm data. Costantini and Mazzanti (2012) also tested both the strong and narrowly strong versions of the Porter hypothesis, to understand if such a virtuous cycle is confined into the environmental goods sector or it spreads out through the whole economic system. Using Chinese pollution intensive corporations panel data from 2007 to 2012, Zhao and Sun (2016) explore the Poter Hypothesis mechanism empirically and find that the environmental regulation policy has a significant positive impact on corporations' innovation, but the influence of environmental regulation policy on corporation competitiveness is insignificant negative.

2.3.4 Connections between PHH and PH

The connection between the Pollution Haven Hypothesis and the Porter Hypothesis can be summarized into two points. First, PHH is a static theory, which is transient, while PH is dynamic. Mani and Wheeler (1998) observed that the Pollution Haven effects are expected to be transient, as pollution intensity has an elastic response to income growth in rich countries and some countries tend to lag in pollution control efforts. PHH studies that focus on developing countries have showed that as developing countries income increase with FDI inflow, their environmental regulations become more stringent. So, developing countries' competitiveness of loss regulation is temporary, which means the PHH should only be a transient phenomenon. At the same time, PHH is based on the analogy of traditional static comparative advantage perspective. PHH Empirical studies' firm relocation and environmental regulation policies always occurred at the same time, which means that firm behavior operates at t0 and regulation also issues at t0. So, PHH has a narrow static perspective on firms' reaction to ER (M. E. Porter and Linde, 1995).

Different from PHH, PH asserts that from a dynamic point of view, environmental regulation stringency can inspur efficiency innovation and guide production procedure to be more environment friendly (M. E. Porter and Linde, 1995). So according to PH, if a regulation policy issued at t0, then regulated firms' innovation behavior should occur in a lag time, i.e., t1, t2, or t3 and so on. By introducing lags of three or four years between changes in the severity of environmental regulations and their impact on productivity, Lanoie et al. (2008) found that stricter regulations led to modest long term increases in productivity. Innovations might take several years to develop, and capital expenditures are often delayed for a few years as budgetary cycles and building lags (Ambec et al., 2013).

Second, PHH follows the assumption of profit maximizing firms, while PH is incompatible with it. PH rests on the idea that firms face imperfect information and market failures that force them to ignore profitable opportunities. "The possibility that regulation might act as a spur to innovation arises because the world does not fit the Panglossian belief that firms always make optimal choices (Porter and Linde, 1995)."

2.4 Environmental Regulation and Firm Productivity

From the early 1970s, some studies have focused on the effects of environmental regulation on productivity (Haveman and Christiansen, 1981). Proponents of the neo-classical theory hold that the environmental regulation has deleterious impact on firm productivity. One reason is that firms are force to away from their profit maximizing choice. Another reason is that government regulations always require firms to use inputs directly for regulatory compliance, like using scrubber to reduce gas emissions, operating and maintaining desulfurization equipment, and extra employees for monitoring pollution abatement equipment. As the productivity measurement do not distinguish between inputs used for traditional output production and inputs for pollution abatement actions, neo-classical microeconomic analysis believe that environmental regulation will reduce firm productivity. Most empirical research supports stringent environmental regulation would have adverse effect on firm productivity.

Barbera and McConnell (1990) develop a theoretical approach to measure the impact of environmental regulation on industries' total factor productivity growth. They estimate the U.S. five most affected polluting industries' total factor productivity and the direct and indirect productivity effects of environmental regulations. Their model separated conventional inputs of labour, capital, energy, and materials from abatement capital which is used as an input to control pollution. In this model, they distinguished the effects of required abatement capital on industries' total factor productivity growth into direct effect and indirect effect. The direct effect is measured by the direct cost of the abatement equipment, and the indirect effect is calculated by a translog cost function for industries' output production. The conclusion is that the effect of environmental regulation on TFP is fairly small. The total effect of environmental regulation is to reduce all five industries' total factor productivity by 10% to 30%, while the indirect effect is smaller than the direct effect from 1960 to 1980.

Boyd and McClelland (1999) calculate the loss of paper plants productivity brought by environmental constraints. They wanted to use a general measurement of productivity that contains environmental regulation to figure out whether U.S. manufacturing plants will reduce input use and pollution output under environmental constraints. They choose the paper industry because it is a capital intensive, energy intensive, and pollution intensive industry. By using plant-level data from U.S. Longitudinal Research Database (LRD) in 1988-1992, Boyd and McClelland (1999) investigate plant performance which is measured by input distance function of productivity and data envelopment analysis (DEA) method. The conclusion is that environmental regulation reduces production by 9%, and 25% of the contribution belongs to pollution abatement capital constraints.

Gray and Shadbegian (2003) investigate the impact of environmental regulation on the productivity of plants with different vintage and technology. They wanted to figure out whether plants with different ages and different technologies in the same industry spend different abatement costs when facing environmental regulation. The data they used, including 116 pulp and paper mills' vintage, technology, productivity, and pollution abatement operating costs data, is from the annual

Census Bureau information and the Pollution Abatement Costs and Expenditures (PACE) survey from 1979 to 1990. The estimation model used in this paper is a long linear Cobb–Douglas production function model that has three inputs. The result shows that plants have a negative relationship between pollution abatement costs and productivity levels, i.e., more pollution abatement spends accompanied with less plant productivity. For plants' technology, integrated mills' productivity is much more affected by abatement costs, about 9.3%, while non-integrated mills' productivity is affected less (0.9%). For plants' vintage, the effect of abatement costs on older and newer plants' productivity is the same.

Lanoie et al. (2008) empirically test the negative impact of environmental regulation on TFP in the Quebec manufacturing sector. They bring one-year, two-year, and three-year lagged variables into the linear regression to capture the dynamics of the Porter Hypothesis. The result also shows that polluting sectors and sectors who are exposed to international competition have shown a more obvious negative effect environmental regulation on sector's TFP.

Greenstone et al. (2012) estimate the impact of air quality regulations on U.S manufacturing plants' productivity denoted by plants' total factor productivity (TFP) levels. This paper focuses on the 1970 Clean Air Act Amendments in the U.S. Based on these amendments, the Environmental Protection Agency (EPA) established separate air quality standards for four criteria pollutants, carbon monoxide (CO), tropospheric ozone (O3), sulphur dioxide (SO2), and total suspended particulates (TSPs), which is tested separately by Greenstone et al. (2012). This paper divide samples into two groups and make an important independent variable whether a sample plant located in a nonattainment or attainment county because every U.S. county annual nonattainment or attainment designations for each of the four pollutants. Related pollutant emitters located in the county who is nonattainment will face more stringent regulatory oversight.

Using plant-level microdata, Greenstone et al. (2012) assume a Cobb-Douglas production function for manufactures. To test dynamic effect, they introduce lagged nonattainment status in the specification including one and two years of lagged attainment status. They find that a year's nonattainment designation has at least three years' impact on a plant's productivity. This finding is consistent with the hypothesis that the nonattainment designation results in firms investing in pollution abatement equipment which cannot increase firms output or productivity. The final result of this paper is that for surviving polluting plants, stringent air quality regulations lead to 2.6 percent decline in TFP; for specific pollutants, ozone regulation has large negative effects on productivity, and carbon monoxide regulations have positive effects on productivity. The annual economic cost of regulations on manufacturing plants is about $21 billion, which is 8.8% of the manufacturing sector profits of that period.

On the contrary, there are also studies find evidence that environmental regulation can benefit firm productivity, which supports the Porter Hypothesis. Berman and Bui (2001) studied the effect of air quality regulation on the productivity of the oil refineries in the U.S during the period 1979 and 1992. The Pollution abatement control expenditures (PACE) is used to denote the environmental regulation. Their regression uses plant-level data and has two steps. The first step is to estimate the effect of regulations on abatement costs. While the second step is to estimate the impact of regulations on plant productivity. They found that environmental regulation increased the investment of abatement cost and has improved regulated area refinery plants' productivity, while in the same period refinery productivity decreased in other regions.

2.5 Environmental Regulation and Firm Profitability

In studies about the effect of environmental regulation on firm profitability, proponent of the Neo-classical Theory and the Porter Hypothesis also cannot achieve a consensus. Literature supports the neo-classical theory hold that environmental regulation reduces firm profitability level that is harmful for the economy.

Brännlund et al. (1995) use simulated data to research the impact of environmental regulations on firm profits in the Swedish pulp and paper industry. They developed a non-parametric programming model of the technology to calculate the regulated and unregulated profits for each mill and a short-run profit maximization model to evaluate the cost of regulation. The empirical result shows that most firms faced less severe regulation burden in 1990, while some firms do experience reduced profits under regulation.

Alpay et al. (2002) theoretically examine the impact of pollution regulation on the profitability of Mexican and U.S. food industries. In this paper, they built a total factor productivity model to exploit the profit function which can show the relationship between primal and dual productivity growth, technical change, and capital quasi-fixity. And then, the empirical result shows that U.S. pollution regulation has no significant effect on U.S. food manufacturing's profitability or productivity growth, while Mexico's environmental regulation leads to their manufacturing's reduced profitability.

Rassier and Earnhart (2015) empirically studies the effect of environmental regulation on profitability. The policy they focused on is the Clean Water Act regulation in the U.S. The data used is firm-level financial performance data. They use permitted wastewater discharge limits imposed on specific facilities to measure the water regulation level and the return on sales (i.e., the ratio of sales over profits) to measure the profitability of publicly held firms in the chemical manufacturing industries. By doing linear specification and panel data analysis, they conclude that more stringent water regulation reduces industries profitability. Through the method of reinterpreting profitability in terms of sales and costs, they find that under certain scale levels, more stringent water regulation increases firms' costs. To be specific, a 10% tightening of the regulation leads to a 1.7% reduction of scales. So, their research against the strong version of the Porter Hypothesis.

Greenstone (2002) is about the impact of the U.S. Clean Air Act's impact on polluting manufactures. It shows the relationship between environmental regulations and industrial activity, including the growth of employment, capital stock, and shipments. Greenstone (2002) mentions that in the absence of a situation that environmental regulations are randomly assigned to plants, an experiment that similar plants face different levels of regulation could be used in their research. So, this research focuses on the U.S. Clean Air Act and divides samples into nonattainment or attainment ones. The data used is from the five quinquennial Censuses of Manufactures from 1967 to 1987, which is manufacturing level microdata. The estimation method for this paper is fixed effect regression using the growth rate of firms' activities, such as the growth rate of employment, capital stock, and the value of shipments. The final result shows that during 1972 to 1987, the first 15 years when the Clean Air Act takes force, nonattainment counties (relative to attainment ones) lost approximately 590,000 jobs, $37 billion in capital stock, and $75 billion (1987 dollars) of output in pollution-intensive industries. Regulations on the new nonattainment counties will bring employment, investment, and shipments decrease in polluting industries.

However, some literature finds the positive relationship between environmental regulation and firms' profitability, which supports the PH empirically.

King and Lenox (2002) test the direction and significance of the relationship between different kinds of pollution regulation instruments and firm profitability. They disaggregate pollution reduction into different factors, waste prevention, and onsite and offsite waste treatment, and test each factors' profitability effect and where profit lies for firms. The indicators they used to denote fanatical performance is return on assets (ROA) and Tobin's q that is calculated by the ratio of the sum of firm equity value, the book value of long-term debt, and net current liabilities divided by total assets. For data, 2,837 firm level observations from 1991-1996 were used in the research. In their analysis, they found that only waste prevention can lead to financial gain and support for the “pays to be green” hypothesis. They also find that “the more a firm prevents waste, the higher its financial performance”, which is where the benefits of waste prevention come from.

From the resource-based view of the firm, Russo and Fouts (1997) imply that environmental performance and economic performance has a positive relationship that could be moderated by industry growth. They also proved that high growth industries are related to higher returns to environmental performance. They test 243 firms in 1991 and 1992. The environmental regulation is denoted by independently developed environmental ratings, and the firm performance is denoted by return on assets (ROA). From the resource-based view of the firm, this paper analysed two kinds of policies, the compliance strategy and the prevention which is an approach to source reduction and process innovation. Their result supports "it pays to be green" hypothesis.

Rassier and Earnhart (2015) estimate the effect of clean water regulation on the profitability of chemical manufacturing firms in the U.S. They separated the profitability into actual profitability and investors’ expectations of profitability, and assess the effects of environmental regulation on them. The actual profitability is captured by an accounting-based measure of profitability, return on sales (profits divided by sales). Accounting-based measures of profitability can reflect a firm’s financial statements. Accounting-based measure of profitability reflects a firm’s financial statements. The expected profitability is captured using Tobin’s q, market value divided by replacement costs, which is a market-based measure of financial performance. As an independent variable, environmental regulation is measured by the permitted wastewater discharge limits for biochemical oxygen demand (BOD) and total suspended solids (TSS). Their estimation results show that more stringent clean water regulation, which is denoted by BOD and TSS’s lower permitted discharge limits, leads to higher chemical firms’ returns on sales. Specifically, a 10% decrease in the average firm’s permitted discharge limit will lead to a 20% increase in a firm’s return on sales. However, Tobin’s q value of chemical firms is reduced by more stringent regulation. 10% decrease in an average firm’s permitted discharge limit causes a 0.0076% reduction in the average firm’s Tobin’s q ratio, which is about $1.8 million.

Khanna and Damon (1999) evaluate the effect of the voluntary environmental instruments on firm short run and long run economic performance. Different from other papers, the policy analysed in this paper is a voluntary environmental instrument, firms individually decided whether to follow the rules, that is the U.S. 33/50 Program. They focus on its impact on the U.S. chemical industry from 1991 to 1993 using from level data. The estimation method in this paper is a two-stage generalized least-squares method that could control self-selectivity bias and firm specific characteristics. The first step of estimation is using a Probit model to investigate the determinants of firms' participation decisions. The second step of this estimation examines the Program's impact on firms' releases and firms' short run and long run economic performance. They use return on investment (ROI) and the ratio of Market Value of a Firm-Book Value of Assets divided by Sales (EV/S) as a dependent variable to indicate economic performance. The empirical result shows that rational economic self-interest decided the motivation of firms' participation decisions. Expected gains and fear of high costs of compliance future mandatory environmental regulations lead to firms' incentives to participate in the 33/50 Program. Their analysis demonstrates that the Programme significantly reduced firms release. They also find that the effect of the Programme on firms' ROI is negative. In the short run, the cost of regulation cannot be offset by gains from efficiency. But, in the long run, investors anticipate that this Programme could improve firms' profitability.

Lanoie et al. (2011) test three different versions of the Porter Hypothesis, weak, narrow, and strong version. The dataset used in this paper includes 4200 facilities in seven OECD countries, and the data was collected through a postal survey in early 2003. From the conceptual framework, they explain the reason why environmental policy can directly or indirectly influence the three dependent variables used, Environmental R&D, Environmental Performance, and Business Performance. They assume that Environmental R&D which is a 0,1 variable affects the other two dependent variables. By using three different estimation approach (Probit approach, two stage least square, instrumental variable Probit approach) for three different equations, they find strong evidence to support the weak version of the PH, limited evidence to support for the narrow version, but no evidence to support the strong version.

2.6 China specific research

2.6.1 Empirical Studies for the PHH and Neo-classical Theory

In China specific research, some researchers find evidence to support the PHH. Q. Wang et al. (2015) use the conditional logit model to estimate the entry decision of Chinese firms that are regulated by environmental policies. They prove the PHH by estimating the entry decision of Chinese firms that are regulated by China's Environmental Protection Law. This is a firm level data analysis using data from the NBS dataset from 2006 to 2008. They investigate the entry decision of firms with different ownership and industries during various policy regimes. They use the removal rate of SO2, SO2 abatement divide the sum of SO2 abatement and final SO2 discharge, to denote environmental regulation. Their conclusion is that there is a positive relationship between environmental regulation and firms', but private-owned enterprises, foreign-owned enterprises, and collective owned enterprises are more likely to enter loss environmental policies region from 2003 to 2005, while show reversed pattern from 2006 to 2008.

Greaney et al. (2017) uncover that under stricter pollution control foreign firms with a larger size, higher productivity and exporting are less likely to relocate to new regions compare to domestic firms in China. The paper, focusing on the Two-Control-Zone (TCZ) pollution control policy, estimated the exit rate of firms located in TCZ zones from the city level and firm level respectively.

Shen et al. (2019) directly prove the Pollution Haven Hypothesis from the prefecture level. They focused on the impact of the migration of pollution-intensive industries (PIIs) on local environmental efficiency in China's Guangdong Province from 2001 to 2014. The Data Envelopment Analysis (DEA) model was used to calculate environmental efficiency of different cities in Guangdong. After PMG/ARDL regression analysis, environmental efficiency has a negative relationship with pollution-intensive industries migration in areas the industries moved out. They proved the Pollution Haven Hypothesis by showing that pollution industries moved from the Pearl River Delta to peripheral Non-Pearl River Delta areas.

Wu et al. (2017) investigate the effect of the 11th Five-Year Plan's water pollution reduction command in China on new polluting firms' location choice. In 2007, "Pollution Reduction Performance Assessment" was implemented by the MEP. According to the assessment, governments fail to meet the pollution reduction mandates would face a reduction of their government officer's rank as a punishment. So, the 11th Five-Year Plan's water pollution reduction mandates researched in this paper is a very effective environmental policy. The firm level data used in this research containing 31,380 new polluting firms of 31 manufacturing industries from 2005 to 2010. All these firm level emission data are from the Environmental Statistics (ES) dataset. The estimation method in this paper is the conditional logit model. The result shows that there is a significant relationship between pollution reduction mandates and new polluting firms' location choice. For foreign polluting firms, the relationship is negative. For domestic polluting firms, after the implementation of the "Pollution Reduction Performance Assessment", domestic polluting firms changed their location choice from coastal provinces to western provinces.

J. Yang et al. (2018) examines new manufacturing firms' location decisions under environmental regulation in Jiangsu, China. The firm level emission data used is from the Environment Statistics (ES) database of China's Ministry of Environmental Protection (MEP) since 2006 to 2010. Three different environmental indicators are used to test the Pollution Haven Hypothesis. J. Yang et al. (2018) adopts the McFadden conditional logit model to examines the relationship between new firms' location choice and environmental policy. Their results against the PHH and shows that new firms tend to locate in the northern Jiangsu who has higher pollution abatement cost.

