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The Impact of Environmental Policy on Firm Performance: Microeconomic Evidence from China

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Abstract

The swift degradation of environmental quality and depletion of natural resources in China have raised significant concerns, leading to a demand for more stringent and comprehensive environmental management practices. This thesis focuses on the effect of environmental regulation on firm performance in China. I examine the Two Control Zone (TCZ) policy, which aims to address one of the most serious air pollutants in China, sulphur dioxide emissions. It divides counties into two groups. Only firms located in the counties listed by the policy are subject to regulation. Firm-level databases containing emissions and accounting information are utilized for the period from 1998 to 2007. In Chapter 4, I investigate the impact of the TCZ policy on Chinese firms' emissions and performance. Using the difference-in-difference approach, I find the trade-off between firm productivity and firm environmental performance under environmental regulation. Regulated firms apply two different methods to reduce their emissions: increasing pollution abatement devices and improving production technology. The first approach reduces firms' productivity and the second stimulates it. In Chapter 5, I work on overcoming the trade-off between firm productivity increases and increasing emissions. I propose a novel measure for environmental efficiency and environmental misallocation, which applies a production function with emissions as a by-product of the production process to compute firms' marginal emissions of energy. This chapter investigates how environmental regulation policy affects firms' environmental efficiency and its role in shaping environmental misallocation across firms. The result shows that the TCZ policy leads to a drop in firms' marginal emission of energy and an increase in its dispersion. In Chapter 6, I developed the most suitable approach, the Difference-in-Difference framework decomposition, to uncover the sources of emission declines from different components, which mitigates the problem of panel regression analysis. This chapter investigates the difference between the emission declines of the in-TCZ zone and the out-TCZ zone. The result shows that environmental policy has reduced firms' weighted average emission compared with the firms unregulated, which can be broken down into the contributions of surviving, entering, and exiting firms. One limitation of the study is that I did not compare the environmental efficiency of Chinese firms with a frontier level, such as that of American firms.

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Dedication

This dissertation is dedicated to my parents, whose unwavering love and support have been my guiding light throughout my academic journey. To my wife, your constant encouragement, patience, and belief in me have been my greatest source of strength. And to my unborn child, you are the future I am working to build, and this work is dedicated to creating a better world for you.

Declaration

I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

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Chapter 1

Introduction

Air pollution is widely viewed as a factor preventing social and economic development. Emerging research has been investigating the effect of air pollution on the economy or welfare of both developed and developing countries. In a developing country with a significant manufacturing sector, such as China, it is crucial to examine the impact of environmental regulations on manufacturing firms' performance and behaviours. Governments in developing countries are concerned with both emission reduction and economic growth. Their pursuit of green development hinges on achieving a reduction in emissions without compromising productivity. This thesis contributes to the discussion relating to the link between environmental policy and firm performance in China.

Literature with aggregate-level analysis examines the effect of environmental policy on GDP growth (Muller and Mendelsohn, 2007) and population (Chen et al., 2022; Gao et al., 2022; Cramer, 2002). Literature with firm-level analysis examines the effect of environmental analysis on firm productivity (Fu et al., 2021), and labour market decisions and labour productivity (Hanna and Oliva, 2015; Zivin and Neidell, 2012; Chang et al., 2019; Lichter et al., 2017). However, the debate about whether environmental regulation hinders firm performance remains controversial. Some study shows the negative effect of policy regulation which reduces firm competitiveness, performance, or employment (Jaffe and Palmer, 1997; Greenstone, 2002a; Greenstone et al., 2012; Walker, 2011), while other studies find the opposite result (Copeland and Taylor, 2004; Porter, 1990; Porter and Linde, 1995). To fill this gap, I investigated the channels of environmental regulation's impact. It shows that the sign (positive or negative) of the policy impact is influenced by the heterogeneity in firm emission abatement behaviour. The "end of pipe" and "change in process" channels are investigated to answer the sources of the negative effect of environmental policies.

In order to connect the economic development and the damage caused by economic activities, air pollution, a growing body of literature recommends developing a green accounting to GDP (Hamilton and Atkinson, 1996; Muller and Mendelsohn, 2007) or a green GDP (Zheng and Chen, 2020). They are modifications for the GDP computation, which displays the environmental cost of economic development. In 2002, the OECD defined the term 'decoupling' refers to breaking the link between 'environmental bads' and 'economic goods'. However, a rare study that investigates the trade-off between economic growth and emission increases from a micro-level perspective. Meanwhile, Choi (2020) and He and Qi (2021) examine energy resource allocative efficiency on total factor productivity (TFP), which applies energy consumption as an additional input in the production function. However, the emission variable is not employed in the production function as the by-product of production. My research fills the gap in these two strands of literature, which applies a firm-level analysis using a production function with energy input and emission by-product. My analysis provides an approach to realise environmental decoupling from the firm-level perspective.

For the reason why I am studying the Chinese context. First, China has experienced an economic miracle since the late 1970s, but that has brought environmental costs as well (Zheng and Kahn, 2017). The size of an economy and its growth rate play pivotal roles in shaping environmental outcomes, a phenomenon particularly pronounced in the context of China. In the early 2000s, the rapid expansion of the Chinese economy was accompanied by a surge in environmental degradation, marked by severe SO2 emissions. Around 2000, China's GDP growth rate was about 10%, but the growth rate of energy consumption exceeded that, reaching 11.58%. The severity of China's environmental pollution problem has intensified because the consumption of coal has surged. This phase underlined the trade-off relationship between economic development and environmental challenges. However, what makes China an especially compelling setting for examination is the subsequent and noteworthy decline in SO2 emissions. This reduction occurred even amid the backdrop of sustained economic growth. China is making regarding its economy, energy use, and the atmospheric environment are increasingly affecting the future of the global environment. Its sheer size, rapid economic growth, and reliance on fossil fuels have propelled China to the forefront of national carbon dioxide (CO2) emissions, greenhouse gases, and other air pollutants (like sulphur dioxide SO2 and nitric oxide NOx). Understanding how China managed to curtail SO2 emissions during a period of rapid economic growth holds significance for policymakers globally.

Second, reforms in environmental policy were significant contributors. The lessons drawn from China's experience could provide insights for other nations grappling with comparable challenges in addressing emissions. In order to meet the people's increasing living standards and the need for a healthy living environment, the environmental policies adopted by Chinese government departments are constantly improving. This initiative involves a multifaceted approach to enhance environmental sustainability, reduce pollution, and promote green practices across various sectors. Key aspects of the reform include stricter regulations, increased focus on renewable energy, and measures to curb emissions of pollutants like sulfur dioxide (SO2).

Third, the Two Control Zone (TCZ) policy I want to examine is an important environmental policy for improving Chinese air quality. It has a specific and solitary (the only designated target) target, SO2 pollutant. The singular policy goal excludes the impacts brought about by other environmental policies. As firms' SO2 emission information is included in the database too, the direct effects of environmental policy can be explored. Meanwhile, it is a successful policy that achieves clear outcomes. In 2010, 94.9% of TCZ cities achieved the national Class II standard, and there were no TCZ cities with SO2 concentrations exceeding national Class III standards (*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 target for reduction of SO2 emissions was 10% and a total reduction of 14.29% was achieved. The regulation policy reached its conclusion in the year 2010. As a policy successfully addressed the SO2 pollutant in China,

Finally, I am using the Environmental Survey and Reporting Database (ESR) which is the most comprehensive environmental dataset in China. This database provides firm-level information on emissions and environmental management of Chinese polluting sources from 1998 to 2012. It is collected and maintained by the Ministry of Environmental Protection (the former State Environmental Protection Administration). Polluting sources that contribute to the top 85% of total emissions in a county are monitored by the ESR database. The investigation of detailed firm emissions information holds significant promise for research in developing countries characterized by substantial manufacturing activities. Especially, there are two main kinds of firm ownership in China: state-owned firms and private firms. State-owned firms are more likely to be affected by government intervention (Hsieh and Klenow, 2009; Chen et al., 2011), while private ones still face financing constraints (Ding et al., 2013). In summary, I am using a reliable dataset that provides information on the majority of polluting companies in China.

For the environmental policy in this research, I only focus on the Two-Control-Zone (TCZ) policy which aims at reducing the pollutant sulphur dioxide in China. It is the most suitable environmental policy for my study. This policy has one (and only one) specific object, sulphur dioxide (SO2), which is the pollutant monitored by the ESR dataset. Firm-level SO2 emission information provides us with the opportunity to understand the link between regulation and firm emissions. A quasi-natural experiment approach is employed to investigate the difference between the two zones' firm performance.

There are two clusters of regulated counties or two zones in TCZ policy. Geographically, given the reliance on coal burning for heating, the SO2 pollution control zone is located in Northern China; and given its humid climate, the acid rain control zone is located in Southern China. (SO2 emissions lead to the formation of acid rain.) The two zones have the same pollutant sources (SO2), while the various names are a result of different climate phenomena. The SO2 control zone city includes areas whose yearly average ambient SO2 concentrations exceed the grade two air quality standards and whose daily average ambient SO2 concentrations exceed grade three air quality standards (State Environmental Protection Administration, 1998). The acid rain zone city means places monitored PH values of precipitation are at or below 4.5, sulphur deposition levels that exceed local critical levels, or heavy SO2 emissions areas. 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.

1995, 1998, and 2000 are three key time points for the TCZ policy. It was proposed in 1995, approved in 1998, and implemented as a national policy from 2000 to 2010. In August 1995, the 15th meeting of the Standing Committee of the National People's Congress (SEPA) amended the 1987 Air Pollution Prevention and Control Law of the People's Republic of China (APPCL). This modification includes a new chapter which concerns how to manage air pollution and SO2 emissions that result from coal combustion. This amended law's Article 27 first suggested the mapping of Two Control Zones. It was not until January 1998 that SEPA's Official Reply of the State Council Concerning Acid Rain and SO2 Pollution Control Zones (the 1998 Reply hereafter) was approved by the State Council, official approval of the "Two-Control-Zone Policy" (TCZ policy). In 2000, *the Tenth Five-Year Plan for the Prevention and Control of Acid Rain and Sulphur Dioxide Pollution in the Two Control Areas* displays a detailed action plan for the TCZ policy. It is the beginning of the implementation of the TCZ policy. Only the firms in the TCZ area are affected by the policy.

I start this research by answering a basic question: what is the effect of the TCZ policy on Chinese firms' emissions and performance? Chapter 4 contributes to providing the answers. Many empirical studies indicate that environmental policy is correlated with firm performance and productivity (Porter and Linde, 1995; Jaffe and Palmer, 1997; Copeland and Taylor, 2004; Greenstone, 2002a; Lanoie et al., 2011; Rassier and Earnhart, 2015), even though findings vary as to whether the effect is positive or negative. In Chapter 3, I examine the effect of the Two Control Zone (TCZ) policy on firm SO2 emissions and firm performance using the difference-in-difference (DID) estimation approach. The result shows that the TCZ policy resulted in a 28.9% reduction in the amount of SO2 discharged, a 29.8% reduction in the amount of firm SO2 generated, and a 35.7% loss in firm TFP, but no influence on firm profitability outcomes. During China's 11th Five-Year Plan, 2006-2010, this policy was to cause a 99.43 to 413.2 billion RMB total output loss based on 2006 industrial output of 23893.86 billion RMB.

The findings of Chapter 4 prove the trade-off between firms' economic performance and environmental performance subject to the TCZ policy. However, it inspired us to ask a series of new questions: do firms in the same sector have the same environmental efficiency? if not, can I reduce the aggregate emission subject to current production by reallocating firm production or resources? Resource distortion is widely acknowledged as prevalent in China generating significant welfare losses (Hsieh and Klenow, 2009; Hovakimian, 2011; Ek and Wu, 2018; Ding et al., 2021). It is concluded that ownership and financial frictions are the key sources of resources distortion in China (Brandt et al., 2013; Wu, 2018). Ownership and financial friction could also result in variations in environmental efficiency among firms even within the same sector. I try to answer these questions and discuss their connections in Chapter 5.