Some empirical papers test Chinese firm location decisions useing indirect measures. Guo et al. (2010) use China-U.S. international trade to embody the CO2 emissions leak and proved the PHH by international trade. The input-output model is used to support their research. They show that, in 2005, by consuming input goods from China, U.S. emissions reduced but global CO2 emission increased. China- U.S. international trade has increased global CO2 emissions. López et al. (2013) also develop an input-output framework to analysis whether bilateral trade between Spain and China has increased global emissions. Similar to Guo et al. (2010), they find that Spain–China trade relationship increased global emission level because Spain input more pollution intensive goods from China. Indirectly proved the PHH, they show that Spain pollution industries moved to China through international trade.

By investigating FDI, some paper using capital input movement to prove the PHH indirectly. Cai et al. (2016), Zhang and Fu (2008) and J. He (2006) prove the negative effect between FDI flow and China environmental regulation stringency, using firm-level data, provincial level data, and industrial level data respectively. Cai et al. (2016) investigate whether multinational firms prefer to invest and product in places with less stringent regulations in China. They compared firms choose to locate in cities implementing TCZ policy and firms choose to locate in cities without TCZ policy. To tackle the potential endogeneity of environmental regulation, this paper uses an instrumental variable approach, using the ventilation coefficient as the instrument for the TCZ status, and the difference-in-difference (DID) method. The main method used is the DD analysis and difference-in-difference-in-difference (DDD) analysis. The data used in this paper is from two large-scale firm level data sets. One is two censuses data sets covering all establishments in 1996 and 2001, and the other is the survey data on foreign invested enterprises (FIEs) covering more than 75% of total foreign firms in China in 2001. These data could show the FDI flow in China from 1996 to 2001. Finally, they find that a one-standard-deviation increase in pollution intensity leads to 8 percentage points decrease of FDI flows, which shows the negative effect of environmental policy and confirms the Pollution Haven Hypothesis. Meanwhile, they find that multinational firms who have tougher environmental policies than China are insensitive to the Chinese toughening environmental policy, TCZ policy, while multinational firms who have looser environmental policies than China show strong negative responses.

Zhang and Fu (2008) identified the intra-county pollution haven effect in China, by estimating provincial socioeconomic and environmental data. They try to figure out whether intra-county differences in environmental regulation will affect FDI location choice in China. The result shows that FDI prefers to locate in regions with loose environmental policies.

J. He (2006) uses the simultaneous model to study the FDI–emission nexus in China. He explored both the dynamic recursive FDI entry decision and the linkage from FDI entry to final emission results by combining the composition effects and technique effects. The data used is industrial level data covering 29 Chinese provinces from 1994 to 2000. Different from other research, he treats environmental regulation as an endogenous variable to study the FDI–emission nexus and prove the negative relationship between FDI and emission. Ren et al. (2014) apply a two-step GMM model with input-output analysis to test the impact of FDI and international trade on China's CO2 emission. Their data include 18 industries of China from 2000 to 2011. The result shows that China has become a pollution haven of its foreign consumers and China's growing trade surplus leads to the rising emissions in China.

2.6.2 Empirical studies for the PH

In research about Chinese environmental regulations, however, some literature proves environmental regulation have a favourable effect on firms. X. Wang et al. (2019)confirm the Porter effect and against the PHH effect at the county level using the conditional logit method. They do not focus on a specific environmental policy but pay attention to the name list of the most polluting firms from 2010 to 2015 in China. The firm level data, including name and location, is from the Nation Key Monitoring Enterprises (NKMEs) which is issued annually from the Ministry of Environmental Protection. It is collected by the Environmental Protection Bureau of each province, and the emission of these listed firms accounted for 65% of total pollution emission. Using this annually firm level data, X. Wang et al. (2019) obtain location place information of new firms and relocation information of existing firms. They conclude that pollution firms located in the eastern area of China invest more in provinces with stringent environmental policies, while north-eastern region's firms react the opposite.

Milani (2017) examines empirically the impact of environmental regulations on R&D intensities and R&D expenditures in 21 manufacturing industries in 28 OECD countries from 2000 to 2007. The result proved that regulated industries innovate relatively more as environmental regulations increase in stringency. They also found that more pollution intensive firms innovate less and industries who are less "footloose" innovate relatively more under stringent environmental policies, which means immobility factors are much more important on R&D intensity than pollution factors.

Tan et al. (2013) find that CO2 emission reduced during China-Australia bilateral trade from 2002-2010, which against the PHH. At the same time, they find that the scale effect contributes more to the increase of CO2 emissions caused by the bilateral trade, while the composition effect is the major driver of the reduction of CO2 emission.

2.6.3 Chinese Environmental Regulation and Firm Productivity

In China specific research, G. He et al. (2018) shows the cost of stricter environmental regulation, which support the neo-classical theory. G. He et al. (2018) estimates the effect of water quality regulation on firm productivity using Geographic Regression Discontinuity (GRD) approach. They focus on the geographic location of water monitoring stations and divide firms into geographic upstream firms and downstream firms of water monitoring stations. As the monitoring station only captures upstream firms' emissions, environmental regulation tend to be more stringent for upstream firms than downstream ones. They found that upstream polluting firms have a 27% reduction in TFP and a 48% reduction in emissions comparing to downstream firms. And this phenomenon only exists in polluting industries. They calculated that the China's water-pollution abatement target (2016-2020) would cause approximately one trillion Chinese Yuan loss in industrial output value. In 2003, President Hu proposed the "Scientific Outlook of Development" (SOD). Then the original "National Environmental Quality Monitoring Network Surface Water Monitoring System" (NEQMN-SWMS) issued in 1993 was updated into a new version in 2003. So, the new NEQMN-SWMS is the policy this paper focusing on. It's worth noting that when investigate the relationship between environmental regulation and productivity (calculated by OP method and LP method), this paper only used the Annual Survey of Industrial Firms (ASIF) dataset without emission data; while when investigate the relationship between environmental regulation and firm emission, this paper used firm-level emission data from China's Environmental Survey and Reporting (ESR) database. They also present a theoretical framework to uncover how environmental regulation affects firm productivity negatively.

Much more literature, however, shows the Chinese environmental regulation has no effect or positive effect on firm productivity. C. Wang et al. (2018) is about the impact of the Chinese central government's environmental policy, the "three rivers and three lakes basins" (3Rs3Ls) policy, on related firms' emissions of chemical oxygen demand (COD) and firms' productivity. They found that this regulation policy leads to small and heavily polluting firms closed, but it had no significant effect on surviving firms' productivity results from the ineffectiveness of the 3Rs3Ls on reducing firms' COD emissions. This paper is the first one using Chinese firm-level emission data to study the impact of water regulation policy on manufacturers' productivity. To test the relationship between water regulation policy and firms' productivity, this paper does the basic regression using TFP which represents productivity as a dependent variable, and the interaction of COD and whether the policy was issued as an independent variable. The result shows that the water quality regulation policy had no statistically significant effect on the productivity of surviving firms in major COD-emitting industries in the 3Rs3Ls basins during the study period (1998-2007).

C. Wang et al. (2018) provide two possible explanations for the basic result: the regulation policy did not successfully force firms to reduce emission that connected to productivity; or as Porter Hypothesis, stringent environmental policy promotes firms to innovate new technologies to reduce their emission, which finally improved firm's productivity. To test the first explanation, C. Wang et al. (2018) estimate an emission function that links a firm's COD emission level to its water quality regulation status, using emission value as the dependent variable. To test the second explanation, C. Wang et al. (2018) estimate a production function that takes emission as an input for producing output, here using output growth rate as a dependent variable and emission value as an independent variable. If COD emissions are a by-product of producing output under current production technology, then the reduction of COD emissions will accompany the decline of output level, at least in the short term. Finally, their result supports the first explanation.

Huang and Liu (2019) investigate the influence of environmental regulation on firm productivity and firm exports. They test this relationship theoretically and empirically. They first introduced environmental regulation into a Melitz-style model which includes customer perspective, producer perspective, and deducing the equilibrium in a closed economy and the equilibrium in an open economy. And then they test the model using firm level data from 2005 to 2009. The dataset empirical analysis used is from the Annual Surveys of Industrial Production conducted by China's National Bureau of Statistics (NBS). There is no specific environmental policy in this paper but using TCZ policy in a robustness check. By using reduced form regression, they conclude that environmental regulation has a positive lagged effect on firm productivity and a U-shaped with firm exports. But, as China is to the left part of the U-shape, environmental regulation harms firm exports.

From the industrial level by province, Zhu and Ruth (2015) test the overall effects of provincially differentiated regulation of energy saving in China on industrial activities. This research investigates the association between environmental regulation and changes, such as output, input, factor substitution, and productivity, in industrial sectors, which can comprehensively understand the policy effect on industrial location, factor allocation, and technical change. Zhu and Ruth (2015) hold that the advantage of researching China policy within provinces (relative to multinational policy) is that market barriers are lower domestically within provinces so that industries changes caused by environmental regulation is more obvious and easier to be observed. The policy in this paper is China's Energy Saving Policy in China from 2005 to 2010. The data used in this paper are from different kinds of Chinese Statistical Yearbooks, and the dataset consists of 20 two-digit manufacturing sectors across 29 provinces. They conclude that energy saving policies initially cause the deduction on energy-intensive industries' output and productivity, and then this effect passed on to other industries via the capital market and energy intensive goods market. They also find that under stringent regulation, energy-intensive industries tend to be capital-intensive, can recover their productivity more quickly, and increase export rates, while other industries become more labour-intensive, hard to recover, and low export rates. So, in their opinion that because of capital investment and factor reallocation, Chinese environmental policy could improve industrial energy efficiency with no loss in competitiveness and no carbon leakage.

From the province level, Stavropoulos et al. (2018) also test the association between environmental regulations and Industrial competitiveness in China from 2001 to 2010. They use superior productivity to denote different industrial's competitiveness. The data they used is from different kinds of Chinese Statistical Yearbooks, and the dataset used covers 30 provinces. Using the spatial regression model, Stavropoulos et al. (2018) identify the U-shaped relationship between environmental regulation and productivity.

3 Background of the Two Control Zone Policy (TCZ)

3.1 Description For the TCZ policy

China's long-term reliance on coal-burning for energy lead to two environmental problems, air pollution and acid rain. In 1993, 62.3% of Chinese cities' annual average ambient SO2 concentration values exceed the national Class II standard, 60 ug/m3 (Cai et al., 2016). The acid rain area increased from 1.7 million km2 in the early 1980s to more than 2.7 million km2 in the mid-1990s. It expanded from south-eastern China to south of China, east of the Qinghai-Tibet Plateau, and the entire Sichuan Basin (Hao et al., 2001). In central of China, Changsha, Guangzhou, Nanchang, and Huaihua, above 90% frequency of acid rainfall, are cities the most seriously affected by acid rain (Pu et al., 2000). According to the (State Environmental Protection Administration. Action Plan for Integral Prevention and Control of Acid Rain and SO2, Environmental Protection 1998, 4, 4), the acid rain caused nearly 12 billion dollars economic loss in 1995, which accounts for 2% of the GDP.

Thus, in the late 1970s and early 1980s, the central government of China ambitiously entered the business of restricting the emission of pollutants into the air.

Since 1982, the State Environmental Protection Administration (SEPA) which is the original National Environmental Protection Agency (NEPA) has stipulated acceptable SO2 ambient concentration levels. A pilot taxation policy that aims to levy pollution fee on coal burning industries' SO2 emissions was founded by the State Council in 1992. In August 1995, the 15th meeting of the Standing Committee of the National People's Congress amended the 1987 Air Pollution Prevention and Control Law of the People's Republic of China (APPCL). This modification includes a new chapter which is about how to manage the air pollution and SO2 emissions result from coal combustion. This amended law's Article 27 first appeal to the mapping of Two Control Zones. To match with the Article 27, the SEPA issued the new emission standards in May 1996, the total emissions load control (TELC), which is a method regulating discharge by control the total loading of a pollutant, instead of controlling the concentration level of that pollutant (Decision on certain Issues concerning Environmental Protection). Not until January 1998, SEPA's The Official Reply of the State Council Concerning Acid Rain and SO2 Pollution Control Zones (the 1998 Reply hereafter) was approved by the State Council, which is the official approvement of the "Two-Control-Zone Policy" (TCZ policy). After enacting the TCZ policy in 1998, the SEPA started the process of issuing the National Action Plan for Acid Rain and SO2 Control (the TCZ action plan) in 1999. Local government who has the jurisdiction over the region or city has the responsibility to implement the policy and emission standards set by the central government.

A rough introduction about the SO2 control zone and the acid rain zone is mentioned in The Article 27 of the amended APPCL. The SO2 control zone city means areas whose yearly average ambient SO2 concentrations outgoing the grade two air quality standards and the daily average ambient SO2 concentrations exceeding the grade three air quality standards (State Environmental Protection Administration, 1998). The acid rain zone city means places where the monitored PH values of precipitation at or below 4.5, sulphur deposition levels that exceed local critical levels, or heavy SO2 emissions areas. These two zones include 1.09 million km2 which encompass 380 prefecture-cities and 175 cities. They account for 11.4% of the nation's territory, 40.6% of the population, 62.4% of GDP, and 58.9% of total SO2 emissions in 1995 (Hao et al., 2001). The 1998 Reply, however, clearly list the names of cities regulated by the TCZ policy. As shown in the 1998 Reply, the acid rain control zone accounts for 8.4% of the total area of China and consists of 12 provinces and two municipalities south of the Yangtze River; the SO2 pollution control zone accounts for 3.0% of the total area of China and consists of 64 cities north of the Yangtze River, but very poor demographic areas are not included in the claims. Geographically, as the reliance on coal burning for heating, SO2 pollution control zones are located in Northern China; and as the humid climate, acid rain control zones are located in southern China. Figure 1 shows the geographic scope of TCZ zones. The green parts denote the acid rain control area, and the blue parts denote the SO2 control area.

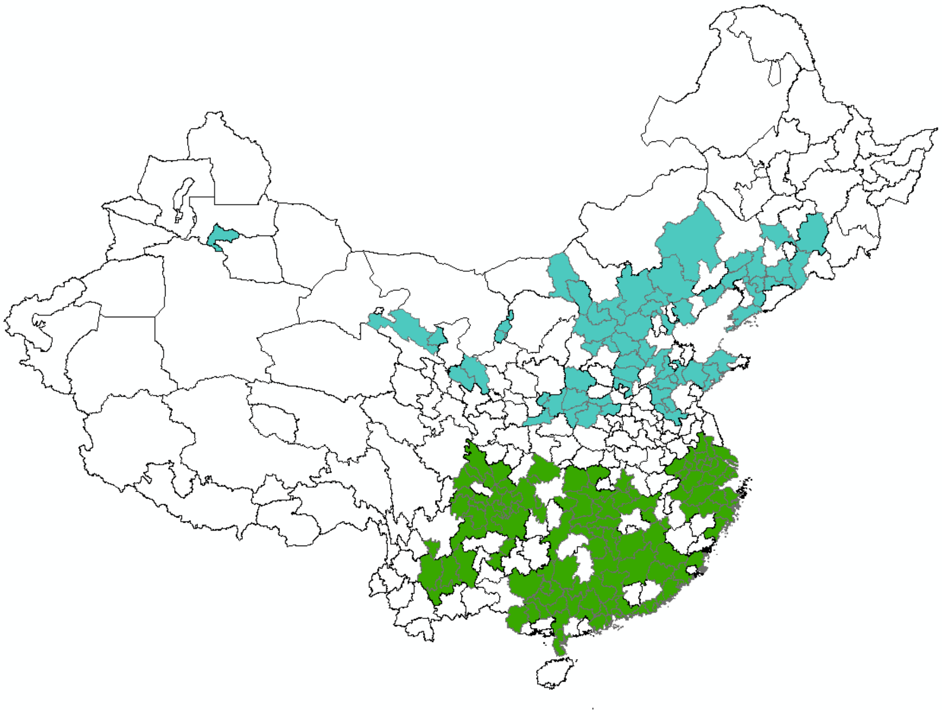

Figure 1: The scope of TCZ area

3.2 Policy Enforcement and Outcomes

For cities in the name list of the TCZ policy, they would bear tougher environmental regulatory policies. From January 1st, 1998, the opening of new collieries for coal with sulphur content greater than 3% were prohibited. Existing collieries in operation should reduce their production gradually and eventually shut down. Local government authorities also could not approve new coal-burning thermal power plants in urban district and suburbs of large and medium cities. Furthermore, newly constructed or renovated coal-burning thermal power plants using coal with sulphur content greater than 1.5% had to install sulphur-scrubbers, while existing coal-burning thermal power plants have to adopt SO2 reduction measures by 2000. In 2002, the Tenth Five-Year Plan for the Prevention and Con-

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[0] Source: The Official Reply of the State Council Concerning Acid Rain and SO2 Pollution Control Zones

Table 1: TCZ cities (and counties for municipality) in China

Acid Rain control Zone				SO2 control Zone			
Province/municipality	City	Province/municipality	City	Province/municipality	City	Province/municipality	City
Shanghai	Shanghai	Guangxi	Nanning	Beijing	Dongcheng district	Jiangsu	Xuzhou urban area
Jiangsu	Nanjing		Liuzhou		Xicheng district		Pizhou
	Yangzhou		Guilin		Xuanwu district		Xinfen
	Nantong		Wuzhou		Chongwen district	Shandong	Jinan urban area
	Zhenjiang		Yulin		Chaoyang district		Zhangqiu
	Changzhou		Guigang		Haidian district		Qingdao urban area
	Wuxi		Nanning area		Fengtai district		Jiaonan
	Suzhou		Liuzhou area		Shijingshan district		Jiaozhou
	Taizhou		Guilin area		Mentougou district		Laixi
Zhejiang	Hangzhou		Hezhou		Tongzhou district		Zibo urban area
	Ningbo		Hechi area		Fangshan district		Zaozhuang urban area
	Wenzhou	Chongqing	Yuzhong district		Changping county		Tengzhou
	Jiaxing		Beijiang district		Daxing county		Weifang urban area
	Huzhou		Shapingba district	Tianjin	Tianjin urban area		Qingzhou
	Shaoxing		Nanan district	Hebei	Shijiazhuang urban area		Gaomi
	Jinhua		Jiulongpo district		Xinji		Changyi
	Quzhou		Dadukou district		Gaocheng		Yantai urban area
	Taizhou		Yubei district		Jinzhou		Longkou
Anhui	Wuhu		Beipei district		Xinle		Laiyang
	Tongling		Banan district		Luquan		Laizhou
	Maanshan		Wansheng district		Handa urban area		Zhaoyuan
	Huangshan		Shuangqiao district		Wuan		Haiyang
	Chaohu area		Fuling district		Xingtai urban area		Jining urban area
	Xuancheng area		Yongchuan city		Nangong		Qufu
Fujian	Fuzhou		Hechuan city		Shahe		Yanzhou
	Xiamen		Jiangjin city		Baoding urban area		Zoucheng
	Sanming		Changshou county		Zhuozhou		Taian urban area
	Quanzhou		Rongchang county		Dingzhou		Xintai
	Zhangzhou		Dazu county		Anguo		Feicheng
	Langyan		Qijiang county		Gaobeidian		Laiwu urban area
Jiangxi	Nanchang		Bishan county		Zhangjiakou urban area		Dezhou urban area
	Pingxiang		Tongliang county		Chengde urban area		Leling
	Jiujiang		Tongnan county		Tangshan urban area		Yucheng
	Yingtan	Sichuan	Chengdu		Zunhua	Henan	Zhengzhou urban area
	Fuzhou area		Zigong		Fengnan		Gongyi
	Jian		Panzhihua		Hengshui urban area		Luoyang urban area
	Ganzhou		Luzhou	Shanxi	Taiyuan urban area		Yanshi
Hubei	Wuhan		Deyang		Gujiao		Mengjin county
	Huangshi		Mianyang		Datong urban area		Jiaozuo urban area
	Jingzhou		Suining		Yangquan urabn area		Qinyang
	Yichang		Neijiang		Shuozhou urban area		Mengzhou
	Jingmen		Leshan		Qizhou		Xiuwu county
	Ezhou		Nanchong		Yuci		Wen county
	Qianjiang		Yibin		Linfen		Wuzhi County
	Xiannig area		Guangan area		Yuncheng		Boai county
Hunan	Changsha		Meishan area	Neimenggu	Huhehaote urban area		Anyang urban area
	Zhuzhou	Guizhou	Guiyang		Baotou urban area		Linzhou
	Xiangtan		Zunyi		Shiguai miner area		Sanmenxia urban area
	Hangyang		Anshun area		Tumote		Yima
	Yueyang		Xingyi		Wuhai		Lingbao
	Changde		Kaili		Chifeng urban area		Jiyuan urban area
	Zhangjiajie		Duyun	Liaoning	Shenyang urban area	Shanxi	Xian urban area
	Chenzhou	Yunnan	Kunming		Xinmin		Tongchuan urban area
	Yiyang		Qujing		Dalian urban area		Weinan urban area
	Loudi area		Yuxi		Anshan urban area		Hancheng
	Huaihua		Shaotong		Haicheng		Huayin
	Jishou		Gejiu		Fushun urban area		Shangzhou
Guangdong	Guangzhou		Kaiyuan		Benxi urban area	Gansu	Lanzhou urban area
	Shenzhen		Chuxiong		Jinzhou urban area		Jinchang urban area
	Zhuhai				Linhai		Baiyin urban area
	Shantou				Huludao urban area		Zhangye
	Shaoguan				Xingcheng	Ningxia	Yinchuan urban area
	Huizhou				Fuxin urban area		Shizuishan urban area
	Shanwei				Liaoyang urban area	Xinjiang	Wulumuqi urban area
	Dongguan			Jilin	Jilin urban area		
	Zhongshan				Huadian		
	Jiangmen				Jiaohe		
	Foshan				Shulan		
	Zhanjiang				Siping urban area		
	Zhaoqing				Gongzhuling		
	Yunfu				Tonghua urban area		
	Qingyuan				Meihekou		
	Chaozhou				Jian		
	Jieyang				Yanji		

Note: Wenzhou (urban area and Ruian city, Yongjia county, Cangnan county), Quzhou (urban area and Jiangshan city, Qu county, Longyou county), Nanning area (Shanglin county, Chongzuo county, Binyang county, Heng county), Liuzhou area (Heshan city, Laibin county, Luzhai county), Hechi area (Hechi city, Yizhou city), Guilin area (Linshan county, Quanzhou county, Xingan county, Lipu county, Yongfu county), Hezhou (Hezhou county, Zhongshan county)

trol of Acid Rain and Sulfur Dioxide Pollution in the Two Control Areas approved by the State Council clearly made the implementation effect of the "two control areas" policy one of the criteria for evaluating local government officials. High polluting industries, like four major coal-using industries, chemicals, metallurgy, nonferrous metals, and construction materials industries, are also under severe regulation. Facilities in these industries are encouraged to adopt total process control during production and gradually phrase out technologies and equipment lead to severe pollution. The specific approach includes using low-pollution materials, using advanced and energy-saving equipment, and using end-of-pipe controls for pollution. For firms in the TCZ area, in addition to pay exhaust gas excess discharged fees according to the exhaust gas charging standards stipulated in the Interim Measures for the Collection of Pollutant Discharge Fees issued by the State Council in 1992 (National Law [1992] No. 21), sulfur dioxide discharge fees shall also be levied according to (Huanfa [1998] No. 6), but the sulfur dioxide excess discharge fees shall no longer be levied. So, the sulfur dioxide discharge fees are an additional fee for TCZ firms. Enterprises that do not report their exhaust gas emissions truthfully or shut down their exhaust gas treatment facilities without authorization will be levied twice the sulfur dioxide emission fee. Existing literature sort environmental regulations into command-and-control regulations; market-based regulations; and government subsidies. Thus, the TCZ policy used both the command-and-control regulations and the market-based regulations. Restricting production and shutting down high-sulfur coal mines and thermal power plants, strictly controlling new thermal power plants, and restricting fuel sulfur content are typical command-and-control environmental regulations. But the enforcement of emission fee is a market-based regulation.

According to the 1998 Reply, the TCZ policy has a short run and a long run policy goal. For the short goal, the policy requires that, in TCZ area, the total emission levels in 2000 do not overcome the emission values in 1995, and major cities' SO2 concentrations should meet the national air quality standards in 2000 (here major cities means municipalities, provincial capitals, coastal open cities, special economic zones, and the main tourist cities). But due to the lag in policy implementation and without national TCZ action plan until 1999, the TCZ policy was not systematically implemented before 2000. In 2000, only 102 TCZ cities achieved the national Class II standard for average ambient SO2 concentrations (China Environment Yearbook, 2001). The long run policy goal is that by 2010, TCZ cities reduce their SO2 emission level by 10% compared to the 2000 level, and all TCZ cities' ambient SO2 concentrations should achieve the national air quality standards. Finally, the long run policy goals achieved as we see a significant improvement in air quality. In 2010, 94.9% of TCZ cities achieved the national

Class II standard, and there were no TCZ cities' SO2 concentrations exceed the national Class III standard (Report of the Ministry of Environmental Protection of the People's Republic of China, 2011). During China's 11th Five-Year Plan, from 2006 to 2010, the total SO2 emissions were reduced by 14.29% with the target being 10%.

4 Data, variables, and estimation strategy

Our analysis is based on two firm level datasets, the Annual Survey of Industrial Firms Database (ASIF) and the Environmental Survey and Reporting Database (ESR). They provide comprehensive information on the production and performance of industrial enterprises and the amount of emissions from heavy polluters respectively.

4.1 Annual Survey of Industrial Firms Database (ASIF)

Our firm production and performance variables are calculated using data from the Annual Survey of Industrial Firms Database (ASIF) from 1998 to 2007. The ASIF dataset, collected by the National Bureau of Statistics of China, includes all state-owned industrial enterprises (SOEs) and all not-state-owned firms with annual sales exceeding 5 million RMB (about $0.65 million). Their overall production accounts for more than 85% of China's industrial output (Jefferson et al., 2008). The dataset contains a rich set of firm information obtained from their accounting books, such as profits, outputs, inputs, sales, employment, and other firm characteristics. Firm detailed location information also included in the dataset, which is used to identify whether a firm is regulated by the TCZ policy. The ASIF data have been used in studies on firm behaviour and productivity in China (see, for example,Brandt et al., 2017; Brandt et al., 2012)

The ASIF dataset is used in several previous studies, but it has some data issues. Following the process of Brandt et al. (2012), we cleaned the raw ASIF dataset and create a panel one. We dropped duplicate observations in terms of ten variables. We allow the existence of two enterprises with same firm code (firm ID), but are of different firm name or legal person representatives. After duplicate data deleting, the number of observations ranges from 162,033 in 1999 to 336,766 in 2007, as shown in Table 1.

We merged the ASIF data into a 10-year panel dataset following the process of Brandt et al. (2012). In this part, two stages are processed with multi-steps in each stage. The first stage is matching any two consecutive years by the following steps (see Table 2 for matched proportions). The first step is that we matched firm observations by firm code (firm ID). Then, the remaining unmatched observations can be matched by firm name, firm legal person representatives, and phone number (with city code) in turn, which are our second to fourth step. After these steps, we still have plenty of observations unmatched. So, in the fifth step, the remaining unmatched observations from step four are matched simultaneously by firm founding year, geographic code, industry code, name of town, and the name of firm's main product. Then, the final step is merging all the matched and unmatched firms to create a file of two consecutive years.

The second stage of data cleaning is matching three consecutive years observations by four steps. In the first step of this stage, we create a three-year balanced panel dataset based on the matching result of the first stage. For the remaining firm observations, we matched the $t-1$ and $t+1$ observations by firm ID and firm name. So, in the third step, a three-year unbalanced panel dataset is created by merging all the matched and unmatched firms from the above two steps. Finally, we repeat these three steps to merge the whole ASIF dataset into a 10-year panel dataset.

Table 2: Number of observations of the ASIF dataset

Year	Original Observations	Cleaned Observations
1998	179,114	165,118
1999	172,208	162,033
2000	167,163	162,883
2001	179,587	169,031
2002	190,419	181,557
2003	208,438	196,222
2004	279,092	279,089
2005	271,845	271,835
2006	301,961	301,961
2007	336,766	336,766

After the panel dataset creating, we drop observations with negative values for value added, employment, fixed capital stock, sales, export value, total tangible fixed assets, and accumulated depreciation minus current depreciation, and unreasonable opening year. In addition, we cleaned the dataset by dropping observations whose key variables' values are outside the range of the 0.5th to 99.5th

Table 3: Fraction of observations matched to previous year observations

Year	Matched by ID	Matched by other information	Total matched
1999	82.39%	3.60%	86.00%
2000	82.05%	0.38%	82.43%
2001	71.11%	16.64%	87.75%
2002	78.98%	8.05%	87.03%
2003	76.46%	5.28%	81.74%
2004	51.77%	32.56%	84.33%
2005	84.76%	6.90%	91.66%
2006	81.14%	10.50%	91.64%
2007	81.11%	1.06%	82.17%

percentile. As the ASIF dataset contains detailed address information for each firm in each year, we can confirm whether an observation is located in the TCZ area and influenced by the policy.

4.2 Environmental Survey and Reporting Database (ESR)

The second data source for this study is the Environmental Survey and Reporting Database (ESR). This database provides firm-level information on emissions and environmental management of Chinese polluting sources from 1998 to 2012. The ESR database, the most comprehensive environmental dataset in China, is collected and maintained by the Ministry of Environmental Protection (or the former State Environmental Protection Administration). It is the specific data source of the Chinese Yearbook of Environmental Statistics published over the years. Information about the polluting activities of all major polluting sources are included in the ESR database, including heavily polluting industrial firms, hospitals, residential pollution discharging units, hazardous waste treatment plants and urban sewage treatment plants. In this study, we use observations in the ESR dataset who are in the same industries and period (1998-2007) as the ASIF observations.

The sampling criteria in the ESR database is the cumulative distribution of firm emission in each county. All polluting sources, including industrial firms, are ranked according to their “criteria pollutants” emission level. And then polluting sources who contributing to the top 85% of total emissions in a county are monitored by the ESR database. For the choose of “criteria pollutants”, only chemical oxygen demand (COD) emissions and sulfur dioxide (SO2) were "criteria pollutants" before 2007. Whether a pollutant source is included in the ESR is determined by their contributions to COD emissions and SO2 emissions. But, in 2007, ammonia nitrogen (NH3) and nitrogen oxides (NOx) also became "criteria pollutants".

For a firm with multi-plants in different counties, all plants are considered as different pollutant sources. Thus, same firm name may appear many times in a year, which shows all these plants reach the sampling criteria. Because of various sampling criteria, the sample size of the ESR is much smaller than the ASIF's. But there are overlap samples between the two datasets, and the annual overlap rate is from 45% to 58% (based on the ESR dataset) in each year, and from 10% to 20% (based on the ASIF dataset) in each year.

Among all the pollutants in the ESR database, SO2 is the one we are interest in, which is the target pollutant in the TCZ policy. The database provides the SO2 generated amount and SO2 removed amount for each pollutant source. Using the amount of waste gas discharge, we corroborate the findings on firm SO2 emissions.

Table 4: Number of Observations of the ASIF, ESR, and matched dataset

Year	ASIF	ESR	Matched dataset
1998	165,118	55,855	21,765
1999	162,033	65,282	26,194
2000	162,883	70,223	27,451
2001	169,031	65,535	25,862
2002	181,557	65,535	27,910
2003	196,222	65,535	28,190
2004	279,089	65,535	32,917
2005	271,835	65,535	33,319
2006	301,961	65,535	33,058
2007	336,766	65,535	32,879

Same as the ASIF data, the ESR database also need to be cleaned. Firstly, there are some abnormal observations in the dataset. We dropped duplicate observations in terms of 13 essential emission related variables. Following G. He et al. (2018), we dropped observations whose SO2 emission amount and COD emission amount are both zero and observations whose SO2 emission amount or COD emission amount is negative. Because of the ESR dataset monitors pollutant source whose emissions accounts for the top 85% of the total emissions in a county, and SO2 and COD are two key "criteria pollutants", it is impossible that these two emission variables are zero or negative in ESR dataset. We also dropped observations with negative values for waste-gas emission, waste-water emission, waste-gas treatment ability, and waste-water treatment ability.

Secondly, the ESR dataset is a pollutant sources level dataset. Several plants of a firm may exist in the dataset. If we want to match the ESR dataset and the ASIF dataset, the plant level ESR dataset need to be transformed into a firm-level one. Specifically, if two observations in a year have same firm code (firm ID), they will be treated as different plants of a firm. The variables of a firm's plants will be added up and turned into this firm's variable value. If two observations in a year have same "firm name", they will also be treated as different plants of a firm. We use the address of firm headquarters to replace the address of plants. Firms whose plants exist both outside and inside the TCZ area are dropped. Firms with multi-plants are quite a few in the ESR dataset, which accounts for about 0.5% of observations in each year. As shown in Table 4, column two shows the original number of observations of the emission dataset. Column three shows the number of duplicate observations deleted in each year. Column four shows the number of firms who have more than one plant. Column five is the final number of observations after duplicates deleting and merge of plants.

Table 5: Number of Observations of the Matched Dataset

Year	Number of Observations	Number of duplicates	Number of firms who have plants	Final observations
1998	55,855	1,593	215	51,947
1999	65,282	1,157	390	62,980
2000	70,223	2,014	220	66,240
2001	65,535	1,017	190	63,253
2002	65,535	561	223	64,400
2003	65,535	1,890	275	62,715
2004	67,529	2,021	228	65,182
2005	67,966	2,570	324	64,946
2006	65,535	31	1,726	63,613
2007	65,535	31	358	65,082

Finally, as shown in figure 2, we matched and merged the ESR and ASIF dataset to make a new dataset. We matched and merged two datasets based on "firm code" and observe year. 275, 017 observations in the emission dataset are matched by "firm code", while 355,377 observations are not matched by. Then, for those observations not matched by "firm code", we merged the two datasets again by "firm name", "region code", and "observe year". The "region code" variable is a 6-digits code which composed of province code, city code, and county code. In the remaining samples, 34,755 observations are matched by "name" and "region code". 320,625 observations are not matched by these two methods. Thus, the new dataset includes 309,733 observations, which accounts for 49.1% of the ESR dataset.

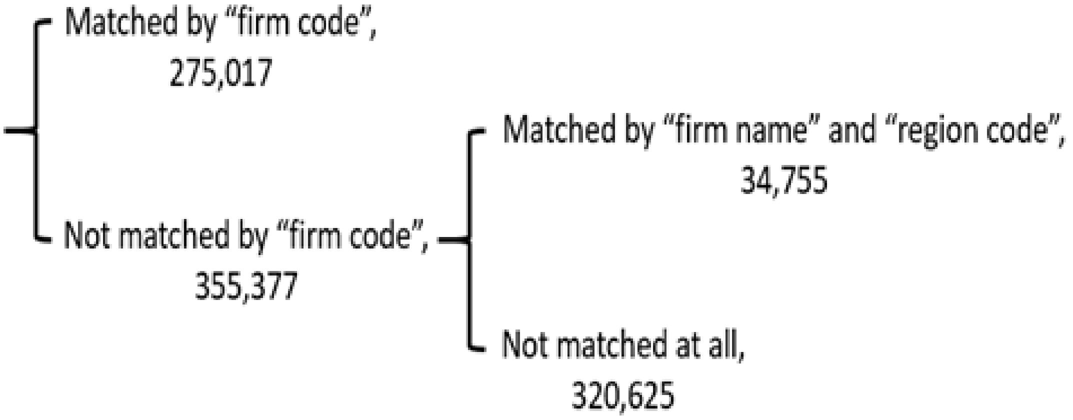

Figure 2: matched process

4.3 Socio-economic Data

In addition to ASIF and ESR data, we obtained a series of province-level data, such as the provincial level Producer Price Index (PPI), from the China Statistical Yearbooks. The province-level PPI is used to deflate firm level variables, like output and sales. The missing PPI values (Tibet from 1998-2005 and Hainan province from 1998-2001) are replaced by the national Producer Price Index. The national industrial output used for deducting the economic cost of the TCZ policy is collected from the China Industrial Economic Statistical Yearbook.