In Chapter 5, I discuss the impact of the TCZ policy on firm-level environmental efficiency and the environmental misallocation across firms in the same sector. The novel measure for environmental efficiency and environmental misallocation proposed is the key contribution of this chapter. I employ the marginal emission of energy to indicate environmental efficiency, and its dispersion is used to denote environmental misallocation across firms. The empirical analysis finds that firms that comply with the environmental policy experienced an increase in environmental efficiency but an increase in environmental misallocation. Firms' level of environmental efficiency has been improved by adopting the TCZ policy. However, the magnitude of environmental efficiency differences across firms in the sector has been aggravated by the policy implementation. My heterogeneity analysis explains why TCZ policy expands environmental misallocation by indicating that the policy has a more effective impact on big firms and private firms than on small firms and SOEs.

However, the panel regression analysis in Chapter 4 and Chapter 5 has missed information on entering firms and exiting firms, which can not display the channels of entrants and exiters on firm emission. Chapter 6 explores the question: what are the sources of the difference between the two zones' emission declines? In Chapter 6, I propose a DID framework decomposition for emission growth, which is the most suitable approach for this research question. The DID framework decomposition not only analyses the TCZ policy's effect but also breaks down emission declines into different contributions. I decompose the gap of the weighted average emission reduced amount between the TCZ area and non-TCZ area into survivors, entry, and exit channels. The contribution of surviving firms is decomposed into the within-firm component and the cross-firm component. When using the amount of SO2 discharged to denote firms' emissions, the difference between weighted average SO2 discharged growth for the in-TCZ and out-TCZ areas is primarily driven by the gap in the surviving firms' channel across the two groups rather than the net exit channel. When using SO2 generated to denote firms' emissions, the result shows that effective policy implementation is driven by the gap in the net exit channel between in-TCZ and out-TCZ groups.

My study has several limitations. First, there is only two years pre-treatment period due to the data limitation. The data span starts from 1998 in the Annual Survey of Industrial Firms Database and the policy implementation year is 2000. The moving trend before policy implementation is unclear. Second, the best production for each firm is not provided in the research. I also do not prove the optimal environmental efficiency for each sector. Based on the existing literature, setting the firms in the U.S. as the frontier could be a possible solution for developing countries. Third, the causal relationship between environmental policy and firm environmental efficiency could be investigated. In Chapter 5, I employed the pooled-OLS approach in the specification, which fails to display the underlying causal relationship.

The remainder of this thesis is structured as follows. Chapter 2 presents the background information on China's economic growth, air pollution, and environmental policies. Chapter 3 illustrates databases used in the following chapters. Chapter 4 is the first topic for the thesis, investigating the effect of the TCZ policy on firm emissions and performance. Section 4.2 summarises literature relating to the first topic. Section 4.3 is about the specification strategy and used variables in this chapter. Sections 4.4 and 4.5 present the empirical results and robustness check. Section 4.6 is the conclusion for the first topic. Chapter 5 is the second topic for the thesis, exploring the effect of the TCZ policy on firm environmental efficiency and environmental Misallocation. Section 5.2 describes literature relating to the second topic. Section 5.3 is about the specification strategy and used variables (especially the proposed metric for environmental efficiency) for the second topic. Sections 5.4 and 5.5 present empirical results and robustness check for Chapter 5. Section 5.6 concludes this chapter. Chapter 6 is the third topic for the thesis, decomposing the average emission reduction into three different channels. Section 6.3 is the literature relating to decomposition methods. Section 6.4 illustrates the DID framework decomposition approach proposed for the thesis. Section 6.4 demonstrates stylized facts. Sections 6.5 and 6.6 present empirical results and robustness checks. Section 6.7 concludes the third chapter. Chapter 7 offers a conclusion and policy implication for the whole thesis.

Chapter 2

Economic growth and the environment in China

2.1 Economic growth and air pollution, the Environmental Kuznets Curve in China

Since the end of the 1970s, China has experienced rapid growth and sustained economic reform, but it has also caused environmental harm through air and water pollution. In the late 1970s and early 1980s, China's industrialization and urbanization were propelled by economic reforms. As a result of expanding industries, transportation networks, and energy production, air pollution levels in the country have increased. Starting from China's economic reform in the 1980s, southern cities have suffered from acid rain resulting from the coal consumption of heavy industries, electricity power plants, and winter heating of households (He et al., 2002).

In their investigation of the environmental impacts of a North American Free Trade Agreement, Grossman and Krueger (1991) observed for the first time the relationship between economic growth and the environment. When a level of income that allows people to demand and afford more efficient infrastructure and a cleaner environment has been reached, they found that the relationship between economic growth and environmental quality may change from positive to negative. Kuznets (1955) hypothesized an environment-growth relationship illustrated by an inverted-U curve, the Environmental Kuznets Curve (EKC). Panayotou (2000) proposed that policy implementation affects the shape of the EKC. The turning point of the EKC could be influenced by the responsiveness of policies to environmental concerns and the growing demand for environmental quality. The height of the EKC depends on income per capita, which reflects the price of economic growth on the environment.

The relationship between economic growth and the environment has been the subject of a great deal of empirical research, which uses the reduced-form specifications method to regress a measure of income per capita on environmental quality indicators. As the independent variable, the indicators of environmental quality consist of certain water and air pollutants (such as heavy metals, sulphur dioxide, carbon dioxide, and particulates), deforestation rate, energy consumption, solid wastes, traffic volume, and environmental R&D (Zhang, 2013). Income per capita, incomes at market exchange rates, and income converted into purchasing power parity are commonly used dependent variables.

Using the data for 112 major Chinese cities from 2001 to 2004, Cole et al. (2011) investigate the relationship between economic growth and industrial pollution emissions in China, which helps to examine the existence of the Environmental Kuznets Curve in China. Four industrial water pollution emissions (wastewater, chemical oxygen dioxide, hexavalent chromium compounds, and petroleum-like matter) and four industrial air pollution emissions (waste gas, sulphur dioxide, soot, and dust) are investigated. Cole et al. (2011) find that China's current income levels will result in more industrial pollution emissions as a consequence of economic development (with current technology levels and policies), i.e., the net effect of economic growth on environment quality is negative. Meanwhile, there is a strong positive relationship between industrial output and industrial pollution emissions, and the impact differs by country of ownership.

Shen (2006) investigated the EKC in China using a simultaneous equations mode. The relationship between per capita income and per capita pollution emissions (denoted by two air pollutants, SO2 and dust fall, and three water pollutants, COD, arsenic, and cadmium) is examined using province-level data from 1993 to 2002. He finds the EKC relationship for all water pollutants, but not for air pollutants. Additionally, government expenditures on pollution control negatively affected pollution, whereas secondary industries positively impacted pollution emissions. Water and air pollution levels in China are influenced by both environmental policy and industrial structure.

Hence, the positive relationship between income and emissions tested by Cole et al. (2011) and Shen (2006) suggests that enforcing environmental regulations in China at all administrative levels and in the early stages of economic development is crucial to alleviating pressure on its natural environment. As the environmental Kuznets curve exits for most pollution emissions at the current income levels in China, China needs to pay attention to the environment itself rather than outgrow environmental problems by simply emphasising economic growth.

Figure 2.1 show the timeline of China's environmental policies from 2000 to 2020. In order to meet the people's increasing living standards and the need for a healthy living environment, the environmental policies adopted by Chinese government departments are also constantly improving. From 1949 to 1989 China's environmental policy was in its early stages. Environmental protection departments of governments at all levels were established during that time. From 1990 to 2010 there was a period of rapid development of China's environmental policies. Around 2000, China's GDP growth rate was about 10%, but the growth rate of energy consumption exceeded that, reaching 11.58%. From 1990 to 2010, China's market-incentive environmental policy was vigorously promoted, and the command-and-control environmental policy was gradually improved. At the same time, the establishment and authority of regulatory agencies were gradually clarified, which helped to promote the rapid development of China's environmental policy.

Fast-growing energy consumption is the key factor driving the deterioration

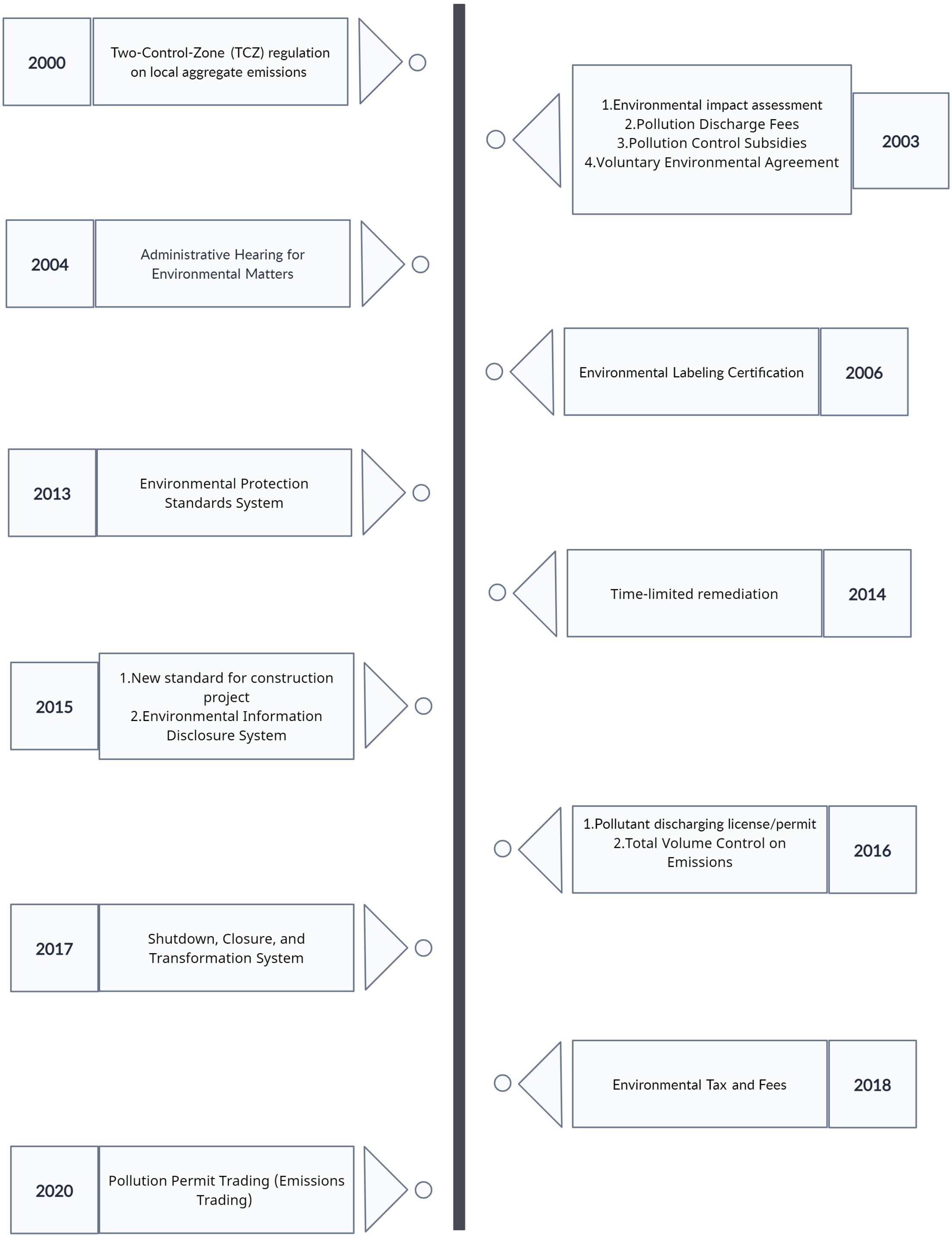


Figure 2.1: Timeline of China's environmental policy

Source: National Bureau of Statistics

of air quality. With a new economic development strategy based on the market economy, the severity of China's environmental pollution problem has intensified in the 21st century because the consumption of coal has surged. Coal has traditionally been the dominant energy source due to the surge in energy demand from industry and transportation. Pollutants (like sulphur dioxide and nitrogen oxide) and greenhouse gases are released during the combustion of coal. As shown in Figure 2.2, between 1980 and 2010 there was an increase in China's coal consumption, from less than 700 million tons to almost 4 billion tons. Around one-third of the world's coal was consumed by China in the late 1990s, but in 2010 it consumed nearly as much coal as the rest of the world combined. From 2000 to 2010, China experienced a substantial and noteworthy annual increase in coal consumption, which is the reason why the country is expected to witness a significant surge in its aggregate emissions of sulphur dioxide, nitrogen oxide, and carbon dioxide. The red line in Figure 2.2 indicates the implementation of the TCZ policy, which was introduced alongside China's significant surge in coal consumption.