4.4 Specification and Variables

The time and regional variations in the adoption of the TCZ policy makes it possible to use the difference-in-difference approach. Specifically, there are two groups of counties, the treatment group consisting of counties designated as TCZ area in 1998, and the control group comprising non-TCZ area. Thus, we can compare firm emissions and behaviour in TCZ area before and after the implementation of the TCZ policy in 2000 with the corresponding change in non-TCZ cities during the same period.

The DD estimation specification is:

$$Y_{it} = \alpha_0 + \alpha_1 TCZ_i * \ Post_t + \boldsymbol{\beta X_{it}} + \gamma_{pt} + \mu_i + \sigma_t + \varepsilon_{it} \tag{1}$$

where Y_{it} is the measurement of firm emissions, productivity, performance, and factors for channel analysis in firm i at year t; TCZ_{it} indicates whether firm i located in TCZ area in *the 1998 Reply*, i.e., $TCZ_i = 1$ if the firm i belongs to treatment group, $TCZ_i = 0$ otherwise; $Post_t$ indicates the post-treatment period, i.e., $Post_t = 1 \ \forall \ t \geq 2000$, $Post_t = 0$ otherwise; γ_{pt} are local economic shocks with province by year, capturing province p's time-variant features, such as local economic policy, local economic conditions, etc.; μ_i are firm fixed effects, capturing firm i's time-invariant characteristics, like geographic features, natural endowment, etc.; σ_t are year fixed effects, capturing all yearly factors common to all firms such as macro shocks, monetary policy, etc.; and ε_{it} is the error term.

The coefficient we are interested is α_1 which shows the average treatment effect of the TCZ policy. It is the coefficient of the interaction term between treatment variable, TCZ_i, and time period variable, $Post_t$. G. He et al. (2018) investigate the deleterious effect of more stringent Chinese environmental regulation on firm productivity. The negative effect of TCZ on FDI, which indirectly concludes the adverse effect of TCZ, is also investigated by Cai et al. (2016). Thus, it is expected that α_1 is negative, i.e., the TCZ policy would cause firm emission reduction but also have negative effect on firm performance.

The treatment variable, TCZ_i, in our study is a county level one. We accurate the smallest unit of the policy implementation area to county. Previous studies rely on measures of regulation that are aggregated (e.g., city-level measures), see Cai et al. (2016). But, the 1998 Reply listed the name of cities and counties under regulated. It will bring selection bias if we target a regulated city who has counties out of the policy. For some cities, only counties belong to urban area are under regulated. Some cities' regulated area is fuzzy, which includes lots of counties of different cities. Thus, we set firms in the treatment group as the one who located in counties listed in the 1998 Reply.

The time period variable, $Post_t$, indicates the post-treatment period, i.e., for all years after 2000. We choose 2000 not 1998 as the implement year for the TCZ policy because of the following reasons. First, even if the 1998 Reply issued in the 1998, the official action plan for the TCZ policy did not clear until 1999. Second, in the 1998 Reply, the official goal is the SO2 emissions in 2010 will be reduced by 10% compared to 2000. So, the government also set 2000 as the base point of comparison. Third, during 1998 to 2000, although the establishment of the two control zones has restrained the rapid growth of my country's SO2 pollution emissions to a certain extent, it has not helped all regions to achieve pollution reduction targets set in the 1998 Reply. According to statistics from the Ministry of Environmental Protection, only Beijing, Tianjin, Chongqing, and Guizhou have reduced SO2 emissions from 1998 to 2000, while the other 23 provinces and municipalities have not only not reduced their emissions, but also experienced relatively high emissions. Fourth, the Tenth Five-Year Plan started from 2000. The central government made a more detailed five-year plan for the TCZ policy, The Tenth Five-Year Plan for the Prevention and Control of Acid Rain and Sulfur Dioxide Pollution in the Two Control Areas, which would be implemented from 2000 to 2005.

4.4.1 Key control variables

$\boldsymbol{X_{it}}$ shows the vector of control variables, which denote firm characteristics. It includes firm size, Output; emission treatment capacity, *gas treatment capacity*; firm age, *firm age*; the ratio of export value to sales, export; a control for firms' agglomeration effect, agglo; employment number, *employment*; Plant dummy, *Plant*.

Output is firm output amount (10 thousand Yuan), which denotes firm size. The provincial level Producer Price Index (PPI), published by the National Bureau of Statistics of China, is used to deflate firms' Output value. The missing PPI values (Tibet from 1998-2005 and Hainan province from 1998-2001) are replaced by the national Production Price Index. Firm size is correlated with emission levels or emission intensity (see, Greenstone, 2002; G. He et al., 2018; C. Wang et al., 2018). As the Chinese government target large firms and exerts less control over small ones, G. He et al. (2018) shows that large firms with higher emission will have more emission reduction. C. Wang et al. (2018) hold larger firms usually have a lower emission intensity. Thus, it is expected that the coefficient of *Output* is positive when using emission level indicators as dependent variable, and is negative when using SO2 intensity as dependent variable. Chinese Large firms always have higher increasing productivity than average rate (Brandt et al., 2012). G. He et al., 2018 find that the TFP impacts are significant only for larger firms. We expected that the coefficient of *Output* is positive when using TFP and profitability indicators as dependent variable.

gas treatment capacity is the natural log of capacity of waste gas treatment facilities (cubic meter per hour). This variable is used to control firms' capacity of waste gas treatment. M. Liu et al. (2018) and P. He and Zhang (2018) shows that pollution abatement capacity is correlated with firm behaviour and firm emission levels. Higher emission firms need more abatement devices for pollution treatment, which means high emission firms always accompanied by high pollution abatement capacity (M. Liu et al., 2018). It is expected that the coefficient of *gas treatment capacity* is positive when using emission level indicators as the dependent variable.

firm age is the natural log of firm age. This factor was found to be correlated with firm emissions (Greenstone, 2002; Greenstone et al., 2012; G. He et al., 2018; C. Wang et al., 2018) and productivity (Brandt et al., 2017; Greenstone et al., 2012; G. He et al., 2018; Syverson, 2011) . Firm age often used as an indicator of firms' technology level and firms' governmental embeddedness (J. Sun et al., 2019). As older firms have better communication power with local government and long-established management systems in production and pollution control, they may not be active in improving their pollution reducing technologies (J. Sun et al., 2019). It is investigated that older firms may polluted more in their production (Greaney et al., 2017; M. Liu et al., 2017; J. Sun et al., 2019; C. Wang et al., 2018). We expected that the coefficient of *firm age* is positive when using emission level indicators as the dependent variable. Because of the learning-by-doing effect, older firms have higher productivity (Ding et al., 2016; Ding et al., 2019). It is expected that the coefficient of *firm age* is positive when using TFP as the dependent variable.

export is the ratio of export value over sales. This variable is used to control firms' export status. It is found to be correlated with firm performance (Ding et al., 2016; C. Wang et al., 2018) and firm productivity (Brandt et al., 2012; Syverson, 2011). We expected that the coefficient of *export* is positive related to TFP for two reasons. One reason is that export is often accompanied by large R&D investments, which raise exporters' productivity levels (Syverson, 2011). Another reason is that as the "learning-by-exporting" hypothesis, exporters' productivity advantage grows after entry into the export market (De Loecker, 2007; Van Biesebroeck, 2005).

agglo is the total employment of firm i's 2-digit industry in the same city. It is calculated by adding up the number of employees in same 2-digit industry and same city. This indicator is used as a control for firms' agglomeration effect in the US (Greenstone, 2002; Krugman, 1991), China (Brandt et al., 2017; C. Wang et al., 2018), and other developing countries (Dethier et al., 2011). Because of the thick-input-market effects and knowledge transfers discussed in the context of classic agglomeration mechanisms (see, Syverson, 2011), industries with high agglomeration are more likely share abatement technologies inside the sectors. C. Wang et al. (2018) proved the negative relation between agglomeration and emission intensity. We expect that the coefficient of *agglo* is negative when using SO2 intensity as the dependent variable. But the relation between emission levels and agglomeration is unclear. As agglomeration-type productivity spillovers (see, Syverson, 2011), it is expected that the coefficient of *agglo* is positive when using TFP as the dependent variable.

Plant. Plant dummy indicating whether the firm has multi plants. $Plant = 1$ if a firm has multi plants, $Plant = 1$ otherwise. Greenstone et al. (2012) and C. Wang et al. (2018) introduce it as one of the control variables. It is expected that the coefficient of *Plant* is positive when using emission level as the dependent variable, because large firms always accompanied by multi-plants.

4.4.2 Key dependent variables

The dependent variable used in this paper includes emission indicators, firm performance indicators, and variables used to show mechanism and channels about how the policy influence firm performance.

The ESR dataset allows us to construct emission levels (Greenstone, 2002; Greenstone et al., 2012) and emission intensity measures (G. He et al., 2018; List and Kunce, 2000; Rassier and Earnhart, 2015; C. Wang et al., 2018) for firms. We use SO2 discharged amount (log), SO2 generated amount (log), and SO2 intensity to denote firm emission levels. *SO2 discharged* represents the SO2 discharged amount (log) of firm i at year t, which is the amount of SO2 finally discharged into the atmosphere by firm i. *SO2 generated* denotes the SO2 generated amount (log) of firm i at year t, which is the amount of SO2 generated by firm i during production. As the ESR dataset only has SO2 discharged amount and SO2 removed amount, the SO2 generated amount of firm i should be calculated by using SO2 discharged amount plus SO2 discharged amount. *SO2 intensity* is the rate of SO2 discharged value over gross output (i.e., SO2 discharged amount/Output). It is the SO2 emissions per unit of firm output value. We expect that the coefficient of interaction term, α_1, is negative when using emission indicators as dependent variables, i.e., the TCZ policy induce firms discharge less emissions.

Indicators we used to denote firm performance comprise TFP (log), return on asset (ROA); and return on sales (ROS). TFP is a indicator for firm productivity, and ROA and ROS are indicators for firm profitability.

TFP represents the log of total factor productivity of firm i. We construct firm TFP measures using the Wooldridge (2009) approach and Levinsohn and Petrin (2003) approach. Specifically, the Wooldridge (2009) approach is our main measurement of TFP, and the later one will be used to test the robustness of TCZ policy's effect. Wooldridge (2009) shows how to estimate both the first and second stage of OP or LP procedure simultaneously, and solved the problem of the identification of the parameters in the OP and LP first stage estimation criticised by Ackerberg et al. (2006). It is expect that the coefficient of interaction term, α_1, is negative when using TFP as dependent variables, i.e., the TCZ policy have harmful effect on firm productivity. In the next section, we give details about the TFP measurement.

This paper uses two indicators, return on asset and return on sales, to denote firm profitability. *ROA* is the ratio of firm profit to firm's total assets, which is an accounting-based measure of profitability (Zhao and Sun, 2016). *ROS* is another measurement of productivity, which is the ratio of a firm's profit before interest and taxes over the firm's sales. It reflects results reported in a firm's financial statements (Rassier and Earnhart, 2015). As ROA and ROS used to represent firm competitiveness (see, Rassier and Earnhart, 2015; Zhao and Sun, 2016), it is expected that the coefficient of interaction term, α_1, is negative when using ROA and ROS as dependent variables, i.e., the TCZ policy have negative effect on firm profitability.

In channel analysis, we use "end of pipe" variable and "change in process" variable as the dependent variable in equation (1). we use "end-of-pipe" variable and "change-in-progress" variable to denote two various pollution abatement method, the same approach used as M. Liu et al. (2018), P. He and Zhang (2018), and W. Sun et al. (2019). Firms regulated by environmental policies would choose to invest in "changes in process" technologies, "end-of-pipe" technologies, or do both (Berman and Bui, 2001; C. Wang et al., 2018).

end of pipe is the ratio of SO2 removed amount over SO2 generated amount (P. He and Zhang, 2018; M. Liu et al., 2018; W. Sun et al., 2019,). At the end of production but before pollutants released into environment, firms can take technologies or devices to reduce pollutants that have already generated during production process, such as scrubbers and precipitators, i.e., an indicator for "end of pipe" measurement (Berman and Bui, 2001; P. He and Zhang, 2018; C. Wang et al., 2018). "*End of pipe*" variable denotes firms' ability to remove pollutants.

Higher *end of pipe* means a firm removed more SO2 emission from they generated. Firms under environmental regulation would take more "end of pipe" measurement (P. He and Zhang, 2018; W. Sun et al., 2019). Thus, it is expected that the coefficient of interaction term, α_1, is possitive when using *end of pipe* as dependent variables, i.e., the TCZ policy induce firms take more "end of pipe" measurement. But "end-of-pipe" measurement is also an additional cost for firms, which may reduce firm productivity and profitability.

change in process is the ratio of SO2 generated value over firm output (M. Liu et al., 2018). Folllowing M. Liu et al. (2018), we use *change in process* variable to denote another pollution abatement method, which is reducing pollutants generated in the production process by applying cleaner technologies, using more efficient production equipment, and more environmentally friendly production materials, such as anthracite coal, unleaded gasoline, efficient boiler, and other environmental protection technologies (Berman and Bui, 2001; C. Wang et al., 2018). Lower *change in process* variable means less pollutants per unit of output generated by firms. It is expected that the coefficient of interaction term, α_1, is negative when using *change in process* as dependent variables, i.e., the TCZ policy induce firms take more "change in process" measurement."Change-in-process" measurement reports technological advance which may increase firms' productivity and profitability.

The variable of SO2 treatment facilities capacity linked directly to firms' "end of pipe" activities. We assume that regulated firms have higher capacity of SO2 treatment facilities. The last factor used in the channel analysis is fixed asset investment variable. Fixed asset investment is calculated by the ratio of fixed assets investment on fixed assets. The provincial level Fixed Asset Investment Price Index, published by the National Bureau of Statistics of China, is used to deflate firms' fixed assets investment. Higher fixed asset investment denotes that the firm invest more on the fixed asset. We assume that firms in the treatment group have higher fixed asset investment than firms in the control group after TCZ implementation firms, as regulated firms may invest more on purchasing pollution abatement devices (G. He et al., 2018).

4.5 Measurement of TFP

Total Factor Productivity (TFP) is a commonly used measurement of productivity and efficiency calculated by dividing firm total output by the weighted average of inputs, i.e. labor and capital. It represents growth in output which is in excess of the growth in inputs. In microeconomic research, production function shows the relationship between productive inputs, such as capital and labour, and outputs. But, the estimation of production function needs to face an econometric challenge that is some observed determinants of production by the firm are unobserved to the researcher. If the observed inputs are a function of determinants unobserved by economist, the estimation will confront the endogeneity problem and biased OLS estimates of the coefficients on the observed inputs. In this paper, we use two approaches, Wooldridge (2009) approach and Levinsohn and Petrin (2003) method, i.e., LP method, to calculate firm TFP. The Wooldridge (2009) method is used in our main regression, while the LP measurement of TFP is used as robusteness check.

Wooldridge (2009) made some improvements on the basis of Olley and Pakes (1996), OP method, and Levinsohn and Petrin (2003), LP method. It estimates both the first and second stage of OP or LP procedure simultaneously. Wooldridge (2009) shows that the moment conditions used by OP an LP can be implemented in a generalized method of moments (GMM) framework. In the following sections, a brief summary of OP, LP, and Wooldridge method is given to describe the TFP measurement we uesd.

4.5.1 OP measurement

Olley and Pakes (1996) (OP for short) consider the Cobb-Douglas production function:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + w_{it} + \epsilon_{it} \tag{2}$$

y_{it}, k_{it}, and l_{it} are the log of output, the log of capital input, and the log of labor input respectively. w_{it} is the productivity shock observed by firms while making input decisions but unobserved by the economist. ϵ_{it} represents production or productivity shocks unobservable to both firms and the economist, and it also represent measurement error of output variable. So w_{it} and ϵ_{it} are terms unobservable to the economist. i represents firm i, and t represents the period t. In the equation (1), it is reasonable to put constant term into the w_{it}.

There are three important assumptions in OP method. First, productivity shock w_{it} evolves exogenously following an first-order Markov process. Second assumption is the moment conditions that labor is a non-dynamic input, while capital is a dynamic input. The third one is that investment is a strictly increasing function of current productivity level. Based on these three assumptions, the estimation procedure of OP method has two stages. One is using investment as a proxy of productivity to identify β_l, and the other is using moment conditions to identify β_k.

In this production function, k_{it} and l_{it} may correlated with productivity shock w_{it}. As w_{it} is unobservble to the economist, this is a classic endogeneity problem for identification of equation (1). To address the endogeneity problem, OP bring moment conditions to their calculation of production function, i.e., firms make their maximize profit decisions through different time.

OP assume that productivity shock w_{it} evolves exogenously following an first-order Markov process.

$$p(w_{it+1}|I_{it}) = p(w_{it+1}|w_{it}) \tag{3}$$

or as Wooldridge (2009) shows the dynamics of productivity process.

$$E(w_{it+1}|w_{it}, ..., w_{i1}) = E(w_{it+1}|w_{it}), t = 1, 2, ..., T \tag{4}$$

where I_{it} is firm i's information set at period t. For period $t+1$, information I_{it} shows current and past realizations of w, $(w_{it}, ..., w_{i1})$ belongs to I_{it}.

In OP method, they assumed that labor is non-dynamic input, while capital is a dynamic input based on an investment process. As labor is a non-dynamic input, the profit of a firm after period t will not be influenced by the firm's labor choice on period t. In contrast, as capital is a dynamic input, a firm's capital level for period t subject to investment and capital level in period $t-1$.

$$k_{it} = K(k_{it-1}, i_{it-1}) \tag{5}$$

This assumption regarding moment conditions helps to solve endogeneity problem related to capital k_{it}. As k_{it} is determined at period $t-1$, k_{it} belongs to the information in period $t-1$, i.e. I_{t-1}. So k_{it} is uncorrelated with the unexpected productivity innovation from period $t-1$ to period t (the unexpected innovation in w_{it} is denoted as ξ_{it}, $\xi_{it} = w_{it} - E[w_{it}|I_{it-1}] = w_{it} - E[w_{it}|w_{it-1}]$). This orthogonality condition, k_{it} is uncorrelated with ξ_{it}, can help to form a moment to identify capital coefficient β_k in OP method.