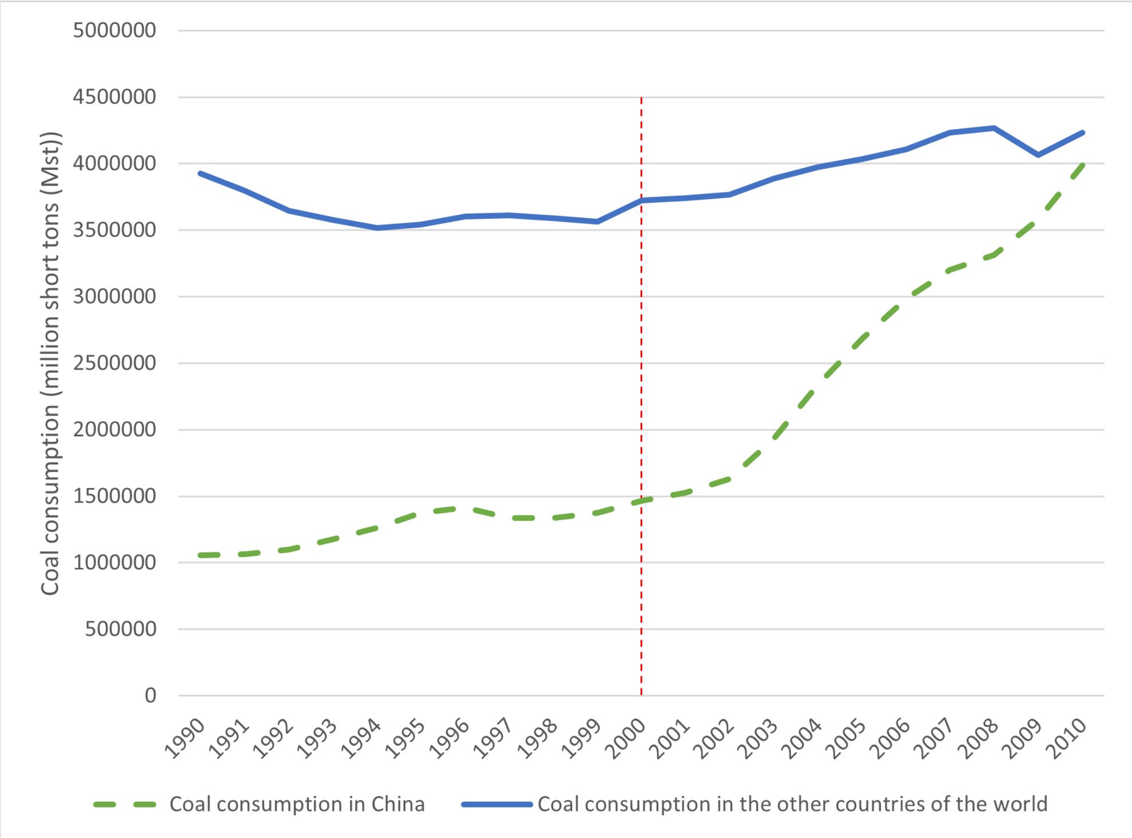


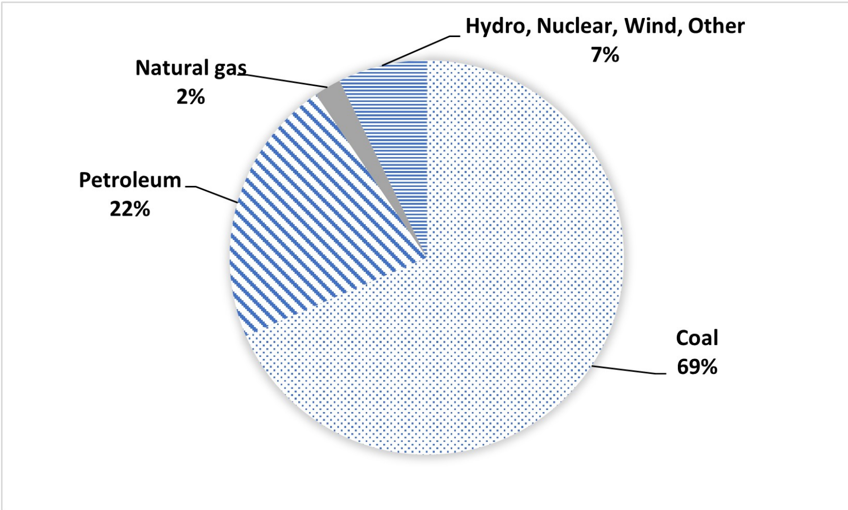
Figure 2.2: Coal consumption over the years

Source: US Energy Information Administration,

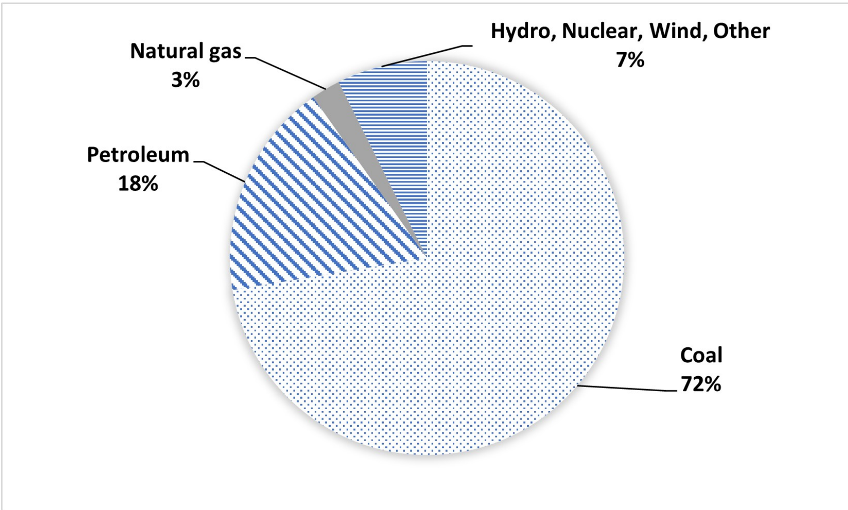
Coal's persistent dominance uncovers a number of big changes in the economy and in energy consumption. Total energy consumption more than doubled between 2000 and 2010, increasing from 1.5 billion tons of standard coal equivalents to 3.6 billion tons of standard coal equivalents (source: National Bureau of Statistics). The high rate of growth of gross domestic product is accompanied by high growth in energy use. The coal share in energy use rose from 68% to a peak of 73% in 2007 and had fallen to 69% in 2010. The historical peak value of the coal share in energy use is 76% in 1985–1992 (Nielsen and Ho, 2013). Figure 2.3 gives China's energy consumption in 2000, 2005, and 2010. The oil share kept decreasing from 22% in 2000 to 17% in 2010, while the gas share had more than doubled since 2000 but still made up less than 4%. The other category consists of hydroelectric, nuclear, and wind power. Their share was no more than 9% in 2000-2010. Overall, coal is the main energy resource of China, which also serves as a prominent source of sulphur dioxide (SO2). The TCZ policy aims at reducing the pollutant (SO2) generated by coal consumption which is the dominant energy source in China.

Industrialization is the second key factor driving environmental degradation. Over the past twenty years, China has experienced phenomenal industrial growth. As industries have expanded, so emissions have also increased. Carbon dioxide, sulphur dioxide, nitrogen oxides, and particulate matter are all pollutants released into the air by the combustion of fossil fuels, especially coal. There has been unprecedented growth in China's manufacturing sector, making it the world's factory for a wide variety of products. As a cheap fuel source, coal was often used to produce goods such as textiles, electronics, chemicals, and heavy machinery. As China exports goods to other countries, a portion of its growing emissions is ultimately attributed to world consumption. Figure 2.4 gives the ratio of industrial SO2 emissions to total SO2 emissions in China. Industrial emissions account for the vast majority of total emissions. More than 80% of the total SO2 emissions comprise industrial SO2 emissions. This ratio reached its peak in 2007.

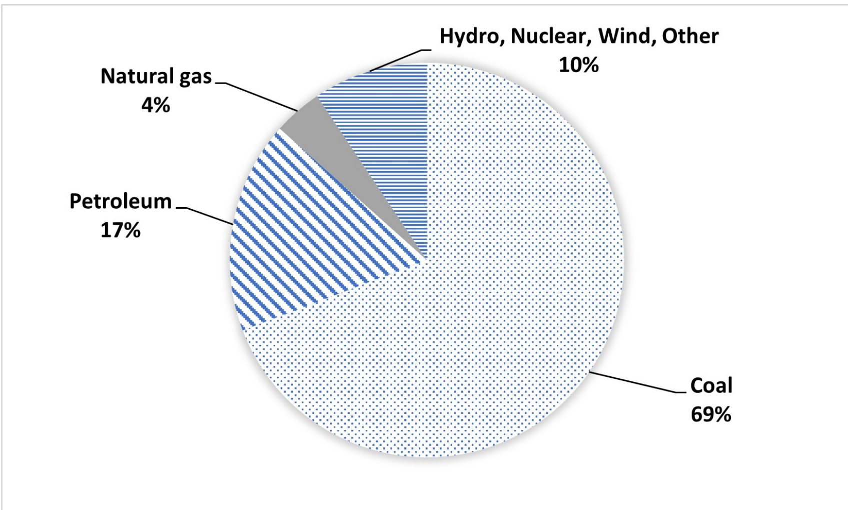
The electric power industry and the cement industry are two industries experiencing rapid growth along with China's industrialization. Coal-fired power plants are the primary source of air pollutant emissions. In China, coal has been the primary fuel for thermal power generation for many years, with very small amounts of natural gas. Coal consumption by Chinese power plants increased from 560 to 1300 million tons (Mt) between 2000 and 2007, the period of fastest development in the power sector over the past 30 years (Nielsen and Ho, 2013). Since power generation consumes the most coal, it has been considered the biggest contributor to air pollution in regional areas. Cement production is another sector causing air pollutants and CO2 emissions. Globally, China produces and consumes the most cement. China's construction boom, which was driven by rapid urbanization and infrastructure development, needs vast quantities of resources, such as cement and steel. During cement production, enormous quantities of air pollutants such as sulphur dioxide (SO2), nitrogen oxides (NOX), carbon monoxide (CO), and total particulate matter (PM) are emitted, causing significant regional and global environmental problems.



(a) Energy consumption in 2000



(b) Energy consumption in 2005



(c) Energy consumption in 2010

Figure 2.3: China's energy consumption in million tons of standard coal equivalents (Mtce) in 2000, 2005, 2010

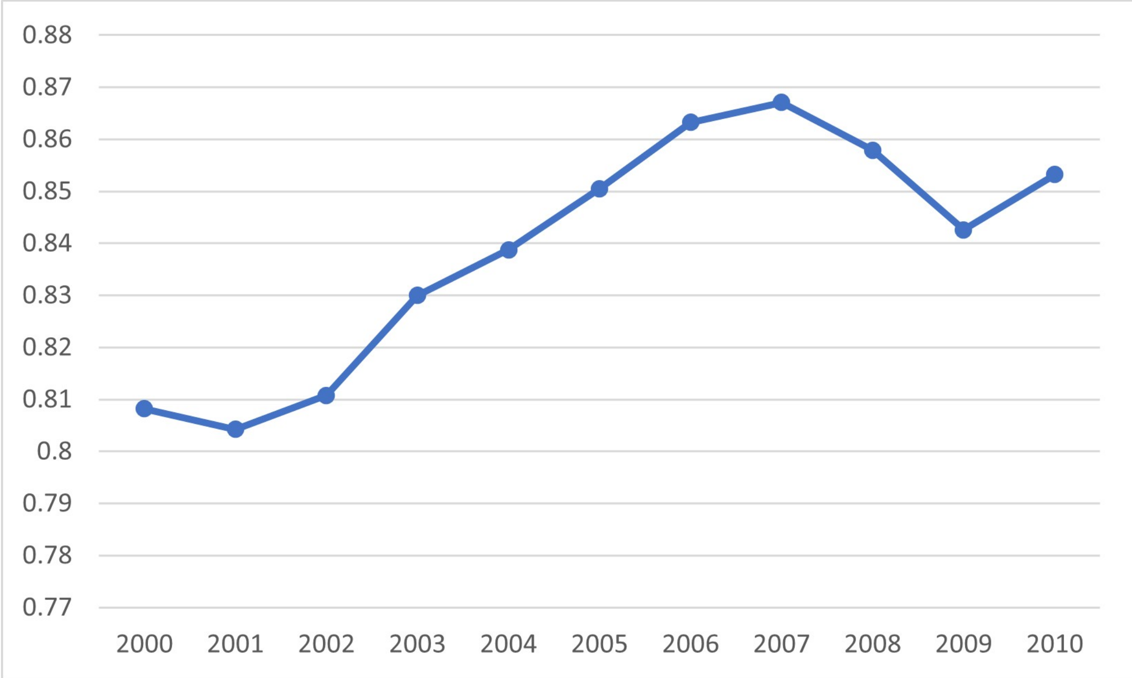


Figure 2.4: Ratio of industrial SO2 emissions to total SO2 emissions

Source: The China Statistical Yearbook on Environment

In addition to industrialization, urbanization is the third key factor leading to environmental degradation. The air quality in China is severely and persistently degraded, especially in densely urbanized areas. Due to the migration of people from rural areas to urban centrers in search of better opportunities, cities have experienced exponential growth, resulting in significant impacts on air quality. The concentration of people in cities leads to increased energy consumption and pollution as a result of increased demands on transportation, infrastructure, energy, and housing.

2.2 China's Environmental expenditure

Due to rapid urbanization and industrialization, China has experienced remarkable growth in environmental expenditure since 2000. The Chinese government has been heavily investing on green initiatives and environmental protection as part of its commitment to achieving sustainable development. Pollution control and remediation are among the primary environmental expenditure areas in China. A considerable amount of funding is allocated to projects aimed at reducing emissions, improving water quality, and restoring contaminated lands in the country due to significant air, water, and soil pollution. As a result of the use of advanced pollution control technologies and the upgrading of industrial facilities, pollution levels have been reduced and environmental damage has been minimized. The Chinese government has gradually increased its spending on the environment since the turn of the twenty-first century. In 2000, the value was 23.48 billion CNY and that increased to a peak of 55.24 billion CNY in 2007, declining to 29.7 billion CNY in 2010.

The proportion of expenditure on waste gas control to the total expenditure in industrial pollution sources control kept increasing in the period 2000-2010. Environmental expenditure on waste gas control accounts for almost 30% of the aggregate industrial environmental expenditure. Renewable energy and clean technologies also play a significant role in China's environmental expenditure. Solar, wind, and hydroelectric power are being actively promoted as sustainable energy sources, keeping the country from becoming overly reliant on fossil fuels. The transition to a low-carbon economy and the development of a more sustainable energy landscape is being driven by spending on clean technologies, energy-efficient solutions, and electric vehicles. As shown in Figures **??** and 2.3, although coal consumption is the key energy source in China, its proportion keeps decreasing and the proportion of clean energy consumption (light blue area) increased a lot from 2000 to 2010.

China's environmental expenditure is closely linked to GDP in order to keep environmental sustainability and economic growth in balance. Figure 2.5 shows the proportion of environmental expenditure to GDP in China. The proportion of total environmental expenditure to GDP was 1.02% in 2000. Except for 2006 and 2009, the proportion keeps increasing and reached 1.24% in 2010. With its scaling ratio of environmental expenditure to GDP, China shows that it is proactive in achieving a greener and more sustainable future. This represents a shift in priorities for the country, as it emphasizes ecological conservation alongside economic development and the need to address environmental concerns. This change reflects a deeper understanding that a healthy and resilient environment is necessary for sustainable economic growth. Thus, environmental expenditure has become one of China's key development strategies.

Additionally, China's environmental expenditure efforts have been influenced by international commitments. China has taken on the responsibility of protecting the environment and promoting sustainable development through global agreements such as the Paris Agreement and the Sustainable Development Goals of the United Nations. By increasing its environmental expenditure relative to GDP, China is demonstrating its commitment to meeting its international obligations. Overall, environmental sustainability is increasingly entwined with economic growth, as evidenced by the continuous rise of environmental expenditure to GDP in China. As China strives to create an eco-friendly and prosperous future, it is committed to pollution control, renewable energy, environmental infrastructure, as well as the principles of a circular economy.

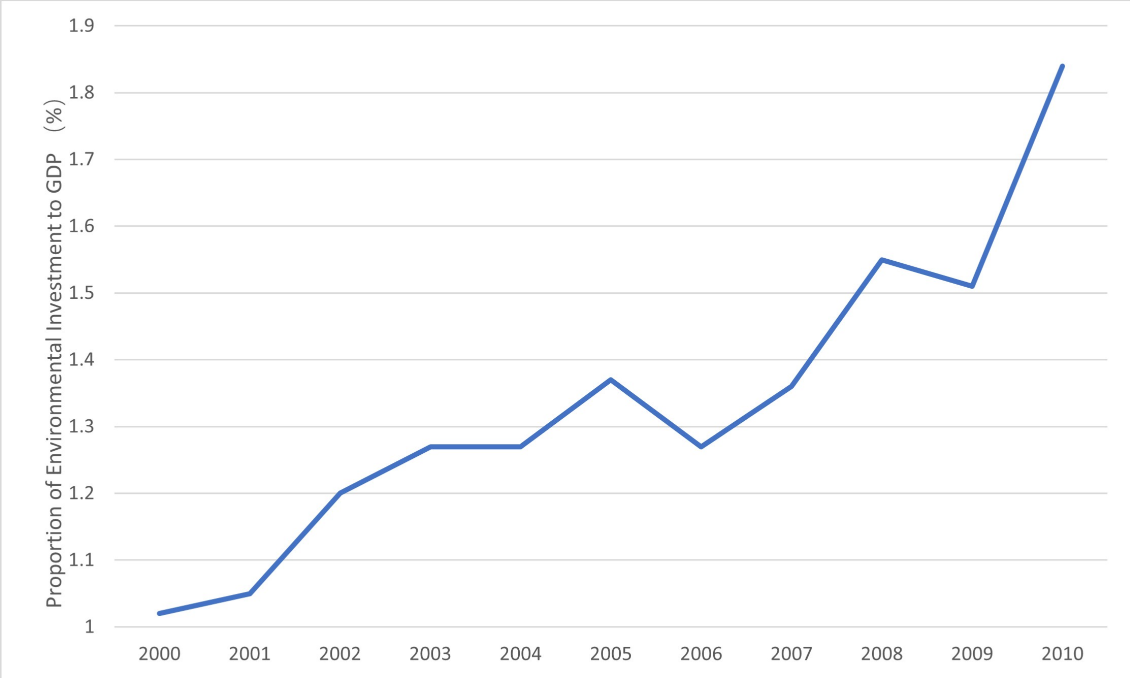


Figure 2.5: Proportion of Environmental expenditure to GDP

Source: National Bureau of Statistics

2.3 Reform of China's environmental regulations

Environmental policy refers to the system in which government departments directly or indirectly intervene in the use of environmental resources through market or non-market means. According to the differences in the objects of environmental regulation, environmental regulation can be divided into three categories: command-control type, market incentive type and voluntary participation type (Xie et al., 2017; Böcher, 2012). Table **??** shows the environmental policies implemented in China. They are divided into three categories of policy type (the first column). The second column of Table **??** shows the specific approaches employed in the policy. The last column is the name of the official article of the environmental policy. The Two-Control-Zone policy, the first policy listed in Table **??**, is the one I am interested in, and it belongs to the command-and-control policy.

The term command-and-control policy means that the government directly monitors and punishes firms' pollutant emission behaviours through administrative approaches such as bans and regulations. The implementer of a command-and-control policy is the central or local government, and the objects are firms, individuals and social organizations. The command-and-control policy always has a significant effect on pollution migration, but it is also criticized for a lack of flexibility. In this research, I investigate the Two-Control-Zone policy, which belongs to the command-and-control type. This environmental regulation policy is a national policy that aims at reducing SO2 pollutants and improving air conditions. For cities in the TCZ area, the central government sets the maximum aggregate emission value for the local government. Whether the pollution reduction target is achieved is linked to the performance appraisal of each local government.

For market incentive policies, the subject and object of environmental regulation are not changed, but the regulatory approaches are extended to market-based financial stimulus measures such as environmental taxes and subsidies. This type of regulation affects the production decision-making of enterprises by changing their cost-benefit status, so as to achieve the purpose of reducing their emissions. The government, directly and indirectly, controls the environmental pollution of enterprises through administrative intervention and market incentives. Although market-based environmental regulations are still mandatory, they provide economic entities such as firms with a greater incentive to reduce emissions.

Finally, for voluntary participation policies, the subjects of environmental regulation are extended. The participation of entities such as enterprises and industry associations enriches the means of environmental regulation. Regulatory tools for voluntary participation are added to the original administrative regulations and market incentives. The public's awareness of environmental pollution and the pressure of public opinion form a hidden environmental regulation and a means to urge enterprises to reduce emissions.

2.4 Background of the Two Control Zone Policy (TCZ)

2.4.1 Description of the TCZ policy

China's long-term reliance on coal-burning for energy has led to two environmental problems; air pollution and acid rain. In 1993, 62.3% of Chinese cities' annual average ambient SO2 concentration values exceeded the national Class II standard, 60 ug/m3 (Cai et al., 2016b). 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, expanding from south-eastern China to the south of China, east of the Qinghai-Tibet Plateau, and the entire Sichuan Basin (Hao et al., 2001). In central China, Changsha, Guangzhou, Nanchang, and Huaihua, with above 90% frequency of acid rainfall, are the 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*

Table 2.1: Classification of Environmental Regulatory Tools in China

Policy type	Approaches	Regulations and implementation time
Command and Control Policy	Two-Control-Zone (TCZ) regulation on local aggregate emissions	*"The Official Reply of the State Council Concerning Acid Rain and SO2 Pollution Control Zones"* (1998)
	Environmental impact assessment	*"Environmental Impact Assessment Law of the People's Republic of China"* (2003)
	Environmental Protection Standards System	*"Technical Specifications for Dye Industry Wastewater Treatment Projects"* (2013)
	Time-limited remediation	*"Measures for Environmental Protection Authorities to Implement Production Restrictions and Production Shutdown for Remediation"* (2014)
	New standard for construction project	*"Environmental Protection Law of the People's Republic of China"* (2015)
	Pollutant discharging license/permit	*"Implementation Plan of the Permit System for Controlling Pollutant Discharge"* (2016)
	Total Volume Control on Emissions	*"Work Plan for Controlling Greenhouse Gas Emissions during the 13th Five-Year Plan."* (2016)
	Shutdown, Closure, and Transformation System	*"Opinions on Further Promoting the Merger, Restructuring, Transformation, and Upgrading of Coal Enterprises"* (2017)
Market-based policy	Pollution Discharge Fees	*"Regulations on the Collection and Utilization Management of Pollution Discharge Fees."* (2003)
	Pollution Control Subsidies	*"Law of the People's Republic of China on Promotion of Cleaner Production" (2003)*
	Environmental Tax and Fees	*"Implementing Regulations for the Law of the People's Republic of China on Environmental Protection Tax."* (2018)
	Pollution Permit Trading (Emissions Trading)	*"Interim Measures for Carbon Emissions Trading Management"* (2020)
Voluntary or Incentive-based policy	Voluntary Environmental Agreement	*"Voluntary Energy Conservation Agreement"* (2003)
	Administrative Hearing for Environmental Matters	*"Interim Measures for Administrative Hearing of Environmental Protection Administrative Licensing"* (2004)
	Environmental Labeling Certification	*"Opinions on the Implementation of Government Procurement of Environmental Labeling Products"* (2006)
	Environmental Information Disclosure System	*"Measures for the Disclosure of Environmental Information by Enterprises and Public Institutions"* (2015)
	Public Engagement System	*"Measures for Public Participation in Environmental Impact Assessment"* (2019)

Control of Acid Rain and SO2, (Environmental Protection 1998, 4, 4), acid rain caused nearly 12 billion dollars of economic loss in 1995, 2% of 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 a 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 concerns how to manage air pollution and SO2 emissions that result from coal combustion. This amended law's Article 27 first suggested the mapping of Two Control Zones. To match with Article 27, the SEPA issued new emission standards in May 1996, known as the total emissions load control (TELC), which is a method regulating discharge by controlling the total loading of a pollutant, instead of controlling the concentration level of that pollutant (Decision on certain Issues concerning Environmental Protection). It was not until January 1998 that SEPA's Official Reply of the State Council Concerning Acid Rain and SO2 Pollution Control Zones (the 1998 Reply hereafter) was approved by the State Council, official approval of the "Two-Control-Zone Policy" (TCZ policy). After enacting that policy in 1998, the following year the SEPA started the process of issuing the National Action Plan for Acid Rain and SO2 Control (the TCZ action plan). Local government which has jurisdiction over a region or city has the responsibility of implementing the policy and emission standards set by the central government.