So, the endogeneity problem focus on the labor input variable, l_{it}. As l_{it} is decided at period t, it is correlated with the productivity innovation in w_{it}, i.e., ξ_{it} which is decided between $t-1$ and t. To solve the endogeneity problem of labor variable, OP method introduce the investment i_{it} as the proxy variable. Here OP make an important assumption that a firm's investment level, i_{it}, is a strictly increasing function of current productivity level w_{it}. The investment level in period t is restrict to productivity and capital in t, i.e.

$$i_{it} = f_t(w_{it}, k_{it}) \tag{6}$$

As the investment function is strictly monotonic in w_{it}, the inverse function of investment is

$$w_{it} = f_t^{-1}(i_{it}, k_{it}) \tag{7}$$

Substituting equation (7) into equation (2).

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + f_t^{-1}(i_{it}, k_{it}) + \epsilon_{it} \tag{8}$$

$$= \beta_l l_{it} + \Phi_t(i_{it}, k_{it}) + \epsilon_{it} \tag{9}$$

where,

$$\Phi_t(i_{it}, k_{it}) = \beta_k k_{it} + f_t^{-1}(i_{it}, k_{it}) \tag{10}$$

The first stage of OP method is the estimation of equation (9) with treating $\Phi_t(i_{it}, k_{it})$ non-parametrically. In this stage, economists can obtain the estimate of β_l and Φ_t, denoted as $\widehat{\beta_l}$ and $\widehat{\Phi}_{it}$ respectively.

The second stage of OP is to estimate β_k given $\widehat{\beta_l}$ and $\widehat{\Phi}_{it}$. Rewriting the productivity w_{it},

$$w_{it} = E[w_{it}|I_{it-1}] + \xi_{it} = E[w_{it}|w_{it-1}] + \xi_{it} \tag{11}$$

ξ_{it} is called the "innovation" component of w_{it}. And it satisfies,

$$E[\xi_{it}|I_{it-1}] = 0 \tag{12}$$

Also because k_{it} is decided at $t-1$, k_{it} belongs to the information in period $t-1$, i.e. $k_{it} \in I_{it-1}$. So ξ_{it} must be orthogonal to k_{it}, where we get,

$$E[\xi_{it}|k_{it}] = 0 \tag{13}$$

So the conditional mean in equation (12) implies that ξ_{it} and k_{it} are uncorrelated. Specifically,

$$E[\xi_{it} k_{it}] = 0 \tag{14}$$

To get the estimates of β_k, we rewrite equation (10) into,

$$f_t^{-1}(i_{it}, k_{it}) = \Phi_t(i_{it}, k_{it}) - \beta_k k_{it} \tag{15}$$

So,

$$w_{it}(\beta_k) = \widehat{\Phi}_{it} - \beta_k k_{it} \tag{16}$$

Then regress $y_{it} - \beta_k k_{it} - \beta_l l_{it}$ on implied w_{it-1} non-parametrically, we can get $\widehat{\Psi}(w_{it-1}(\beta_k))$. (Here Ackerberg, Caves, and Frazer (2006) suggest regressing $\widehat{\Phi}_{it} - \beta_k k_{it}$ on w_{it-1}, i.e. non-parametrically regressing $w_{it}(\beta_k)$'s on $w_{it-1}(\beta_k)$'s)

So one can compute ξ_{it}'s by,

$$\xi_{it}(\beta_k) = w_{it}(\beta_k) - \widehat{\Psi}(w_{it-1}(\beta_k)) \tag{17}$$

Finally, using $\xi_{it}(\beta_k)$'s form equation (17) analogue to moment condition of equation (13). In a GMM procedure, one can set equation (17) as close as possible to zero to get the estimates of β_k

$$\frac{1}{T}\frac{1}{N}\sum_t \sum_i \xi_{it}(\beta_k) \cdot k_{it} \tag{18}$$

With the $\widehat{\beta_l}$ and $\widehat{\beta_k}$, identified value of β_l and β_k, economists can calculate the productivity through equation (2).

4.5.2 LP measurement

Levinsohn and Petrin (2003) (LP for short) also take the Cobb-Douglas production function. However, they introduce an intermediate input into production function and use it as a proxy of productivity w_{it}. LP criticize OP that investment is often lumpy in actual data. So the investment is no longer be a strictly increasing function of productivity. LP method's production function is,

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + w_{it} + \epsilon_{it} \tag{19}$$

where m_{it} is an intermediate input. LP consider electricity, fuel, and material as the intermediate input. LP assume intermediate input m_{it} is a strictly increasing function of productivity w_{it}. They hold that the strict monotonicity condition is much more likely to hold between intermediate input and productivity rather than between investment and productivity.

$$m_{it} = f_t(w_{it}, k_{it}) \tag{20}$$

LP method holds two moment conditions assumptions. One is that intermediate input choice decision is made at the same time of production take place and the same time productivity was decided (i.e., m_{it} is a function of w_{it}). The other one is that labor l_{it} is also chosen simultaneously with m_{it} and w_{it}. So l_{it} does not influence the choice of intermediate m_{it} (if l_{it} is chosen before m_{it}, then it will influence the choice of intermediate input m_{it}).

Because of the monotonic relation between m_{it} and w_{it}, we can get,

$$w_{it} = f_t^{-1}(m_{it}, k_{it}) \tag{21}$$

Substituting equation (21) into equation (19),

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + f_t^{-1}(m_{it}, k_{it}) + \epsilon_{it} \tag{22}$$

$$= \beta_l l_{it} + \Phi_t(m_{it}, k_{it}) + \epsilon_{it} \tag{23}$$

where

$$\Phi_t(m_{it}, k_{it}) = \beta_k k_{it} + \beta_m m_{it} + f_t^{-1}(i_{it}, k_{it}) \tag{24}$$

So the first stage of LP estimation procedure is to estimate equation (23) non-parametrically and get the estimate of β_l.

In the second stage of estimation, LP need to identify both β_k and β_m given $\widehat{\beta_l}$ and $\widehat{\Phi_{it}}$ identified in first stage. One moment condition used in LP is same as OP that ξ_{it} ("innovation" component of w_{it}) is orthogonal to k_{it}, i.e., ξ_{it} and k_{it} are uncorrelated. The other moment condition is that innovation is uncorrelated with previous intermediate input, i.e., ξ_{it} is orthogonal to m_{it-1}. Because w_{it} is observed after m_{it} is chosen, m_{it} may influence productivity and ξ_{it}. But m_{it-1} is decided at $t-1$ and belongs to the information at $t-1$, I_{it-1}.

After regressing ($w_{it}(\beta_k, \beta_m) = \widehat{\Phi}_{it} - \beta_k k_{it} - \beta_m m_{it}$) on ($w_{it-1}(\beta_k, \beta_m) = \widehat{\Phi}_{it-1} - \beta_k k_{it-1} - \beta_m m_{it-1}$) non-parametrically, we can get $\widehat{\Psi}(w_{it-1}(\beta_k, \beta_m))$.

So one can compute ξ_{it}'s by,

$$\xi_{it}(\beta_k, \beta_m) = w_{it}(\beta_k, \beta_m) - \widehat{\Psi}(w_{it-1}(\beta_k, \beta_m)) \tag{25}$$

Finally, using $\xi_{it}(\beta_k, \beta_m)$'s to meet

$$E[\xi_{it}(\beta_k, \beta_m) | k_{it}, m_{it}] = 0 \tag{26}$$

The different between LP and OP is that LP use intermediate input as a proxy of productivity and introduce additional moment condition for intermediate input.

4.5.3 Wooldridge measurement

Wooldridge (2009) proves how to estimate both the first and second stage of OP or LP procedure simultaneously. He shows that the moment conditions used by LP an OP can be implemented in a generalized method of moments (GMM) framework by writing the moment conditions in terms of two equations with the same dependent variable but various set of instruments across equation. Ackerberg et al. (2006) criticise the identification of the parameters in the OP and LP first stage estimation. They hold that labor input is also a deterministic function of unobserved productivity w_{it} and state variables k_{it}, which makes the coefficient on the labor input is non-parametrically unidentified. So, one advantage of the GMM setup over two-step approaches is that it allows the first stage of OP or LP contains identifying information for parameters on the variable inputs, like labor input. Another benefit of joint GMM estimation is that the estimation efficiency is improved by using the cross-equation correlation, and fully robust standard errors are easy to obtain.

Wooldridge (2009) follows the key implications of the theory underlying OP and LP. Unobserved productivity is subject to observed state variables, like capital input, and proxy variables (investment inputs in OP, intermediate inputs in LP).

$$w_{it} = g(k_{it}, h_{it}) \tag{27}$$

where h_{it} is a vector of proxy variables. Then the following regression function:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + g(k_{it}, h_{it}) + \epsilon_{it} \tag{28}$$

In equation (28), if labor inputs is decided at the same time as proxy variables, such as intermediate inputs, then l_{it} is a deterministic function of (k_{it}, h_{it}). Under this scenario, β_l is non-parametrically unidentified.

In order to identify β_l and β_k together, Wooldridge (2009) make an additional assumption:

$$E(\epsilon_{it}|l_{it}, k_{it}, h_{it}, l_{i,t-1}, k_{i,t-1}, h_{i,t-1}, ..., l_1, k_1, h_1) = 0, t = 1, 2, ..., T. \tag{29}$$

Same as the assumption in equation (3) and (4) productivity shock, w_{it}, evolves exogenously following an first-order Markov process. Unexpected innovation in w_{it} is denoted as ξ_{it}, $\xi_{it} = w_{it} - E[w_{it}|w_{it-1}]$. A sufficient condition that matches with equation (28) and (29) is

$$E(w_{it}|k_{it}, l_{it-1}, k_{it-1}, h_{it-1}, ..., l_1, k_1, h_1) = E(w_{it}|w_{i,t-1}) = f[g(k_{i,t-1}, h_{i,t-1})]. \quad (30)$$

Plugging $w_{it} == f[g(k_{i,t-1}, h_{i,t-1})] + \xi_{it}$ into equation (2) gives,

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + f[g(k_{i,t-1}, h_{i,t-1})] + \xi_{it} + \epsilon_{it} \quad (31)$$

For now, economists can specify equation (28) and (31) that non-parametrically identify β_l and β_k together using the contemporaneous state (capital) variables, k_{it}, and any lagged inputs as instrumental variables. So, the joint estimation of the parameters leads to simple inference and more efficient estimators in Wooldridge (2009).

4.6 Summary Statistics

Table 5 provides a brief description of the matched dataset. It illustrates the mean value and standard deviation, shown in parentheses, of keep variables across 214,815 observations and 67270 firms. There are about 21,000 firms per year in the matched dataset. For the full sample, the mean SO2 discharged amount for samples in control group (10.06) is higher than the mean in treatment group (9.875). For samples in the high SO2 emission industries and low SO2 emission industries, the mean SO2 discharged amount in control group is also higher than treatment group. While the mean SO2 discharged amount for high SO2 emission industries (10.62) is higher than the mean for low SO2 emission industries (9.497). The mean SO2 generated amount in control groups is higher than the mean in treatment groups no matter in full sample or sub-group samples. Meanwhile, the mean SO2 generated amount for samples in high SO2 emission industries is higher than the mean for samples in low emission industries. Similar patterns exist in the distribution of the mean SO2 intensity.

For the full sample, the mean TFP of treatment group (7.076) is higher than control group (6.957). In high SO2 emission industries and low SO2 emission industries, two sub-groups respectively, the mean TFP of treatment group also higher than control group. By industries, the mean TFP for samples in high SO2 emission industries (7.209) is higher than low SO2 emission industries (6.924). For the full sample and the sub-sample of low emission industries, the mean ROA for samples in control group is higher than the mean of treatment group. But the samples in the high emission industries have the opposite characteristics. By

Table 6: Summary Statistics

	Full Sample			High SO2 emission Industries			Low SO2 emission Industries		
	Treat=0	Treat=1	Total	Treat=0	Treat=1	Total	Treat=0	Treat=1	Total
SO2 Discharged	10.06	9.875	9.936	10.78	10.53	10.62	9.565	9.464	9.497
	(1.938)	(1.907)	(1.920)	(1.961)	(1.937)	(1.949)	(1.761)	(1.768)	(1.766)
SO2 Generated	10.21	10.06	10.11	10.96	10.74	10.82	9.706	9.633	9.657
	(1.967)	(1.949)	(1.957)	(1.980)	(1.970)	(1.976)	(1.788)	(1.810)	(1.803)
SO2 Intensity	4.338	2.863	3.362	7.868	5.174	6.117	1.934	1.417	1.588
	(15.66)	(10.73)	(12.63)	(20.28)	(14.88)	(17.02)	(10.86)	(6.563)	(8.242)
TFP	6.957	7.076	7.036	7.085	7.277	7.209	6.870	6.951	6.924
	(1.239)	(1.227)	(1.232)	(1.160)	(1.153)	(1.159)	(1.282)	(1.255)	(1.264)
ROA	3.895	3.329	3.520	3.561	3.798	3.715	4.123	3.035	3.395
	(16.66)	(13.34)	(14.55)	(16.72)	(14.06)	(15.05)	(16.62)	(12.86)	(14.23)
ROS	-0.905	-0.809	-0.842	-0.287	-0.112	-0.173	-1.325	-1.246	-1.272
	(26.42)	(23.75)	(24.68)	(20.19)	(20.84)	(20.61)	(29.92)	(25.39)	(26.97)
end of pipe	0.0938	0.111	0.105	0.103	0.118	0.113	0.0874	0.107	0.100
	(0.212)	(0.220)	(0.218)	(0.226)	(0.235)	(0.232)	(0.201)	(0.210)	(0.207)
change in process	4.974	3.484	3.988	9.043	6.381	7.313	2.204	1.672	1.848
	(17.28)	(13.00)	(14.61)	(22.80)	(18.31)	(20.04)	(11.37)	(7.512)	(8.978)
Output	7.836	9.562	8.978	7.051	8.727	8.141	8.371	10.08	9.517
	(15.97)	(18.06)	(17.40)	(15.24)	(16.95)	(16.39)	(16.43)	(18.70)	(18.00)
gas treatment capacity	4.905	4.824	4.851	5.504	5.423	5.451	4.497	4.449	4.465
	(4.613)	(4.659)	(4.644)	(4.919)	(4.941)	(4.933)	(4.345)	(4.433)	(4.404)
firm age	2.419	2.442	2.434	2.336	2.353	2.347	2.475	2.498	2.490
	(0.998)	(0.942)	(0.961)	(0.979)	(0.912)	(0.936)	(1.007)	(0.955)	(0.973)
export	0.0713	0.132	0.111	0.0412	0.0718	0.0611	0.0918	0.170	0.144
	(0.242)	(0.372)	(0.335)	(0.173)	(0.215)	(0.202)	(0.278)	(0.438)	(0.394)
agglo	10.07	10.96	10.66	10.37	11.27	10.95	9.857	10.77	10.47
	(1.502)	(1.428)	(1.514)	(1.320)	(1.212)	(1.322)	(1.581)	(1.516)	(1.597)
employment	5.643	5.560	5.588	5.498	5.393	5.429	5.742	5.665	5.691
	(1.068)	(1.094)	(1.086)	(0.984)	(1.017)	(1.006)	(1.111)	(1.128)	(1.123)
Plant	0.00532	0.00485	0.00501	0.00486	0.00422	0.00445	0.00564	0.00524	0.00537
	(0.0728)	(0.0695)	(0.0706)	(0.0695)	(0.0649)	(0.0665)	(0.0749)	(0.0722)	(0.0731)
Observations	72,700	142,115	214,815	29,446	54,687	84,133	43,254	87,428	130,682

industries, the mean ROA for samples in high SO2 emission industries (3.715) is higher than samples in low emission industries (3.395).

For the "*end of pipe*" variable, the mean in treatment groups is higher than the mean in control groups, which mean firms in TCZ area use more end-of-pipe devices than firms outside TCZ area. The mean "*end of pipe*" amount for samples in high SO2 emission industries (0.113) is higher than low emission industries (0.100). For the full sample, the mean "*change in process*" amount for samples in treatment group is lower than samples in control group. Same patterns show in high and low SO2 emission industries.

Table 6 indicates that, over the years, the mean SO2 discharged amount, generated amount, and SO2 intensity is fluctuated. But all three emission variables have lower amount in treatment group than the mount in control group in each year. Figure 3 and Figure 4 indicates the mean trend for SO2 discharged amount and SO2 intensity respectively. It implies that no mater for SO2 discharged amount and SO2 intensity, emission variables have parallel trend between treatment group and control group before 2000.