A rough introduction of the SO2 control zone and the acid rain zone is given in Article 27 of the amended APPCL. The SO2 control zone city includes areas whose yearly average ambient SO2 concentrations exceed the grade two air quality standards and whose daily average ambient SO2 concentrations exceed grade three air quality standards (State Environmental Protection Administration, 1998). The acid rain zone city means places monitored PH values of precipitation are 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 areas with few people live are not included. Geographically, given the reliance on coal burning for heating, SO2 pollution control zones are located in Northern China; and given its humid climate, acid rain control zones are located in Southern China. Figure 2.6 shows the geographic scope of TCZ zones.

Figure 2.6: The scope of the TCZ area

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

Note: the blue area is SO2 control zone. The green area is the acid rain control zone.

Table 2.2 shows the key dates of the TCZ policy. 1995, 1998, and 2000 are three key time points for the TCZ policy. It was proposed in 1995, approved in 1998, and implemented as a national policy from 2000 to 2010. In August 1995, the 15th meeting of the Standing Committee of the National People's Congress (SEPA) amended the 1987 Air Pollution Prevention and Control Law of the People's Republic of China (APPCL). This modification includes a new chapter which concerns how to manage air pollution and SO2 emissions that result from coal combustion. This amended law's Article 27 first suggested the mapping of Two Control Zones. It was not until January 1998 that SEPA's Official Reply of the State Council Concerning Acid Rain and SO2 Pollution Control Zones (the 1998 Reply hereafter) was approved by the State Council, official approval of the "Two-Control-Zone Policy" (TCZ policy). In 2000, *the Tenth Five-Year Plan for the Prevention and Control of Acid Rain and Sulphur Dioxide Pollution in the Two Control Areas* displays a detailed action plan for the TCZ policy. It is the beginning of the implementation of the TCZ policy. Only the firms in the TCZ area are affected by the policy.

Existing literature commonly uses the year 1998 as the start of the TCZ policy (see Cai et al. (2016a)). However, I choose 2000 as the start year of the policy implementation because of the following reasons. First, although the 1998 Reply was issued in 1998, the official detailed action plan for the TCZ policy was not clear until 2000. Second, in the 1998 Reply, the official goal was that SO2 emissions in 2010 would be reduced by 10% compared to 2000. So, the government also set 2000 as the base point of comparison. Third, from 1998 to 2000, although the establishment of the two control zones restrained the rapid growth of China's SO2 pollution emissions to a certain extent, it did not help all regions to achieve the pollution reduction targets established in the 1998 Reply. According to statistics from the Ministry of Environmental Protection, only Beijing, Tianjin, Chongqing, and Guizhou reduced SO2 emissions between 1998 and 2000, while the other 23 provinces and municipalities not only failed to reduce their emissions but actually experienced relatively high emissions. Fourth, the Tenth Five-Year Plan started in 2000 (see in Table 2.2). 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 Sulphur Dioxide Pollution in the Two Control Areas*, which was implemented from 2000 to 2005.

Table 2.2: Key TCZ Policy Time Point

Year	Policy phases	Official document
August 1995	TCZ policy is proposed.	*Amended 1987 Air Pollution Prevention and Control Law of the People's Republic of China*
January 1998	TCZ policy is approved.	*Official Reply of the State Council Concerning Acid Rain and SO2 Pollution Control Zones*
2000	TCZ policy is implemented with a detailed action plan.	*Tenth Five-Year Plan for the Prevention and Control of Acid Rain and Sulphur Dioxide Pollution in the Two Control Areas*

2.4.2 TCZ Policy's Enforcement and Outcomes

Cities named in the TCZ policy were to see tougher environmental regulatory policies. From January 1st, 1998, the opening of new collieries for coal with a sulphur content greater than 3% were prohibited. Existing collieries in operation had to reduce their production gradually and eventually shut down. Local government authorities could not approve new coal-burning thermal power plants in urban districts and suburbs of large and medium cities. Furthermore, newly constructed or renovated coal-burning thermal power plants using coal with a sulphur content greater than 1.5% had to install sulphur-scrubbers, while existing coal-burning ther-

Table 2.3: TCZ cities (and counties for a municipality) in China

Acid Rain control Zone				SO2 control Zone			
Province	City	Province	City	Province	City	Province	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)

mal power plants had to adopt SO2 reduction measures by 2000. In 2002, the Tenth Five-Year Plan for the Prevention and Control of Acid Rain and Sulphur 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 phase out technologies and equipment that 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 paying 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), sulphur dioxide discharge fees would also be levied according to (Huanfa [1998] No. 6), but the sulphur dioxide excess discharge fees were no longer be levied. So sulphur dioxide discharge fees were 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 would have to pay twice the sulphur dioxide emission fee. The existing literature sorts environmental regulations into command-and-control regulations; market-based regulations; and government subsidies. The TCZ policy used both command-and-control regulations and market-based regulations. Restricting production and shutting down high-sulphur coal mines and thermal power plants, strictly controlling new thermal power plants, and restricting fuel sulphur content are typical command-and-control environmental regulations. But the enforcement of emission fees 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-term goal, the policy requires that, in TCZ areas, the total emission levels in 2000 should not exceed emission values in 1995, and major cities' SO2 concentrations should meet 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 lack of a 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 was 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 national air quality standards. Finally, the long-run policy goals have been 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 with SO2 concentrations exceeding national Class III standards (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 target for reduction of SO2 emissions was 10% and a total reduction of 14.29% was achieved.

Chapter 3

Data

My 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. I collect the province-year price information of coal and oil from the China Price Information Centre (the CPIC database).

3.1 Annual Survey of Industrial Firms Database (ASIF)

The 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 non-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 information about firms obtained from accounting books, such as profits, outputs, inputs, sales, employment, and other firm characteristics. Detailed information about firms' locations is 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., 2012, 2017)).

The ASIF dataset has been used in several previous studies, but it has some data issues. Following the process of Brandt et al. (2012), I cleaned the raw ASIF dataset and created a panel one. I dropped duplicate observations in terms of ten variables. I allow the existence of two enterprises with the same firm code (firm ID), but with different names or legal person representatives. After duplicate data deleting, the number of observations ranges from 165,118 in 1998 to 336,766 in 2007, as shown in Table 3.1.

I 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 involves matching any two consecutive years by the following steps (see Table 3.2 for matched proportions). The first step is that I 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 my second to fourth steps. After these steps, I still have plenty of observations unmatched. So, in the fifth step, the remaining unmatched observations from step four are matched simultaneously by the firm founding year, geographic code, industry code, name of town, and the name of the firm's main product. Then, the final step involves merging all the matched and unmatched firms to create a file of two consecutive years.

The second stage of data cleaning is matching observations for three consecutive years by four steps. In the first step of this stage, I create a three-year balanced panel dataset based on the matching result of the first stage. For the remaining firm observations, I match 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, I repeat these three steps to merge the whole ASIF dataset into a 10-year panel dataset.

Table 3.1: Number of observations of the ASIF dataset

Year	ASIF observation number	Observations number after data cleaning
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

Table 3.2: 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%

After the creation of the panel dataset, I 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, I clean the dataset by dropping observations whose key variables' values are outside the range of the 0.5th to 99.5th percentile. As the ASIF dataset contains detailed address information for each firm in each year, I can confirm whether an observation is located in the TCZ area and influenced by the policy.

3.2 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 (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, I use observations in the ESR dataset which are in the same industries and period (1998-2007) as the ASIF observations.

The sampling criterion for the ESR database is the cumulative distribution of firm emissions in each county. All polluting sources, including industrial firms, are ranked according to their "criteria pollutants" emission level. Then polluting sources that contribute to the top 85% of total emissions in a county are monitored by the ESR database. For the choice of "criteria pollutants", only chemical oxygen demand (COD) emissions and sulphur dioxide (SO2) were "criteria pollutants" before 2007. Whether a pollutant source (firm) is included in the ESR is determined by its contributions to COD and SO2 emissions. In 2007 though, ammonia nitrogen (NH3) and nitrogen oxides (NOx) also became "criteria pollutants".

For a firm with several plants in different counties, each plants is considered as a different pollutant source. Thus, the same firm name may appear many times a year, which shows that 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 varies 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 I am interested in, the target pollutant in the TCZ policy. The database provides the amount of SO2 generated and removed for each pollutant source. Using the amount of waste gas discharge, I corroborate the findings on firm SO2 emissions.

As for the ASIF data, the ESR database also needs to be cleaned. First, there

Table 3.3: Number of Observations of the ASIF, ESR, and matched dataset

Year	ASIF observation number	ESR observation number	Matched dataset observation number
(1)	(2)	(3)	(4)
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

Note: Column (2) shows the observation number of the ASIF database over the years. Column (3) shows the observation number of the ESR database over the years. Column (4) shows the observation number of the merged database I used for empirical analysis in the following chapters.

are some abnormal observations in the dataset. I drop duplicate observations in terms of 13 essential emission-related variables. Following He et al. (2020), I drop observations whose SO2 and COD emissions are zero or negative. Because the ESR dataset monitors pollutant sources whose emissions account for the top 85% of the total emissions in a county, and SO2 and COD are two key "criteria pollutants", it is impossible for these two emission variables to be zero or negative in the ESR dataset. I also drop observations with negative values for waste-gas emission, waste-water emission, waste-gas treatment ability, and waste-water treatment ability.

Second, the ESR dataset is a pollutant sources level dataset. Several plants of a firm may appear in the dataset. If I want to match the ESR dataset and the ASIF dataset, the plant-level ESR dataset needs to be transformed into a firm-level one. Specifically, if two observations in a year have the 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 the same "firm name", they will also be treated as different plants of a firm. I use the address of the firm headquarters to replace the plants' address. Firms whose plants exist both outside and inside the TCZ area are dropped. There are quite a few firms with multi-plants in the ESR dataset, which accounts for about 0.5% of observations in each year. Column 2 in Table 3.4 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 have been deleted and plants merged.

Figure 3.1 shows the process of creating the final database for the empirical analysis in Chapter 4, Chapter 5, and Chapter 6.

Table 3.4: Number of Observations of the Matched Dataset

Year	Matched dataset observation number	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

3.3 Energy price information

Price information is collected from the China Price Information Centre (the CPIC database) which provides monthly data on more than 170 commodities in cities across the country from 1989 onwards. The CPIC database is the most detailed and comprehensive price information dataset in China, which is collected and released by the Price Monitoring Centre of the National Development and Reform Commission.