Table 7: The mean time trends of emission variables

	SO2 Discharged			*SO2 Generated*			*SO2 Intensity*		
	T=1	T=0	Total	T=1	T=0	Total	T=1	T=0	Total
1998	10	10.11	10.04	10.10	10.21	10.14	3.876	5.077	4.273
	(1.964)	(1.944)	(1.958)	(1.993)	(1.957)	(1.982)	(13.21)	(15.30)	(13.95)
1999	9.880	10.02	9.929	10.01	10.13	10.05	3.265	4.288	3.623
	(1.941)	(1.921)	(1.935)	(1.971)	(1.948)	(1.964)	(12.26)	(17.77)	(14.43)
2000	9.861	10.03	9.918	10.02	10.19	10.08	3.334	4.781	3.818
	(1.922)	(1.940)	(1.930)	(1.955)	(1.968)	(1.961)	(12.43)	(18.56)	(14.78)
2001	9.927	10.12	9.992	10.09	10.26	10.15	3.390	5.106	3.956
	(1.883)	(1.932)	(1.902)	(1.915)	(1.958)	(1.931)	(12.14)	(17.96)	(14.34)
2002	9.847	10.08	9.920	10.05	10.25	10.11	2.970	4.525	3.461
	(1.902)	(1.930)	(1.914)	(1.946)	(1.967)	(1.955)	(11.32)	(13.35)	(12.02)
2003	9.906	10.06	9.958	10.12	10.24	10.16	2.822	4.654	3.430
	(1.916)	(1.932)	(1.923)	(1.957)	(1.971)	(1.962)	(10.23)	(17.32)	(13.05)
2004	9.980	10.17	10.04	10.19	10.35	10.25	2.966	4.927	3.629
	(1.907)	(1.960)	(1.927)	(1.950)	(1.978)	(1.961)	(9.515)	(15.58)	(11.96)
2005	9.934	10.09	9.984	10.16	10.29	10.20	2.759	4.636	3.358
	(1.920)	(2.010)	(1.950)	(1.974)	(2.027)	(1.992)	(11.47)	(16.32)	(13.24)
2006	9.834	10.07	9.918	10.04	10.24	10.11	2.222	3.885	2.804
	(1.878)	(1.937)	(1.902)	(1.928)	(1.968)	(1.945)	(7.883)	(14.79)	(10.84)
2007	9.604	9.858	9.701	9.790	10.02	9.878	1.358	2.251	1.699
	(1.819)	(1.868)	(1.842)	(1.876)	(1.911)	(1.893)	(4.433)	(7.859)	(5.995)
Total	9.875	10.06	9.936	10.06	10.21	10.11	2.863	4.338	3.362
	(1.907)	(1.938)	(1.920)	(1.949)	(1.967)	(1.957)	(10.73)	(15.66)	(12.63)

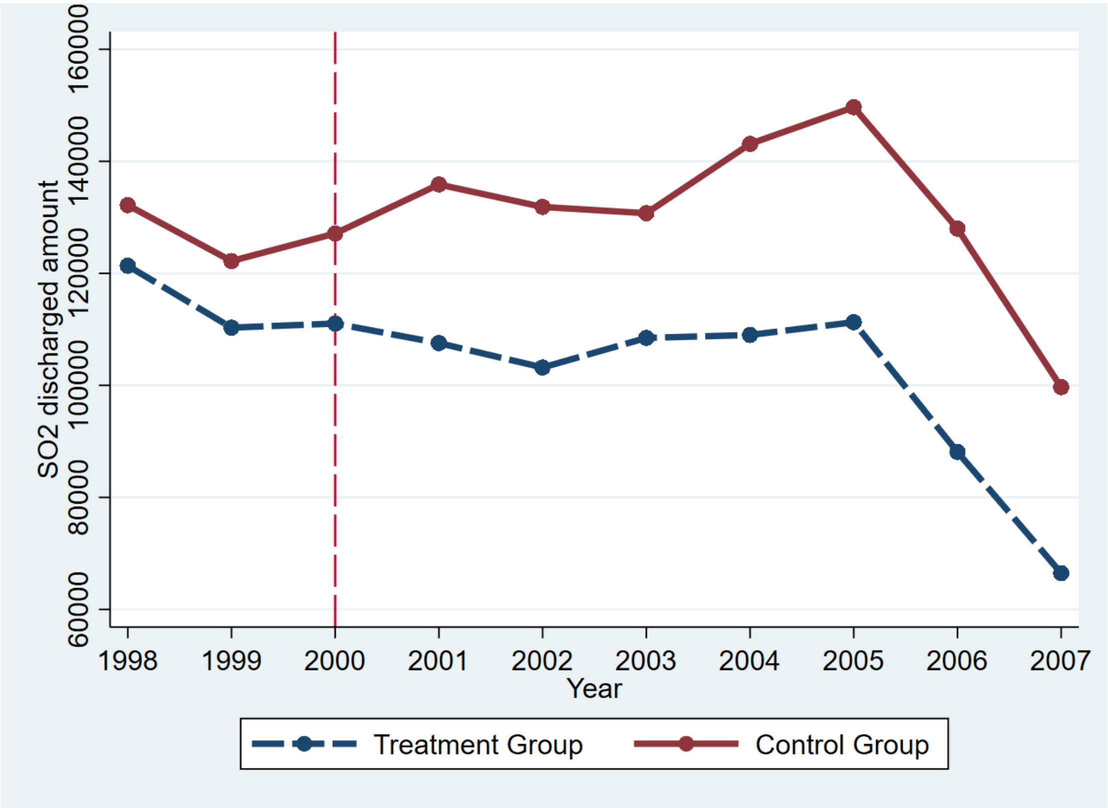

Figure 3: Mean trend for SO2 discharged amount

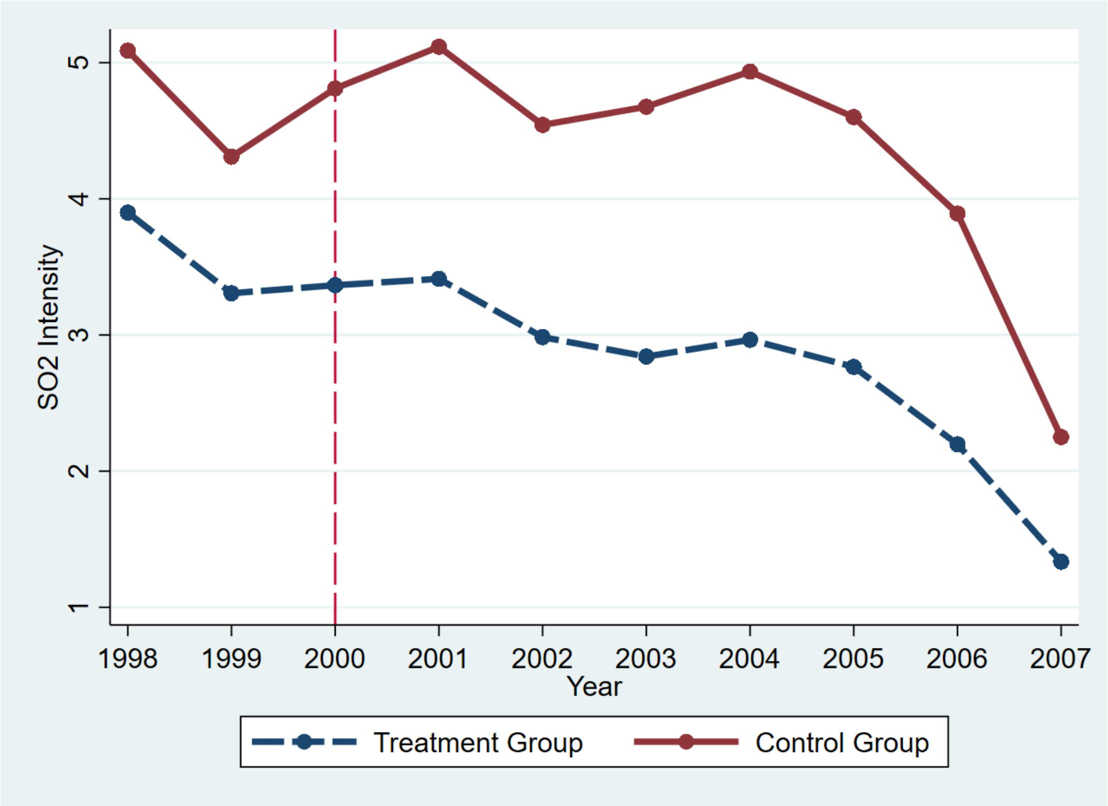

Figure 4: Mean trend for SO2 Intensity

5 Regression Result

5.1 Basic Result

Table 8: The impact of TCZ on firm emissions

Dep. Var.	(1) SO2 Discharged	(2) SO2 Generated	(3) SO2 Intensity
$TCZ_i * Post_t$	-0.243***	-0.212***	-0.767***
	(-11.23)	(-10.08)	(-3.60)
Output	0.008***	0.008***	-0.029***
	(14.83)	(15.46)	(-10.99)
gas treatment capacity	0.021***	0.032***	-0.016
	(15.94)	(24.50)	(-1.44)
firm age	0.056***	0.058***	-0.148**
	(8.65)	(9.23)	(-2.22)
export	0.019	0.021*	0.004
	(1.62)	(1.72)	(0.07)
agglo	0.006	0.005	-0.292**
	(0.57)	(0.49)	(-2.44)
Plant	0.773***	0.770***	3.428***
	(12.61)	(12.72)	(5.19)
Constant	9.812***	10.097***	3.602**
	(56.53)	(58.44)	(2.08)
Observations	214,815	214,815	214,815
R-squared	0.041	0.038	0.010
Number of firms	67,270	67,270	67,270
Company FE	YES	YES	YES
Year FE	YES	YES	YES
Local Economic Shocks	YES	YES	YES

Note: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 8 reports the estimated effect of the TCZ policy on firm emissions. Using SO2 discharged amount, SO2 generated amount, and SO2 intensity as the proxy for firm emissions respectively, the coefficients of $TCZ_i * Post_t$ in column (1) to (3) are significantly negative, consistent across all specification. All three columns using equation (1) control for firm fixed effect, year fixed effect, and local economic shocks as C. Wang et al. (2018). The results suggest the robust impact of TCZ policy on firms inside TCZ area compared to what would have happened there with no such intervention. Therefore, the TCZ policy has caused regulated firms significantly reduce SO2 discharged amount, SO2 generated amount, and the intensity of the SO2 discharges. Regarding magnitudes, the result in column

Table 9: The impact of TCZ on firm performance

Dep. Var.	(1) TFP	(2) ROA	(3) ROS
$TCZ_{it} * Post_{it}$	-0.030**	-0.175	-0.375
	(-2.28)	(-1.10)	(-0.82)
Output	0.025***	0.138***	0.165***
	(49.71)	(23.13)	(17.98)
firm age	0.024***	-0.052	-0.422***
	(5.61)	(-0.84)	(-3.72)
export	0.039**	-0.240	0.108
	(2.17)	(-1.42)	(0.40)
agglo	0.035***	-0.062	0.056
	(4.07)	(-0.65)	(0.42)
gas treatment capacity	0.001*	0.006	-0.000
	(1.82)	(0.49)	(-0.01)
Plant	-0.018	-0.688*	-0.907
	(-0.55)	(-1.94)	(-0.98)
Constant	7.113***	7.213***	-0.091
	(49.82)	(4.51)	(-0.02)
Observations	208,904	214,814	214,815
R-squared	0.180	0.040	0.011
Number of firms	66,379	67,270	67,270
Company FE	YES	YES	YES
Year FE	YES	YES	YES
Local Economic Shocks	YES	YES	YES

Note: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

1 implies that the TCZ policy has reduced firms' SO2 discharged levels by 28.9% ($e^{(-0.243)-1}$); column 2 shows that the TCZ policy regulated firms' SO2 generated amount decreased by 29.8% ($e^{(-0.212)-1}$); column 3 shows the regulated firms' SO2 intensity decreased by 0.767.

Most of the control variables are significantly correlated with firm emission indicators. Large firms have significantly higher SO2 discharged and generated amount, which are in line with G. He et al. (2018), as they may do more production than small firms. But, large firms have significantly smaller SO2 intensity consistent with the result reported by C. Wang et al. (2018). Gas treatment ability is positively correlated with firm SO2 emission amount. High emission firms always accompanied by high pollution abatement capacity (P. He and Zhang, 2018; M. Liu et al., 2018), because they need more abatement devices for pollution treatment.

Similar to the results of existing literature, like Greaney et al., 2017; M. Liu et al., 2017; W. Sun et al., 2019; C. Wang et al., 2018, firm age is found to be positively correlated with firm SO2 emission amount significantly in Table 8. Older firms have better communication power with local government and long-established management systems in production and pollution control, which means they may not be active in improving their pollution reducing technologies (W. Sun et al., 2019). This finding is consistent with the "grandfather" phenomenon, which holds new environmental policies are often designed or implemented in such a way that older firms can be exempted from tighter regulations. This phenomenon is occurred because the cost of building new sources with cleaner technology is lower than that of retrofitting existing facilities (C. Wang et al., 2018). In column 3 of Table 8, the coefficient of firm age is significantly negative, which is inconsistent with the "grandfather" phenomenon, but can be explained as older firms have higher output growth compare to the growth of emission.

The coefficient of firms' export to sales ratio is significantly positive when using SO2 generated amount as dependent variables, but it is statistically insignificant when using SO2 generated amount or SO2 intensity as dependent variables. This result is in line with C. Wang et al. (2018) which suggest a statistically insignificant effect of export ration on firm emission intensity. For the variable for controlling industry agglomeration, *agglo*, we do not find significant correlation between industry agglomeration and firm SO2 discharged or generated amount. But, similar to the result of C. Wang et al. (2018), we find industry agglomeration negatively correlated with firm SO2 intensity at 5% significance level. Firms in industries with higher agglomeration discharge less polluting than firms with low agglomeration under the same output. *Plant* dummy is found to be positively correlated with firm SO2 emission indicators and the intensity of SO2 emission, which is consistent with Greenstone et al. (2012) and C. Wang et al. (2018).

Table 9 reports the effect of the TCZ policy on firm performance denoted by productivity and profitability. Using equation (1), all three columns control for firm fixed effect, year fixed effect, and local economic shocks. In column (1) to column (3), this paper uses TFP as the proxy for firm productivity and uses return on assets and return on sales as the proxy for firm profitability respectively. The coefficient of $TCZ_i * Post_t$ in column (1) is significantly negative, which means that the TCZ policy has caused TFP reduction for firms inside TCZ area compared to what would have happened there with no such intervention. This reuslt is in line with the Neo-classical theory and existing literature such as Barbera and McConnell (1990), Greenstone et al. (2012), and G. He et al. (2018). Regarding magnitudes, the result in column (1) implies that the TCZ policy has reduced firms' TFP by 35.7 % ($e^{(-0.030)-1}$). Column (2) and column (3) shows the impact of the TCZ policy on firm profitability is statistically insignificant at conventional levels. Although it is statistically insignificant, we see a tendency that firms outside TCZ area earn more profit despite not producing more product.

Most of the control variables in column (1) are also significantly correlated with firm TFP. The coefficient of *Output* is significantly positive, which implies large firms are accompanied by higher productivity. The result is in line with Brandt et al. (2012) that Chinese Large firms always have higher increasing productivity than average rate. Similar to result of existing literature, like Ding et al. (2016) and Ding et al. (2019), we find older firms have higher productivity, the positive coefficient of *firm age*. It is explained as the learning-by-doing phenomenon, in which firms can improve their productivity by long time learning process. The ratio of export value over sales also find to be significantly positive correlated with firm TFP, which is consistent with Brandt et al. (2012) and Syverson (2011). Syverson (2011) suggest that export is often accompanied by large R&D investments, which raise exporters' productivity levels. Positive coefficient of agglomeration is in line with Syverson (2011) who attribute this productivity increase to agglomeration-type productivity spillovers. Firms with higher gas treatment capacity are found to have higher TFP, while the *Plant* dummy is insignificantly correlated with TFP, which is inconsistent with Greenstone (2002) as few of observations with multi-plants.

In column (2) and column (3) of Table 9, most control variables are insignificant except firm size variable, *Output*. The positive correlation between firm size and profitability is in line with Russo and Fouts (1997) and Zhao and Sun (2016), which implies large firms may have higher profitability. Column (2) shows firms with multi-plants would have lower return on assets. While, in column (3), we find that new firms have higher return on sales than old firms. But this paper do not find evidence suggesting the significant effect of export ratio, firm agglomeration, or gas treatment ability on firm profitability. This is inconsistent with existing literature, in particular, export and agglomeration has found to be beneficial for firm productivity (Russo and Fouts, 1997).

Table 10: Economic Channels

	(1)	(2)	(3)
Dep. Var	end of pipe	change in process	SO2 Treatment Ability (ln)
$TCZ_{it} * Post_{it}$	0.017*** (4.89)	-0.672*** (-2.83)	0.133*** (8.11)
Observations	214,815	214,815	214,815
R-squared	0.047	0.009	0.129
Number of firms	67,270	67,270	67,270
Control variables	YES	YES	YES
Company FE	YES	YES	YES
Year FE	YES	YES	YES
Local Economic Shocks	YES	YES	YES

Note: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

5.2 Economic channels and mechanisms

How do firms respond to the TCZ regulation? We examine the channels through which TCZ policy affects firms' behaviour. In Table 10, we estimate the impacts of TCZ policy on several key variables, end of pipe, change in process, and SO2 treatment ability. Using "end-of-pipe" variable and "change-in-progress" variable, we estimate two various pollution abatement activities under environmental regulation, taking abatement devices for removing pollutant after production and improving production technologies to reduce generated pollutant during production, the same approach used as M. Liu et al. (2018), P. He and Zhang (2018), W. Sun et al. (2019). Berman and Bui (2001) suggest that firms regulated by environmental policies would choose to invest in taking "changes in process" activities, "end-of-pipe" measurement, or do both.

In column (1) of Table 10, we focused on "end of pipe", calculated by the ratio of SO2 removed amount over SO2 generated amount. The coefficient of $TCZ_i * Post_t$ in column (1) is significantly positive (0.017), which means that the TCZ policy has caused "end of pipe" activities increase for firms inside TCZ area compared to what would have happened there with no such intervention. This finding implies that regulated firms take more "end of pipe" activities for pollutant abatement after production, which is in line with P. He and Zhang (2018) and W. Sun et al. (2019). They removed more SO2 pollutant from the generated compared to the counterfactual after production. But "end-of-pipe" activities also bring an additional cost for firms, which is harmful for firm productivity and profitability. Thus, the estimated increase of “end-of-pipe” activities for regulated firms is a support for the neoclassical theory on environmental economics.

In column (2) of Table 10, we focused on "change in process", calculated by the ratio of SO2 generated amount over firm output. The coefficient of $TCZ_i * Post_t$ in column (2) is significantly negative (-0.672), which implies that the TCZ policy also induced "change in process" activities increase for regulated firms compared to what would have happened there with no such intervention. The result suggests that regulated firms also take take more "change in process" activities for reducing SO2 pollutant generated during production. As "change in process" activities always accompanied by improved technologies or improved production process, taking more "change in process" activities can promote firm productivity, which suggesting the Porter Hypothesis.

In column (3) of Table 10, we focused on firm SO2 treatment ability (Kg/h) who linked directly to firms' “end of pipe” activities. The coefficient of $TCZ_i * Post_t$ in column (3) is significantly positive (0.133), which is in line with column (1). The TCZ policy has caused SO2 treatment ability increase for firms inside TCZ area compared to what would have happened there with no such intervention. This is another evidence that proving the TCZ policy has enforced regulated firms invest more in devices on SO2 abatement. The TCZ policy has induced firms take more pollutant abatement activities and also brought more additional cost.

5.3 Heterogeneous analysis

As firms would react differently in response to the TCZ policy, the argument on the impact of environmental regulation on firm behaviour can be extended to investigate heterogeneous patterns through different firm characteristics. In this section, we explore whether the effect of TCZ policy on firm behaviour varies by emission characteristics, ownership, firm size and upstreamness.