In my research, the information about coal and oil prices is from the CPIC database. The coal price data is at province-month-level starting from 2006, and the gasoline price data is at city-month-level starting from 2001. The coal price is the transaction price at the coal mine mouth when it was first produced. After the transaction is completed, buyers need to transport the coal back to their own provinces and take the transportation cost. For the period from 2001 to 2005, CPIC only provided coal price information for Qinhuangdao Port instead of a province-level database. Thus, the provincial coal price before 2006 is computed by the information of Qinhuangdao Port's coal price (2001-2010) and the provincial coal price (2006-2010). In practice, I start by using the average monthly price of coal in a province to compute the province-year coal price from 2006 to 2010. The ratio of a province's coal price to the Qinhuangdao Port's price can be calculated in the period 2006-2010. I then denote the average value of this ratio in a province over the years (2006-2010) as the constant ratio of the province's coal price to Qinhuangdao price. Finally, the province-year level coal price data before 2006 can be computed by calculating the product of the constant ratio and Qinhuangdao coal price prior to 2006.

Qinhuangdao Port is the most essential coal transaction market in China and its coal price is generally considered as the price of China. The port is located

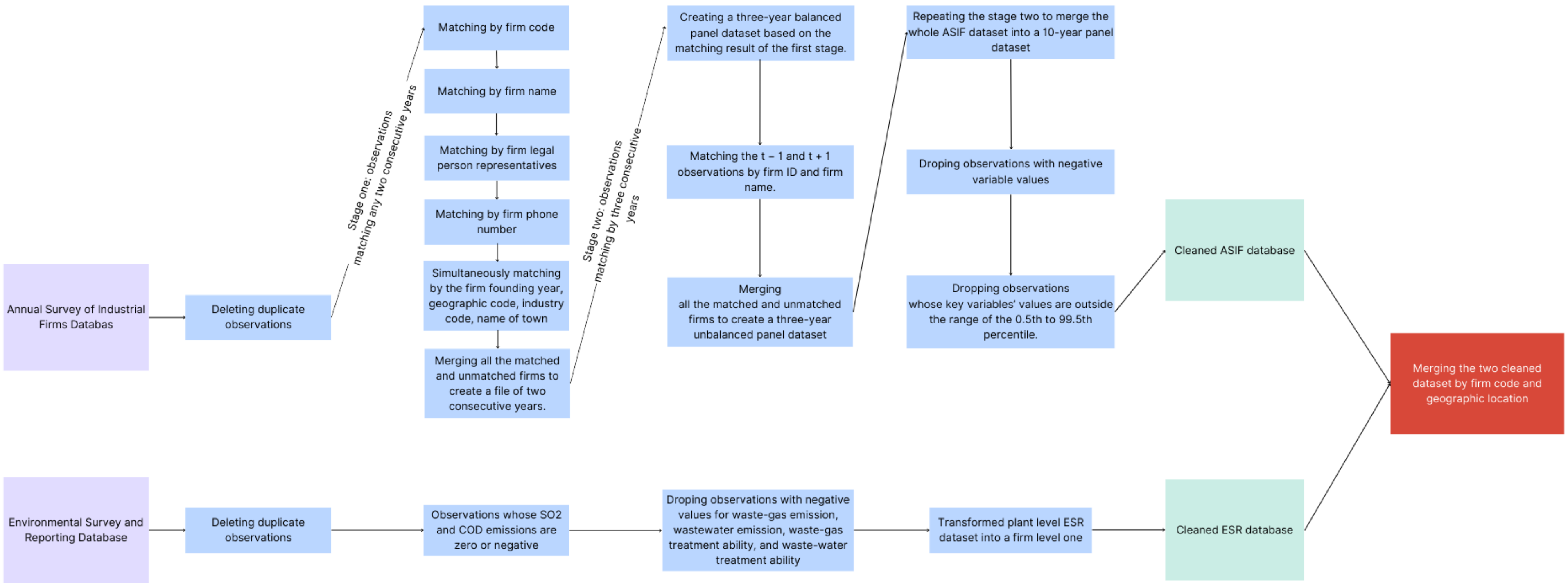


Figure 3.1: Matching process

on the west side of Liaodong Bay in Bohai Sea and on the northeast side of the coastal plain in Hebei Province. Coal resources in China are concentrated in the northern provinces. In particular, Shanxi, Shaanxi and western Inner Mongolia have the most coal reserves and produce a lot of coal. The port is adjacent to these three provinces, which makes it the main port for coal and oil transport in China. Domestic transshipment of coal at Qinhuangdao Port flows to Shanghai, Zhejiang, Jiangsu, Fujian, Shandong, Guangdong, Guangxi, Hainan, Liaoning and nine other provinces and cities. The quantity of transshipment of coal through Qinhuangdao Port accounts for more than 70% of China's coastal coal transport.

Qinhuangdao Port has developed external communications and superior transportation conditions. There are four trunk railways (Beijing-Shan, Shen-Shan, Beijing-Qin and Daqin) that reach Qinhuangdao Port directly. The highway of Qinhuangdao connects with National Highways 102 and 205, which reach Beijing, Tianjin, Shenyang and other provinces directly. Qinhuangdao Port is a natural deep water port. Until 2016, it had 21 professional berths for coal. It is responsible for electricity coal transportation along the southeast coast. The annual quality of coal discharged from Qinhuangdao Port accounts for 50% of the total coal discharged from the coastal ports of China. In 2001, port transportation volume exceeded 100 million tons for the first time.

With its good geographic location and transportation conditions, Qinhuangdao has attracted many coal-related mining enterprises, road transport enterprises, electric power enterprises, coal dealers, maritime and river transport enterprises. More than 400 coal dealers trade in Qinhuangdao Port. Its coal transaction situation, price trend, inventory change and the fluctuation of coal throughput affect China's coal market trend and coal price changes, and also draw the attention of the relevant state ministries and commissions and distribution enterprises. Thus, the coal price of Qinhuangdao Port is generally considered to be the price of China.

Figure 3.2 shows the panels of the distribution of coal price in eight major coal-producing provinces over the years. The vertical axis is the price of coal (CNY/ton). The horizontal axis is in years, from 2001 to 2007. The blue line denotes the average coal price in each province across the years, and the red line is the national average coal price (Qinhuangdao coal price before 2006 and average national coal price for 2006 and 2007). The average national coal price is collected from the *Chinese Year Book* and calculated by the ratio between the production value of the coal industry and the production quantity.

As shown by Figure 3.2, except Heilongjiang province, other provinces' coal price experiences the same increasing moving trend as the national price. He-

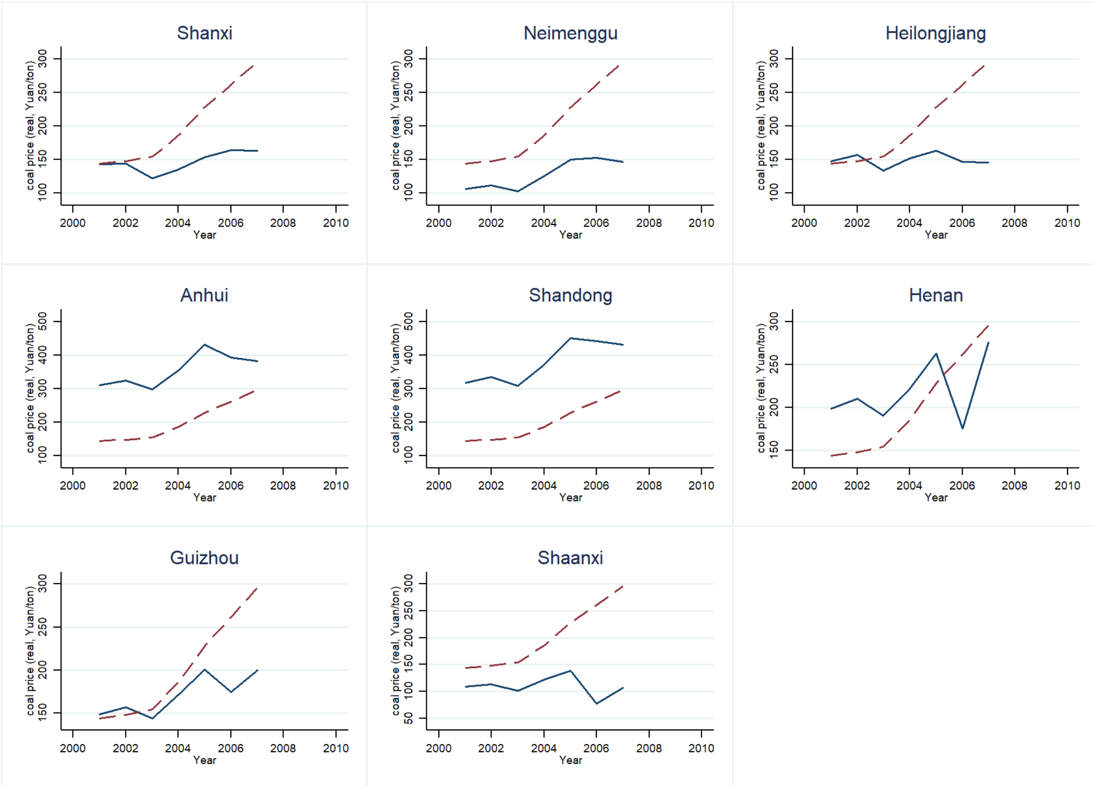


Figure 3.2: Coal price across provinces

Note: The blue line denotes the average coal price in each province across the years, and the red line is the national average coal price.

longjiang's coal price had been fluctuating around 150 CNY/ton. Comparing the blue lines across panels, all provinces' coal prices appeared to escalate in 2003 and drop in 2005 and then increase again in 2007. Thus, it is reasonable to base the province coal price on the Qinhuangdao coal price.

Figure 3.3 shows the panels of the distribution of oil prices in eight provinces over the years. The vertical axis is the price of oil (CNY/ton). The horizontal axis is in years, from 2001 to 2007. The blue line is the oil price in each province, and the red line is the national oil price collected from the *Chinese Year Book*. Except Heilongjiang, other province's oil price shows the same moving trend as China's mean price of oil. Some provinces' oil price even shows a moving trend in parallel with the country's oil price.

3.4 Socio-economic Data

In addition to the above three datasets, I obtained a series of province-level data, such as the provincial-level Producer Price Index (PPI), from the China Statistical

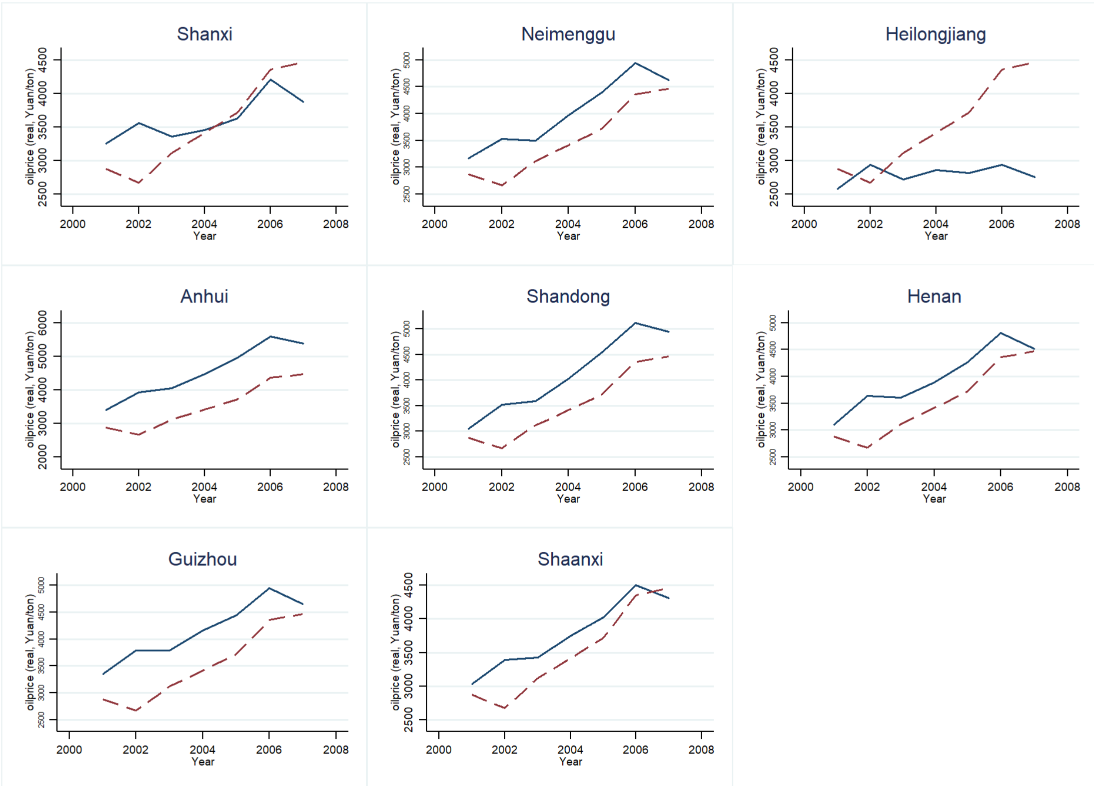


Figure 3.3: Oil price across provinces

Note: The blue line denotes the average oil price in each province across the years, and the red line is the national average oil price. This figure only displays the oil prices of eight coal-producing provinces, which are the same provinces in Figure 3.2. It shows that the increasing trend in oil prices is similar to the trend in coal prices. The information on oil prices of other provinces is available and employed in the empirical analysis.