5.3.1 High and Low SO2 emission industries

We divide the firms in merged dataset into high-polluting industries and low-polluting industries based on the definition of polluting industries used by the MEP. According to *the First Pollution Census Report* published in 2010 jointly by the Ministries of Environmental Protection, the National Bureau of Statistics,

Table 11: The impact of TCZ on firm emissions across polluting groups

Dep. Var	(1) SO2 discharged	(2) SO2 generated	(3) SO2 intensity	(4) end of pipe	(5) change in process
			Panel A. high SO2 polluting industry		
$TCZ_{it} * Post_{it}$	-0.258***	-0.221***	-1.485***	0.018***	-1.331**
	(-6.83)	(-5.99)	(-3.10)	(2.84)	(-2.49)
Observations	84,133	84,133	84,133	84,133	84,133
R-squared	0.039	0.039	0.019	0.039	0.016
Number of firms	26,503	26,503	26,503	26,503	26,503
			Panel B. low SO2 polluting industry		
$TCZ_{it} * Post_{it}$	-0.225***	-0.200***	-0.225	0.016***	-0.167
	(-8.69)	(-7.93)	(-1.31)	(3.82)	(-0.87)
Observations	130,682	130,682	130,682	130,682	130,682
R-squared	0.055	0.051	0.010	0.060	0.009
Number of firms	42,098	42,098	42,098	42,098	42,098
Empirical p-value	0.085*	0.260	-	0.150	-
Control Variables	YES	YES	YES	YES	YES
Company FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Local Economic Shocks	YES	YES	YES	YES	YES

Note: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 12: The impact of TCZ on firm performance across polluting groups

Dep. Var	(1) TFP	(2) ROA	(3) ROS
	Panel A. high SO2 polluting industry		
$TCZ_{it} * Post_{it}$	-0.025	0.145	0.215
	(-1.23)	(0.55)	(0.47)
Observations	80,931	82,889	82,889
R-squared	0.196	0.052	0.023
Number of firms	25,904	26,209	26,209
	Panel B. low SO2 polluting industry		
$TCZ_{it} * Post_{it}$	-0.044***	-0.479**	-0.864
	(-2.61)	(-2.50)	(-1.48)
Observations	126,879	130,682	130,682
R-squared	0.176	0.040	0.013
Number of firms	41,482	42,098	42,098
Empirical p-value	-	-	-
Control Variables	YES	YES	YES
Company FE	YES	YES	YES
Year FE	YES	YES	YES
Local Economic Shocks	YES	YES	YES

Note: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

and the Ministry of Agriculture, 6 industries together account for 88.5% of SO2 emissions from industrial sources, which are defined as high-polluting industries. These 6 sectors, 2-digit industrial codes, are “the production and supply of electric power and heat 44”, “non-metallic mineral products 31”, “ferrous metal smelting and calendering industry 32”, “manufacturing of chemical raw materials and chemical products 26”, “nonferrous metal smelting and calendering industry 33”, and “petroleum processing, coking and nuclear fuel processing industry 25”.

In Table 11, we estimate the DD by firm emission type and find that high-polluting firms and low-polluting firms adopted different abatement strategy subject to the TCZ policy, although the policy effectively reduce firm emissions for both high-polluting and low-polluting firms. Panel A are samples from high-polluting industries, and Panel B are firms in low-polluting industries. In column (1) of Table 11, it implies that the TCZ policy has reduced high-polluting firms' SO2 discharged amount by 28.4% ($e^{(-0.258)-1}$) and has reduced low-polluting firms' SO2 discharged amount by 29.4% ($e^{(-0.225)-1}$). The empirical p-value in column (1), used to provide evidence regarding whether the coefficient of variable interested in two groups have a significant difference when both of them are separately statistical significant, indicates that the coefficient difference of $TCZ_i * Post_t$ in two emission type groups is significant at 10% significance level. The environmental regulation is more efficient in reducing low-polluting firms' pollutant discharged amount. In column (2), we find the policy significantly reduce firms' SO2 generated amount in both groups, but the difference of coefficient is insignificant. In column (3), the policy significantly reduced high-polluting firms' SO2 intensity, but the coefficient of $TCZ_i * Post_t$ is insignificant in low-polluting group.

The results of column (4) and column (5) in Table 11 shows the abatement strategy adopted by the two groups. It implies that high-polluting firms take both "end of pipe" activities and "change in process" activities for pollution abatement, while low-polluting firms merely take "end of pipe" activities. Their strategies of abatement can influence whether does TCZ policy significantly influence firm productivity and profitability. As shown in Table 12's Panel A, the TCZ policy does not have significant effect on high-polluting firms' productivity and profitability, because they take both two abatement measures, one is harmful for firm performance the other one is beneficial for it. Panel B of Table 12 shows the significant negative impact of TCZ policy on firm TFP and ROA as low-polluting firms only take "end of pipe" activities which increase firm production cost.

The result in Table 11 shows that high-polluting firms and low-polluting firms take various measures in emission reduction. One explanation is that, for high-polluting enterprises, only adopting "end of pipe" method is not enough to effectively reduce emissions, even if "end of pipe" is the first option of firms for emission reduction. Another explanation is the "learning-by-doing" phenomenon. High-polluting firms have more opportunities and incentives to expose to abatement related technologies, thus "change in process" activities are more likely occur in high-polluting firms. Consider the result in Table 11 and Table 12 jointly, we find the evidence supporting both the neo-classical theory and Poter Hypothesis. For low-polluting firms, the TCZ policy have negative impact on their firm productivity and profitability, as they only take "end of pipe" measure that increase production cost, which is a support for neo-classical theories. High-polluting firms taking "change in process" activities promote firm productivity, supporting the Porter Hypothesis, which compensate the productivity lose brought by "end of pipe" activities.

5.3.2 The Ownership

Table 13: The impact of TCZ on firm emissions across ownership groups

Dep. Var	(1) SO2 discharged	(2) SO2 generated	(3) SO2 intensity	(4) end of pipe	(5) change in process
			Panel A. SOEs		
$TCZ_{it} * Post_{it}$	-0.271***	-0.237***	-1.018**	0.017***	-0.934
	(-7.54)	(-6.79)	(-2.17)	(2.83)	(-1.75)
Observations	40,469	40,469	40,469	40,469	40,469
R-squared	0.064	0.060	0.015	0.057	0.016
Number of firms	12,423	12,423	12,423	12,423	12,423
			Panel B. Private firms		
$TCZ_{it} * Post_{it}$	-0.251***	-0.223***	-0.846***	0.017***	-0.766**
	(-7.02)	(-6.46)	(-3.10)	(2.86)	(-2.53)
Observations	119,350	119,350	119,350	119,350	119,350
R-squared	0.039	0.039	0.014	0.048	0.012
Number of firms	38,501	38,501	38,501	38,501	38,501
Empirical p-value	0.160	0.340	0.500	0.240	-
Control Variables	YES	YES	YES	YES	YES
Company FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Local Economic Shocks	YES	YES	YES	YES	YES

Note: Robust t-statistics in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

In Table 13 and Table 14, we estimate the DD by ownership type, where Panel A is the estimation of SOEs, and Panel B is the estimation of private firms. As shown in Table 13, the results in column (1), (2), and (3) of Panel A indicates the TCZ policy has significantly reduced SOEs' SO2 discharged amount, SO2

Table 14: The impact of TCZ on firm performance across ownership groups

Dep. Var	(1) TFP	(2) ROA	(3) ROS
Panel A. SOEs			
$TCZ_{it} * Post_{it}$	-0.053**	-0.478**	-0.819
	(-2.32)	(-2.17)	(-0.70)
Observations	38,565	40,469	40,469
R-squared	0.134	0.040	0.017
Number of firms	12,057	12,423	12,423
Panel B. Private firms			
$TCZ_{it} * Post_{it}$	0.004	0.073	0.236
	(0.21)	(0.27)	(0.56)
Observations	116,855	119,350	119,350
R-squared	0.213	0.045	0.021
Number of firms	38,179	38,501	38,501
Empirical p-value	-	-	-
Control Variables	YES	YES	YES
Company FE	YES	YES	YES
Year FE	YES	YES	YES
Local Economic Shocks	YES	YES	YES

Note: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

generated amount, and SO2 intensity. Regulated SOEs' SO2 discharged amount has reduced by 28.1% ($e^{(-0.271)-1}$) and SO2 generated amount has reduced by 29% ($e^{(-0.237)-1}$). The result in column (4) and (5) of Panel A implies that SOEs only take "end of pipe" activities to reduce their emission rather than improving production technologies to limit generated pollutant during production.

In Panel B, the result from column (1) to (3) indicate that the TCZ policy also effectively reduced private firms' emission amount. For private firms, SO2 discharged amount has reduced by 28.6% ($e^{(-0.251)-1}$) and SO2 generated amount has reduced by 29.4% ($e^{(-0.223)-1}$). As shown in column (4) and (5), both "end of pipe" measure and "change in process" measure are adopted by private firms for emission abatement.

Table 14's result indicates that the TCZ policy has reduced SOEs' TFP by 34.9% ($e^{(-0.053)-1}$) and also has deleterious impact on SOEs' return on assets, because of SOEs only take "end of pipe" activities. But, it has had insignificant impact on private firms' productivity or profitability, which due to private firms take both two abatement measures. On the one hand, private have less barging power than SOEs concerning the enforcement of environmental regulations such as pollution charges and fines (C. Wang et al., 2018; H. Wang and Wheeler, 2003). For complying with the environmental regulation, private firms would take all measures to reduce emission. Technologies promote "change in process" would benefit firms in the long run. On the other hand, SOEs have advantage in financial accessibility, as they are more likely to be favoured by state-owned banks (Ding et al., 2013; Hsieh and Klenow, 2009), so SOEs would invest more in fixed assets. Meanwhile, SOEs have social and political objectives other than profit maximization in China, which enforce them to take the lead in reducing emissions. Thus, SOEs prefer taking "end of pipe" measures, like purchasing pollutant treatment devices, to quickly and effectively reduce emission in the short run.

5.3.3 Large and small firms

Table 15: The impact of TCZ on emissions across firm size groups

Dep. Var	(1) SO2 discharged	(2) SO2 generated	(3) SO2 intensity	(4) end of pipe	(5) change in process
			Panel A. Large firms		
$TCZ_{it} * Post_{it}$	-0.249***	-0.220***	-0.738***	0.016***	-1.722
	(-10.86)	(-9.87)	(-3.17)	(4.20)	(-0.68)
Observations	175,005	175,005	175,005	175,005	175,005
R-squared	0.044	0.041	0.011	0.048	0.010
Number of firms	54,201	54,201	54,201	54,201	54,201
			Panel B. Small firms		
$TCZ_{it} * Post_{it}$	-0.045	-0.015	-1.512**	0.023*	-1.525**
	(-0.61)	(-0.21)	(-2.39)	(1.86)	(-2.22)
Observations	39,810	39,810	39,810	39,810	39,810
R-squared	0.046	0.046	0.026	0.052	0.024
Number of firms	19,395	19,395	19,395	19,395	19,395
Empirical p-value	-	-	0.040**	0.300	-
Control Variables	YES	YES	YES	YES	YES
Company FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Local Economic Shocks	YES	YES	YES	YES	YES

Note: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

In Table 15 and Table 16, we estimate the DD by firm size type, where Panel A is the estimation of large firms, and Panel B is the estimation of small firms. We consider a firm with more than 100 labour as the large firm, otherwise small firms. As shown in Table 15, the results in column (1), (2), and (3) of Panel A indicates the TCZ policy has significantly reduced large firms' SO2 discharged amount, SO2 generated amount, and SO2 intensity. Regulated large firms' SO2 discharged amount has reduced by 28.7% ($e^{(-0.249)-1}$) and SO2 generated amount has reduced by 29.5% ($e^{(-0.220)-1}$). The result in column (4) and (5) of Panel A

Table 16: The impact of TCZ on firm performance across firm size groups

Dep. Var	(1) TFP	(2) ROA	(3) ROS
Panel A. Large firms			
$TCZ_{it} * Post_{it}$	-0.041***	-0.217	-0.376
	(-3.06)	(-1.38)	(-0.75)
Observations	170,174	175,005	175,005
R-squared	0.189	0.041	0.011
Number of firms	53,441	54,201	54,201
Panel B. Small firms			
$TCZ_{it} * Post_{it}$	0.040	0.766	0.156
	(0.80)	(0.84)	(0.16)
Observations	38,730	39,809	39,810
R-squared	0.209	0.074	0.034
Number of firms	19,046	19,395	19,395
Empirical p-value	-	-	-
Control Variables	YES	YES	YES
Company FE	YES	YES	YES
Year FE	YES	YES	YES
Local Economic Shocks	YES	YES	YES

Note: Robust t-statistics in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

implies that large firms only take "end of pipe" activities to reduce their emission.

In Panel B of Table 15, column (1) and (2) shows that the TCZ policy did not significantly reduce large firms' emission amount. But column (3) indicates that regulated small firms has lower SO2 intensity. In column (4) and (5), both "end of pipe" measure and "change in process" measure are adopted by small firms for emission abatement.

Table 16's result indicates that the TCZ policy has reduced large firms' TFP by 35.3% ($e^{(-0.041)-1}$) as they only take "end of pipe" activities. TCZ policy has had insignificant impact on small firms' productivity or profitability. The result of the impact heterogeneity by firm size can be explained by a China's government policy strategy called "invigorate large enterprises while relaxing control over small ones" (in Chinese, it is called "Zhua Da Fang Xiao"). "Invigorate large enterprises" means that the central government policymaker allows the local government policy enforcer to set large firms as the main regulatory target. "Relaxing control over small ones" means that the policy enforcer exerts less control over smaller enterprises. This policy strategy has been wildly taken in policy implementation (G. He et al., 2018; Hsieh and Song, 2015). (See, for example, "The Top 10,000 Energy-Consuming Enterprise Program," which requires only large firms to abate carbon emissions: http://www.ndrc.gov.cn/zcfb/zcfbtz/201112/t20111229_453569.html). Our heterogeneity test proved that this strategy also been applied to the context of the TCZ policy. The TCZ policy has effectively reduce large firms' emission and brought deleterious effect on their TFP, but it has no impact on small firms' emission amount and performance.

5.3.4 Upstream and downstream firms

Table 17: The twenty least and most upstreamness of China manufacturing industries

I-O sector code	I-O sector name	CIC industry code (3-digit)	upstreamness
	10 lowest upstreamness		
14018	Convenience food manufacturing	143	1.24495
14021	Other food manufacturing	141;142;145;149	1.51117
14019	Liquid milk and dairy products	144	1.57487
36072	Other special industrial equipment	363; 364;365; 366;368;369	1.79667
14020	Seasoning, fermentation products	146	1.84615
13017	Other food processing	137;139	1.96885
35066	Crane transportation equipment	353	1.97876
36071	Agriculture, forestry, animal husbandry and fishing machinery	367	1.98323
40086	Radio, television, and communication	407	1.99966
40082	Telecommunication equipment	401	2.00288
	10 highest upstreamness		
32060	Alloy iron smelting	324	4.78575
17029	Knitted and crocheted fabrics and articles	176	4.79766
17025	Cotton textiles	171	4.81375
32057	Iron-smelting	321	4.88227
26044	Special chemical products	266	5.02258
33061	Nonferrous metal smelting and alloy	331;332;333;334	5.03056
25038	Coking	252	5.18688
43091	Scrap and waste	430;431;432	5.19773
28047	Chemical fibers	280;281;282	5.31606
26039	Basic chemicals	261	5.50584

We classify all samples into upstream and downstream firms following the methodology of Antràs et al. (2012). A 42-sector Input-Output (I-O) Table (2-digit) is provided by the National Bureau of Statistics in every two or three years, and

Table 18: The impact of TCZ on firm emissions across upstream and downstream firms

	(1)	(2)	(3)	(4)	(5)
Dep. Var	SO2 discharged	SO2 generated	SO2 intensity	end of pipe	change in process
			Panel A. Upstream firms		
$TCZ_{it} * Post_{it}$	-0.229***	-0.203***	-0.159	0.015***	-0.005
	(-6.81)	(-6.24)	(-0.75)	(2.62)	(-0.02)
Observations	101,920	101,920	101,920	101,920	101,920
R-squared	0.043	0.042	0.015	0.048	0.012
Number of firms	35,705	35,705	35,705	35,705	35,705
			Panel B. Downstream firms		
$TCZ_{it} * Post_{it}$	-0.235***	-0.194***	-1.239***	0.020***	-1.135***
	(-7.77)	(-6.55)	(-3.98)	(3.94)	(-3.28)
Observations	100,599	100,599	100,599	100,599	100,599
R-squared	0.043	0.040	0.015	0.051	0.015
Number of firms	33,285	33,285	33,285	33,285	33,285
Empirical p-value	0.280	0.360	-	0.420	-
Control Variables	YES	YES	YES	YES	YES
Company FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Local Economic Shocks	YES	YES	YES	YES	YES

Note: Robust t-statistics in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

a more detailed I-O Table (5-digit) is provided in every five years, like the 124-sector I-O Table in 1997, the 122-sector I-O Table in 2002, and the 135 I-O Table in 2007. In these I-O Tables, each 5-digit I-O sector may correspond to one or more 3-digit Chinese Industry Classification (CIC) sectors (see, in Table 17, I-O code 14021 combines four 3-digit CIC codes). The 5-digit-Input-Output-industry-specific (3-digit CIC sectors) upstreamness (or average distance from final use) are calculated on the basis of the detailed Input-Output Table in 1997, 2002 and 2007. Specifically, this research uses the 1997's 124-sector I-O table to calculate 5-digit-Input-Output-industry-specific upstreamness for observations from 1998 to 2001, uses the 2002's 122-sector I-O table to calculate upstreamness for observations from 2002 to 2004, and uses the 2007's 135-sector I-O table to get upstreamness for observations from 2005-2007.

Considering the upstreamness calculation on the basis of 2007's 135 I-O sectors, the measure of upstreamness ranges from a minimum of 1 (Social welfare industry) to a maximum of 6.09 (Non-ferrous metal ore mining industry), with a mean value of 3.17. Table 17 exhibits the twenty least and most upstreamness of China manufacturing industries, where a higher value of upstreamness means a more upstream position. Industries with least value of upstreamness, like food manu-

Table 19: The impact of TCZ on firm performance across upstream and downstream firms

Dep. Var	(1) TFP	(2) ROA	(3) ROS
Panel A. Upstream firms			
$TCZ_{it} * Post_{it}$	-0.039*	0.091	0.715
	(-1.91)	(0.37)	(1.00)
Observations	99,266	101,919	101,920
R-squared	0.195	0.048	0.014
Number of firms	35,215	35,705	35,705
Panel B. Downstream firms			
$TCZ_{it} * Post_{it}$	-0.012	-0.046	-0.066
	(-0.65)	(-0.20)	(-0.11)
Observations	97,625	100,599	100,599
R-squared	0.162	0.040	0.017
Number of firms	32,765	33,285	33,285
Empirical p-value	-	-	-
Control Variables	YES	YES	YES
Company FE	YES	YES	YES
Year FE	YES	YES	YES
Local Economic Shocks	YES	YES	YES

Note: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

facturing, is of output go directly to the end-user or consumers; while, industries with highest value of upstreamness, like basic chemicals and chemical fibres, are producers for raw materials.

The full sample is sub-grouped according the medium value of upstreamness. In Table 18 and Table 19, we estimate the DD by firm upstreamness type, where Panel A is the estimation of upstream firms, and Panel B is the estimation of downstream firms. As shown in Table 18, the results in column (1) and (2) of Panel A indicates the TCZ policy has significantly reduced upstream firms' SO2 discharged amount, SO2 generated amount by 29.3% and 30% respectively. But the TCZ policy has had insignificant on firm SO2 intensity. The result in column (4) and (5) of Panel A implies that upstream firms only take "end of pipe" activities to reduce their emission.

In Panel B, the result from column (1) to (3) indicate that the TCZ policy also effectively reduced downstream firms' emission amount and intensity, SO2 discharged amount was reduced by 29.1% and SO2 generated amount was reduced by 30.3%. As shown in column (4) and (5), both "end of pipe" measure and "change in process" measure are adopted by downstream firms for emission abatement. Table 19's result indicates that the TCZ policy has reduced upstream firms' TFP by 35.4% ($e^{(-0.039)-1}$) as they only take "end of pipe" activities. TCZ policy has had insignificant impact on downstream firms' productivity or profitability. Upstream firms produce raw material or work-in-progress for downstream firms.

5.4 Economic Cost

Our baseline model estimates that the TCZ policy has caused an average reduction in SO2 discharged amount of 0.243 logarithmic units (as shown in column (1) of Table 8), equivalent to a 28.9% drop. In addition, the TCZ policy also has caused an average loss in TFP of 0.03 logarithmic units (as shown in column (1) of Table 9), equivalent to a 35.7% drop. To calculate the economic cost brings by the TCZ policy, a informative counterfactual would be to determine the TFP loss connected with a given amount of emission abatement. We can directly link the TFP estimates with COD estimates using equation (32) (same methodology as G. He et al., 2018). Thus, 10% change in SO2 discharged amount causes a 1.2% ($0.03/0.243 * 10\%$) change in TFP levels.

$$MRS = \frac{TFP_{ATE}}{Emission_{ATE}} \tag{32}$$

Table 20: Economic cost

Dep. Var	(1) TFP	(2) TFP	(3) Labour	(4) Labour
SO2 discharged	0.042***		0.034***	
	(19.60)		(28.10)	
SO2 generated		0.045***		0.036***
		(20.35)		(28.97)
Observations	208,904	208,904	214,815	214,815
R-squared	0.183	0.183	0.146	0.146
Number of firms	66,379	66,379	67,270	67,270
Control variables	YES	YES	YES	YES
Company FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Local Economic Shocks	YES	YES	YES	YES

Note: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

$$TFP_{it} = \alpha_1 Emission_{it} + \beta X_{it} + \gamma_{pt} + \mu_i + \sigma_t + \varepsilon_{it} \tag{33}$$

$$Labour_{it} = \alpha_1 Emission_{it} + \beta X_{it} + \gamma_{pt} + \mu_i + \sigma_t + \varepsilon_{it} \tag{34}$$

Another way calculating the trade-off between emission and TFP is that we estimate the TFP on emissions subject to the TCZ regulation. We keep observations in the treatment group and observations whose observable year is after 2000. Equation (33) is used to calculate the trade-off between emission amount and firm productivity, and equation (34) is used to calculate the trade-off between emission amount and labour loss. Table 20 reports the economic cost of the TCZ policy. Column 1 shows that 10% reduction on SO2 discharged value will lead to 0.42% reduction on firms' TFP. Column 2 shows 10% SO2 generated value reduction brings average 0.45% TFP losses for firms. Column 3 and 4 indicates that 10% reduction on firms' discharged value and generated value brings respectively 0.34% and 0.36% decrease on firms' employment.

The third way we calculating the trade-off between emission and TFP is following Faber (2014)'s methodology, which is the estimation result of equation (35). The advantage of this method is that it can remove fixed effect from regression. The result indicates that 10% change in SO2 discharged amount will lead to 0.55% change in firms' TFP.

$$\begin{aligned} TFP_{i,2007} - TFP_{i,1998} = {} & \alpha(SO2\ Discharged_{i,2007} - SO2\ Discharged_{i,1998}) \\ & + \beta(X_{i,2007} - X_{i,1998}) \end{aligned} \tag{35}$$

During China's 11th Five-Year Plan total, SO2 emissions were reduced by 14.29% from 2006 to 2010 with the target being 10%. If we attribute the entire SO2 reduction from 2006 to 2010 to TCZ firms, the economic cost brings by TCZ on firm output loss is about 99.43 to 413.22 billion RMB during China's 11th Five-Year Plan based on 2006 industrial output 23893.86 billion RMB.

Table 21: Robust test using LP method calculating TFP

Dep. Var: TFP	(1) Basic regression	(2) High SO2	(3) Low SO2	(4) SOEs	(5) Private firms	(6) Large firms	(7) Small firms	(8) Upstream firms	(9) Downstream firms
$TCZ_{it} * Post_{it}$	-0.030**	-0.026	-0.043***	-0.054**	0.003	-0.042***	0.044	-0.038*	-0.013
	(-2.35)	(-1.29)	(-2.60)	(-2.41)	(0.17)	(-3.13)	(0.89)	(-1.91)	(-0.73)
Observations	208,904	80,931	126,879	38,565	116,855	170,174	38,730	99,266	97,625
R-squared	0.180	0.196	0.176	0.136	0.213	0.190	0.209	0.195	0.163
Number of firms	66,379	25,904	41,482	12,057	38,179	53,441	19,046	35,215	32,765
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Company FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Local Economic Shocks	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

6 Robustness test

6.1 Calculating TFP using LP method

To test the robustness of our estimation, we calculate the firm TFP using LP method. Then, we do the basic regression and heterogeneity analysis again using this new TFP value. Table 21 shows the regression result using new TFP value, which is in line with our result of basic regression and heterogeneity analysis.

6.2 Parallel test and robustness test using PSM

Parallel test is a important test for DD regression keeping the samples' characteristics in treatment group and control group have similar trend before policy implementation. Figure 5 shows the parallel test result for SO2 intensity, which is the coefficient of interactions between TCZ_i dummy and year dummy. It reports that the coefficient of the interaction is insignificant in 1998, but it is significant in 1999 at 10% conventional levels. As we only have 2 observe years before the policy implementation, the result may not strong enough to support that two groups are parallel before treatment. For further robustness test, we use the Propensity Score Matching method (PSM) to match firms in two groups and drop observations who are not matched, and do the DD regression for samples remained. Variables for matching include all control variables in basic regression and firms' financial information variables in the ASIF dataset. Figure 6 shows the coefficient of the interactions after PSM, which implies that the two groups have parallel charac-

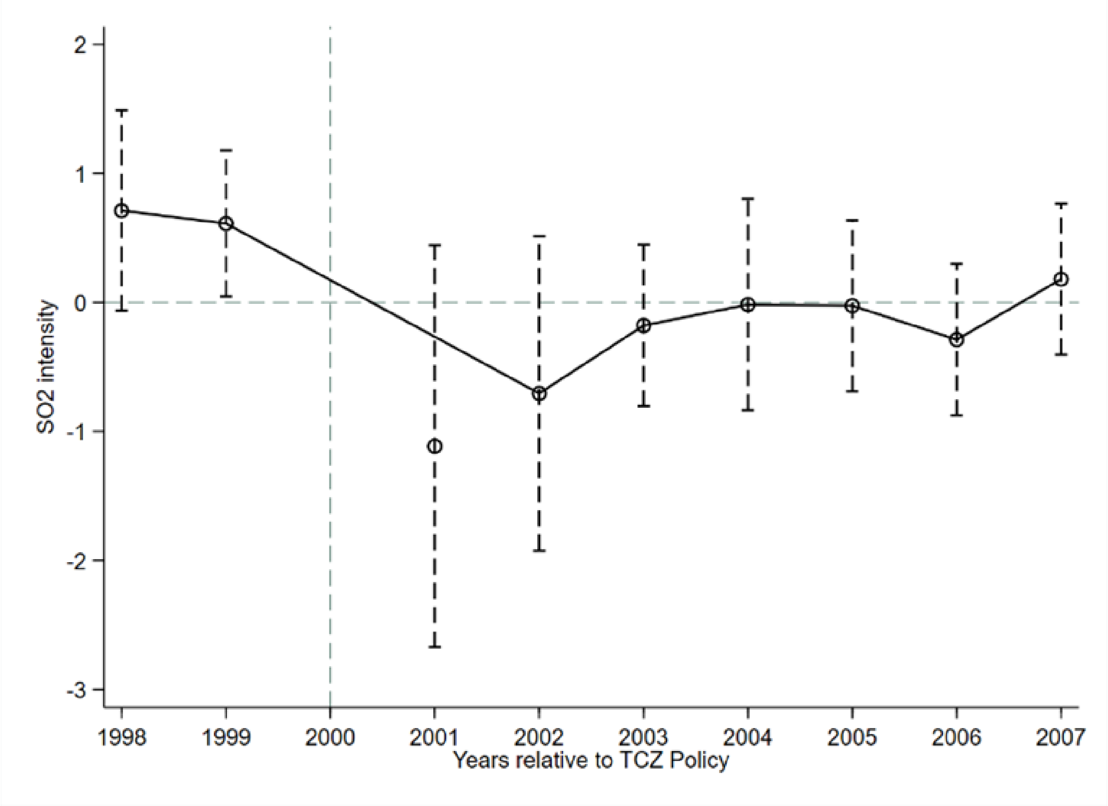

Figure 5: Parallel test before PSM

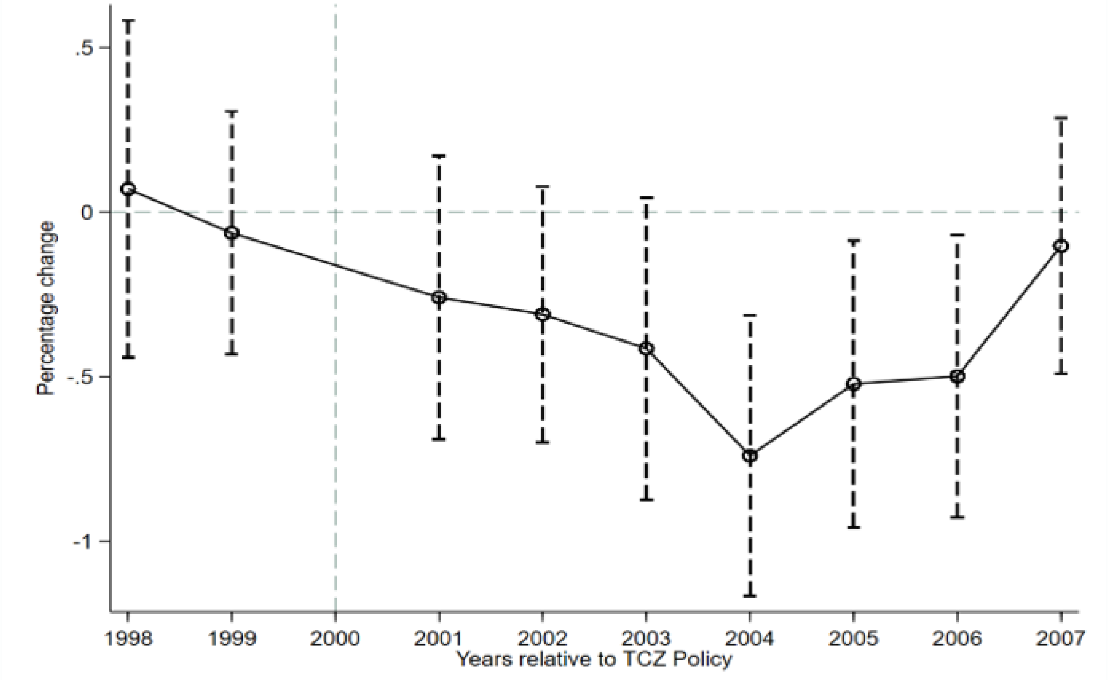

Figure 6: Parallel test after PSM

teristics before 2000. Then, we run the basic regression using the samples after PSM. Table 22 shows the result of this regression. The results in Table 22 are consistent with basic regressions. Our findings are robust after PSM controlling most firm characteristics.

Table 22: DD result after PSM

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	SO2 discharged	SO2 generated	SO2 intensity	end of pipe	change in process	TFP
$TCZ_{it} * Post_{it}$	-0.244***	-0.209***	-0.919***	0.019***	-0.803***	-0.032**
	(-10.53)	(-9.30)	(-3.88)	(4.98)	(-3.06)	(-2.33)
Observations	170,076	170,076	170,076	170,076	170,076	165,784
R-squared	0.048	0.047	0.013	0.046	0.013	0.186
Number of firms	60,963	60,963	60,963	60,963	60,963	60,150
Control Variables	YES	YES	YES	YES	YES	YES
Company FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Local Economic Shocks	YES	YES	YES	YES	YES	YES

Note: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

6.3 Regression except municipalities

Table 23: Regression result dropping municipalities

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	SO2 discharged	SO2 generated	SO2 intensity	end of pipe	change in process	TFP
$TCZ_{it} * Post_{it}$	-0.237***	-0.207***	-0.717***	0.017***	-0.641***	-0.033**
	(-10.83)	(-9.72)	(-3.36)	(4.79)	(-2.69)	(-2.52)
Observations	198,493	198,493	198,493	198,493	198,493	193,436
R-squared	0.035	0.035	0.010	0.040	0.009	0.186
Number of firms	62,156	62,156	62,156	62,156	62,156	61,428
Control Variables	YES	YES	YES	YES	YES	YES
Company FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Local Economic Shocks	YES	YES	YES	YES	YES	YES

Note: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

As municipalities has better economic conditions, they are always chosen as the pilot cities for policies. Chinese four municipalities, Beijing, Shanghai, Tianjin, and Chongqing, implemented the TCZ policy from 1998 as pilot cities. We dropped the observations in these four municipalities to do a robust test for basic regression. Table 23 indicates the regression result dropping municipalities, which is consistent with our basic result.

7 Conclusion

With the increase of Chinese people's income level, China is facing a dilemmatic phenomenon that a trade-off between improving environmental quality and sustaining economic growth. Because it is closely related to people's lives, the air quality of the surrounding environment is more concerned. This paper is the first study to credibly estimate the impacts of the TCZ policy, a national air pollutant control policy, on Chinese firms and provide a assessment of the economic cost of the policy. Using a firm-level panel dataset for Chinese firms in the period of 1998-2007, we exploit a difference-in-difference design based on the criteria of TCZ area and find that the TCZ policy lead to significant emission reduction and TFP loss for firms in TCZ area, but the TCZ policy has insignificant effect on regulated firms' profitability.

We estimate that the TCZ policy reduces SO2 discharged amount by 28.9% and reduces TFP levels by 35.7 % in firms located in the TCZ area. Channel and heterogeneity analysis shows that "end of pipe" and "change in process" are two measures used for emission abatement. Firms only adopt "end of pipe" activities would face TFP loss as a result of increase of production cost. The adoption of "change in process" activities can offset the TFP loss brings by "end of pipe" activities because the TCZ policy has had insignificant effect on TFP for firms taking both two measures for abatement. The deleterious effect of "end of pipe" is in line with the Neo-classical theory on environmental economics, while the influence of "change in process" also supports the Porter Hypothesis, opposite side of the Neo-classical theory. Thus, this paper find evidence that supporting both the Neo-classical theory on environmental economics and the Porter Hypothesis. The final effect of the TCZ policy on firm performance depends on the abatement measure it adopts.

Overall, our findings highlight the negative impacts of the TCZ policy on productivity and emissions. Combining the estimates of TCZ policy on emissions and productivity, we calculate the economic cost of this air pollution control policy. we estimate that a 10% abatement in SO2 emissions can lead to a 0.42%-1.2% drop in firm's TFP. These estimates imply that China's efforts in reducing SO2 emissions from 2006 to 2010 caused a total loss in output of 99.43 to 413.22 billion RMB. The high environmental quality improvement is accompanied by high economic cost, which is particularly salient for fast-growing economies in China.

This research contributes to the literature in estimating the effect of environmental regulation on firm behaviour. Our finding is consistent with literature, like Greenstone et al. (2012), Walker (2011), Berman and Bui (2001), and G. He et al. (2018), that environmental regulations have deleterious effects on firm performance. The magnitude of the effect of Chinese environmental regulation on firm productivity is higher than the result in G. He et al. (2018), and in consistent with C. Wang et al. (2018) who find insignificant effect.

We conclude by pointing out some limitations of this research. First, this research does not investigate the optimal environmental regulation standards for Chinese current economy. Even though existing literature theoretically indicates the optimal emission level for firms, we cannot empirically investigate the optimal emission standards, because we do not know the socio-economic costs of air pollution and people's willingness to pay for cleaner air quality in China. Second, our samples covers a relatively short period of time. Firms' investment and production strategy might be adjusted to environmental regulation in the long run. In particular, firms might promote production technologies to adopt more "change in process" activities in the long run. Investigating the effect of environmental regulation on firms' behaviour over long period of time could be a future research topic. Finally, our merged dataset only contains firms from polluting industries, which makes it impossible to investigate the spillover effect from polluting firms to non-polluting firms. For upstream polluting industries, the impact of environmental regulation on them might have spillover effect on downstream mom-polluting firms.

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