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*.

Chapter 4

The Effect of Environmental Regulation on Firm Emissions and Performance

4.1 Introduction

China has experienced an economic miracle since the late 1970s, but that has brought environmental costs as well (Zheng and Kahn, 2017). In the early 2000s, the rapid expansion of the Chinese economy was accompanied by a surge in environmental degradation (Cole et al., 2011). The rapid industrialization and urbanization processes have contributed to the worsening air quality, posing significant challenges to public health and the environment (Shen, 2006). Meanwhile, the stringent environmental regulation policies brought a subsequent and noteworthy decline in SO2 emissions. The coincidence of these two major trends has raised suspicions that environmental regulations might be a primary causal factor in hindering the "competitiveness" of Chinese firms. In rapidly developing countries such as China, this discourse has captured the attention of both scholars and policymakers. The Two Control Zone policy is one of the national environmental policies aiming at improving Chinese air quality. Current research focuses on examining its impact on FDI (Cai et al., 2016a), employment (Sun et al., 2019b), infant mortality (Tanaka, 2015). However, few research investigates the policy's direct effect, i.e. firms' environmental and economic performance. This study compiles and evaluates the proof concerning the potential connections between the TCZ policy and firm competitiveness. Meanwhile, limited research reveals the strategies that firms would adopt in response to environmental regulations, especially for research on developing countries.

However, the debate about whether environmental regulation hinders firm performance remains controversial. On the one hand, neoclassical theory on environmental economics holds that environmental regulations cause an additional cost for firm production (including the cost of purchasing, operating, and maintaining desulfurization equipment, fines for excessive sewage discharge, and so on), which reduces firm competitiveness (Jaffe and Palmer, 1997). The implementation of environmental regulation can reduce firm emissions while also bringing about a decrease in firm performance or employment (Greenstone, 2002a; Greenstone et al., 2012; Walker, 2011). Based on neoclassical theory, the Pollution Haven Hypothesis (PHH) suggests that regulated firms will relocate to a new place with less regulation to avoid 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 adopt more efficient production methods to reduce firm emissions, which implies that environmental regulation can in turn be beneficial to firm productivity and competitiveness (Porter, 1990; Porter and Linde, 1995).

The adverse impact on firm performance resulting from environmental policy could lead to additional challenges, underlying the significance of examining the connection between environmental regulation and firm performance. First, A significant portion of the discourse has focused on the concern that environmental regulations might diminish the competitiveness of firms in the manufacturing sector, especially in the production of "pollution-intensive" goods, thereby altering a country's trade position (Jaffe et al., 1995). Second, workers may encounter difficulties securing new employment opportunities with comparable wages because sectors most impacted by regulations employ fewer workers (Jaffe et al., 1995; Walker, 2011). Third, The rearrangement in production from pollution-intensive sectors to other industries results in a more extensive range of social costs, particularly in the short term.

China serves as an apt research context for my study. The size of an economy and its growth rate play pivotal roles in shaping environmental outcomes, a phenomenon particularly pronounced in the context of China. In the early 2000s, the rapid expansion of the Chinese economy was accompanied by a surge in environmental degradation, marked by severe SO2 emissions. Understanding how China managed to curtail SO2 emissions during a period of rapid economic growth holds significance for policymakers globally. Moreover, the TCZ policy is an important environmental policy for improving Chinese air quality. It has a specific and solitary target, SO2 pollutant. As firms' SO2 emission information is also included in the emission database, the direct effects of environmental policy can be explored. Especially, the emission database in analysis is the the most comprehensive environmental dataset in China. Detailed information about firm emission and firm abatement behaviour holds significant promise for research in developing countries characterized by substantial manufacturing activities.

To identify the effects of the TCZ policy, I employed a difference-in-difference (DID) estimation method. Specifically, the first difference comes from the comparison of firm emissions, productivity, or performance in TCZ and non-TCZ cities (the firms in the TCZ area are 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 the empirical analysis, firm productivity is denoted by total factor productivity (TFP) as a proxy, and profitability is denoted by return on assets (ROA) and return on sales (ROS) as proxies.

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

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

The present research makes four contributions to the literature. First, this is the first study to investigate the effect of the TCZ policy on 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 the impact of various Chinese environmental regulations on firm behaviour. For example, He et al. (2018) find the establishment of water monitoring stations reduces upstream firm productivity, and Wang et al. (2018a) find that the "three rivers and three lakes basins" (3Rs3Ls) policy has no significant effect on firm emissions and productivity. Both He et al. (2018) and Wang et al. (2018a) focus on water regulations, leaving a gap in the knowledge regarding the economic cost of air pollutant regulation policy 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. Thus, a clearer economic interpretation is shown in my result than the finding that the TCZ policy is associated with neonatal mortality (Tanaka, 2015) and foreign direct investment (Cai et al., 2016b).

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

The third contribution is that this research uses the principal instruments of the TCZ policy, the SO2 emission-specific, county-level TCZ area designations, as its measure of regulation. The smallest unit of the policy implementation area is a county, which is better than other empirical studies of the TCZ policy. Previous studies rely on measures of regulation that are aggregated (e.g., city-level measures; see Cai et al. (2016b)). However, *the 1998 Reply* listed the names of cities and counties under regulation. Some selected cities include counties outside the regulation, which will create selection bias if choosing the city level as the basic unit for the TCZ policy. For accuracy, I set firms in the treatment group as the ones located in counties listed in the 1998 Reply.

Finally, through mechanism analysis, this research proves that firms under environmental regulation would take two different pollution abatement approaches. One is adding up pollution abatement devices after production to reduce emissions, which is an additional cost for firms. The other one is improving cleaner technologies during the production process, which can reduce the pollutants generated during production. My research proves that both methods have been applied by firms 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 approaches. This finding extends the literature on the discussion of whether environmental regulation promotes (Porter, 1990; Porter and Linde, 1995; Jaffe and Palmer, 1997; Costantini and Mazzanti, 2012; Ambec et al., 2013; Stavropoulos et al., 2018) or hinders (Gray, 1987; Gollop and Roberts, 1983; Berman and Bui, 2001; Greenstone, 2002b; Walker, 2011) the economy.

4.2 Literature Review

The stringency of environmental regulation has been increasing in the US since the 1970s (Berman and Bui, 2001; Jaffe et al., 1995). As firm abatement consumption has continued to increase, researchers have begun focusing on the economic costs of environmental regulations. However the debate about whether environmental regulation hinders firms' performance remains controversial. On the one hand, neoclassical theories hold that environmental regulation imposes additional costs for production, slows productivity growth, and thereby reduces firm competitiveness. The implementation of environmental regulation will reduce both firms' emissions and their performance (Greenstone, 2002a; Greenstone et al., 2012). Haveman and Christiansen (1981) go as far as implicating environmental regulations as contributors to the reduction in US productivity 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 environmental regulations argue that appropriate regulation can stimulate polluters to develop cleaner technologies, which reduces the emissions with increased productivity (Porter, 1990; Porter and Linde, 1995; Jaffe and Palmer, 1997). So, based on the idea of the Porter Hypothesis, environmental regulation can in turn be beneficial for firm competitiveness (Porter, 1990; Porter and Linde, 1995).

4.2.1 Neo-classical theory of environmental economics

Conventional wisdom and Neo-classical theory surmise that firms will suffer deleterious effects from stricter environmental regulations. Neo-classical theory 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 regulation constrains their choices.

4.2.1.1 Theoretical literature on proving the neo-classical theory of 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 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 makes several assumptions about 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 represent 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 assumes that the quality of the environment is a public consumption good determined by the amount of emissions, 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 specializing in environment-intensive goods would suffer a welfare loss from international trade because of the reduction of exports in environment-intensive industries. Environment-intensive industries will face a reduction in production and labour.

Siebert (1977) also studied the effect of environmental regulation on the export of environment-intensive goods using a two-sector economy model where pollutants are also treated as a by-product of production. Siebert (1977) makes many similar assumptions to Pethig (1976), such as one commodity is a pollution-intensively good, firms maximize their profits, and a country specializing in pollution-intensive goods would implement regulatory policies to increase environmental quality. The differences are that Siebert (1977) assumed the quantity of pollutants emitted 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 reduction in pollutants emitted 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) finds that for a country that exports pollution-intensive goods, gains from trade are accompanied by environmental degradation. With the implementation of environmental policy in this country, pollution-intensive industries will suffer a reduction in production and trade, which is a similar result to Pethig (1976).

Yohe (1979) also shows the backward incidence of pollution controls using a two-sector model. In this model, the author treats pollution as an input rather than a by-product of production. Polluters pay for their use of environmental 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 function. McGuire (1982) develops an approach which can incorporate regulation into the theory of production, distribution, and trade. This analysis of production function concludes that the effect of regulation on other cooperating factors is equivalent to neutral technical regress, i.e. negative progress. The paper even proved that if production factors are free to flow across borders, regulation policies will drive out regulated industries from the regulated economy to the less regulated economy. The Cobb-Douglas production function and CES production function are taken as an example to clarify the equivalence between regulation and negative neutral technical progress.

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

The empirical literature supports neo-classical theory from various directions. Gray (1987) finds that US environmental regulation reduces productivity growth in the average manufacturing industry by 0.44% per year. Haveman and Christiansen (1981) hold that environmental regulation contributed to the slowdown in productivity growth in the US economy during the 1970's. Ryan (2012) evaluates the welfare cost of US environment regulation through a dynamic model and two-step estimation, finding that regulation significantly increased the sunk cost of entry and brought a loss in product market surplus. In addition, evaluating the industrial or welfare cost induced by environmental regulations, the existing literature also finds a negative impact of environmental regulation on firm competitiveness or behaviour, in employment (Greenstone, 2002a; Walker, 2011), industrial output (Greenstone, 2002a), firm productivity (Gollop and Roberts, 1983; Berman and Bui, 2001; Gray and Shadbegian, 2003; Greenstone et al., 2012), and firm location choices (Henderson, 1996; Becker and Henderson, 2000). This research shows the deleterious effects of stricter environmental regulations on firms, which supports neo-classical theory.

4.2.2 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 costs, and new firms would also choose a place without environmental regulations. The debate among policymakers and economists about whether stricter environmental regulation would drive out existing firms started in the 1970s when developed countries, like the US, implemented more national environmental policies but there was 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 concerns North-South trade under the North American Free Trade Agreement (NAFTA). They predicted that NAFTA would cause environmental degradation in Mexico and job loss in the USA.

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 cause polluting industries (or firms/production facilities) to relocate to countries with weaker environmental policies. 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.

4.2.2.1 Theoretical literature on proving the PHH

The theoretical explanation for 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 sectors are linked by an input-output structure of intermediate production. They considered inter-sectoral linkages between different industries to analyse the incentives for the 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 to locate in and how many plants to establish; in the third stage, each firm chooses their output levels, while the demand of upstream firms is determined endogenously by downstream firms. The purpose of the paper is to find 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 emission levels, a pollution tax is imposed in the domestic country. On the demand side, consumers' utility is determined by two goods and emission levels. To analyse the inward FDI, they assume that capital is internationally mobile, 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 there is a lower pollution tax.

Levinson and Taylor (2008) employ both theoretical and empirical methods to analyse and estimate the Pollution Haven Effect. They develop a multi-sector (partial equilibrium) model and re-examine 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 empirical perspectives. They find that some important econometric and data issues existing in environmental economic research are responsible for the mixed results produced. They also criticize previous research for suffering 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 of 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 considers pollution as a production factor whose cost is the pollution tax established exogenously by the government. This paper's model is based on the classic hypotheses of "the new geographic economy".

4.2.2.2 Empirical literature on proving the PHH

Empirical studies testing the relationship between firm location choice and environmental policies can be classified into direct and indirect measurements. To test this relationship directly, existing literature uses 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 decisions. The advantage of using new plant data is that they are not constrained by sunk cost when making choices and are sensitive to the regulations of different regions.

Henderson (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 US plant location decisions. The dependent variable is the number of plants in different counties from five polluting industries from 1977 to 1987. The independent variable is that attainment counties have less environmental regulation, while in non-attainment counties they are more stringent. The result shows that stringent regulation, i.e., a switch from attainment to nonattainment status, leads to improved air quality but also results in the departure of polluting industries. As polluting industries in non-attainment countries spread out, fewer plants are located in non-attainment areas. This effect is more obvious in dirtier industries.

Becker and Henderson (2000) test the effects of the US Clean Air Act on polluting industries' decisions, including plant locations, births, sizes, and investment patterns. The Clean Air Act divides countries into attainment and non-attainment ones (Greenstone, 2002a; Becker and Henderson, 2000). Becker and Henderson (2000) use plant data from 1963 to 1992 and the panel conditional Poisson approach for estimation. The dependent variable is the birth of plants from four 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 reduction of births 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). Firm production, net export, and emissions are investigated in order to test the effect of environmental policies on firm output flow (Brunnermeier and Levinson, 2004). From the PHH standpoint, stringent environmental regulation policies in developed countries push their polluting industries plants to relocate to developing countries that have loose policies, which causes raised pollution in developing countries (Gill et al., 2018). Thus, some studies use dirty goods industries, such as steel, iron, non-ferrous metals, paper, pulp, chemical products, and the chemical industry, between developed and developing countries to test the PHH, i.e., test the change of output flow after environmental regulation. Because developing countries with loose regulation had a comparative advantage in pollution-intensive goods (Greenstone et al., 2012), they are expected to export more dirty goods after the implementation of environmental policies there.

On the other hand, some literature focuses 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 quite a popular measurement in papers focused on capital movement. Using a two-country model of international factor movements, Rauscher (1997) theoretically predicts that a country implementing 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 prefers to move from countries with stringent environmental regulations to countries with weak environmental regulations. They estimate this 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 enterprises' FDI location decisions, while it is not significant for internationalization decisions.

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

In addition to testing capital movement, some researchers have paid attention to the effect of environmental regulation policies on labour movement. Greenstone (2002a) use a firm-level panel data analysis to research the effect of federal Clean Air Act regulations on polluting manufacturing 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) estimates 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, the paper proves that regulation has resulted in a significant decline in employment.

4.2.3 Porter Hypothesis (PH)

Contrary to neo-classical theory and the PHH, some studies suggest that environmental regulation has a favourable impact on firm performance and competitiveness. They hold that properly designed environmental regulations (especially, market-based policies such as taxes or caps and trade emissions allowances) can trigger innovation (broadly defined) that may partially or fully offset the costs of complying with them in some instances (Porter, 1990; 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 underregulated firms, and also a "win-win" scenario for the government and corporations.

4.2.3.1 Theoretical support on the PH

The PH is theoretically proved by Acemoglu et al. (2012) who build a growth model with environmental constraints to analyse the response of dirty sectors' and clean sectors' technological change in the face of various environmental policies. So, in their model technical change is endogenously and directly studied. They hold that temporary emissions taxes 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 tax" research subsidies and government intervention.

Simon (1947) builds an alternative model of 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 it is assumed 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).

4.2.3.2 Empirical work on the weak version of PH

The empirical evidence proving the Porter Hypothesis can be divided into three strands: the weak version, the strong version, and the narrow version (Jaffe and Palmer, 1997). The weak version contends that environmental regulation only brings firm innovation but has no effect on firm competitiveness and productivity. To reduce additional costs brought about 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 benefitting from the maximal profit conditions, and not always detecting profitable opportunities. Thus, in addition to searching for new ways, new products, and new production processes to comply with environmental regulations, firms are also forced to develop new technological opportunities which can increase their profits and productivity. Under such a scenario, regulation becomes a "free lunch" for firms. Environmental regulation spurs firms' innovation, which further results in higher productivity, meaning increased competitiveness for firms (D'Agostino, 2015). Finally, the narrow version notes that only certain regulation policies spur innovation (Jaffe and Palmer, 1997)). Flexible and market-based regulatory policies in particular are more likely to stimulate firms to innovate, rather than command and control policies that set 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 to test the effect of environmental regulation on firm innovation. They find that the PH effect lags behind environmental regulation for about four to five years.

Exciting facility-level literature finds evidence that environment-related R&D and technologies are positively affected by the perceived environmental policy stringency (Johnstone and Labonne, 2006; Lanoie et al., 2011; Horbach et al., 2013). Comparing firms in the 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 argue that inter-sectoral spillover is a mechanism that explains why environmental regulation can induce innovation (D'Agostino, 2015; Corradini et al., 2014). 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, Popp (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 fades over time. Popp (2001) argues that the reason for fading is diminishing returns to R&D. In the second paper, 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 about by prices is related to induced innovation, while the other two-thirds are related to factor substitution.

4.2.3.3 Empirical works on a strong version of PH

Literature about the estimation of the strong version of PH focuses 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 include pollution abatement investments and environmental-related tax, and indirect proxies, mediated by innovation, include innovation and R&D induced by environmental regulation. But there is no consensus on this topic.

On the one hand, the positive effects of environmental regulation on productivity growth are found by Hamamoto (2006) and 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 supporting 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. There is also a U-shaped relationship between environmental regulation and firm exports.

On the other hand, Lanoie et al. (2008) found a negative impact on industry productivity for regulations. They also found that less polluting industries are more likely than high poluting ones to support the Porter Hypothesis. 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 a connection between inhibiting investment and productivity growth, which could be seen as evidence that induced innovation effects are either small or outweighed by other costs of regulation. Greenstone (2002a) 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 the weak and strong versions, Lanoie et al. (2011) first proposed the Porter Hypothesis causality chain using the "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 to the environmental goods sector or if 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 Porter 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 and negative.

4.2.3.4 Connections between PHH and PH

The connection between the Pollution Haven Hypothesis and the Porter Hypothesis can be summarized in two points. First, PHH is a static theory, which is transient, while PH is dynamic. Mani and Wheeler (1998) observed that 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 shown that as developing countries' income increases with FDI inflow, their environmental regulations become more stringent. So, developing countries experience a temporary competitive advantage brought by less regulation, which means the PHH should only be a transient phenomenon. At the same time, PHH is based on the analogy of the traditional static comparative advantage perspective. In PHH empirical studies, firm relocation and environmental regulation policies always occurred at the same time, which means that firm behaviour operates at t0 and regulation also issues at t0. So, PHH has a narrow static perspective on firms' reaction to ER (Porter and Linde, 1995).

PH is different from PHH, in that it asserts that from a dynamic point of view, environmental regulation stringency can inspire efficiency innovation and guide production procedures to be more environment-friendly (Porter and Linde, 1995). So according to PH, if a regulation policy is issued at t0, then regulated firms' innovation behaviour should occur in a lag time, i.e., t1, t2, 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 lag (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).

4.2.4 Environmental regulation and firm productivity

Since the early 1970s, studies have focused on the effects of environmental regulation on productivity (Haveman and Christiansen, 1981). Proponents of the neo-classical theory hold that environmental regulation has a deleterious impact on firm productivity. One reason is that firms are forced away from their profit-maximizing choice. Another reason is that government regulations always require firms to use inputs directly for regulatory compliance, like using scrubbers to reduce gas emissions, operating and maintaining desulphurization equipment, and taking on extra employees to monitor pollution abatement equipment. As the productivity measurement does not distinguish between inputs used for traditional output production and inputs for pollution abatement actions, neo-classical microeconomic analysis believes that environmental regulation will reduce firm productivity. Most empirical research supports the argument that stringent environmental regulation would have an 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 total factor productivity and the direct and indirect productivity effects of environmental regulations for the five most polluting industries in the US. Their model separated conventional inputs of labour, capital, energy, and materials from abatement capital which is used as an input to control pollution. This model distinguished between the direct and indirect effects of required abatement capital on industries' total factor productivity growth. 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 plant productivity brought about by environmental constraints. They wanted to use a general measurement of productivity containing environmental regulation to work out whether US manufacturing plants would reduce input use and pollution output under environmental constraints. They chose the paper industry because it is a capital-intensive, energy-intensive, and pollution-intensive industry. By using plant-level data from the U.S. Longitudinal Research Database (LRD) in 1988-1992, Boyd and McClelland (1999) investigate plant performance which is measured by the input distance function of productivity and data envelopment analysis (DEA) method. The conclusion is that environmental regulation reduces production by 9%, and 25% comes from 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 determine whether plants of different ages and with different technologies in the same industry spend different abatement costs when facing environmental regulation. The data they used, including data about 116 pulp and paper mills' vintage, technology, productivity, and pollution abatement operating costs, 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 in plants there is a negative relationship between pollution abatement costs and productivity levels, i.e., more pollution abatement spending is accompanied by less plant productivity. For plants' technology, integrated mills' productivity is much more affected by abatement costs, about 9.3%, while the productivity of non-integrated mills' is affected less (0.9%). When it comes to 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 that are exposed to international competition have shown a more obvious negative effect of environmental regulation on the sector's TFP.

Greenstone et al. (2012) estimate the impact of air quality regulations on US manufacturing plants' productivity denoted by plants' total factor productivity (TFP) levels. This paper focuses on the 1970 Clean Air Act Amendments in the US. Based on those 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 are tested separately by Greenstone et al. (2012). This paper divides samples into two groups and makes an important independent variable according to whether a sample plant is located in a non-attainment or attainment county because every US county has annual non-attainment or attainment designations for each of the four pollutants. Related pollutant emitters located in the counties which are in the non-attainment category will face more stringent regulatory oversight.

Using plant-level microdata, Greenstone et al. (2012) assume a Cobb-Douglas production function for manufacturers. To test the dynamic effect, they introduce lagged non-attainment status in the specification including one and two years of lagged attainment status. They find that a year's non-attainment designation has at least three years' impact on a plant's productivity. This finding is consistent with the hypothesis that the non-attainment designation results in firms investing in pollution abatement equipment which cannot increase their output or productivity. The final result of this paper is that for surviving polluting plants, stringent air quality regulations lead to a 2.6% 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.

There are however also studies that 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 oil refineries in the US during the period 1979 to 1992. Pollution abatement control expenditures (PACE) are used to denote environmental regulation. Their regression uses plant-level data and involves two steps. The first step is to estimate the effect of regulations on abatement costs. The second step is to estimate the impact of regulations on plant productivity. They found that environmental regulation increased the investment of abatement costs and improved the productivity of regulated area refinery plants, while in the same period, refinery productivity decreased in other regions.

4.2.5 Environmental regulation and firm profitability

In studies about the effect of environmental regulation on firm profitability, proponents of the Neo-classical Theory and the Porter Hypothesis cannot achieve a consensus either. Literature supporting the neo-classical theory holds that environmental regulation reduces a firm profitability level and is harmful to 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 a less severe regulation burden in 1990, while some firms experienced reduced profits under regulation.

Alpay et al. (2002) theoretically examine the impact of pollution regulation on the profitability of Mexican and US food industries. In their 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. The empirical result shows that US pollution regulation has no significant effect on food manufacturing's profitability or productivity growth, while Mexico's environmental regulation led to reduced profitability for manufacturing.

Rassier and Earnhart (2015) empirically studies the effect of environmental regulation on profitability. The policy they focused on is the Clean Water Act in the US. The data used are 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 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 regulation leads to a 1.7% reduction of sales. So, their research concludes against the strong version of the Porter Hypothesis.

Greenstone (2002a) deals with the impact of the U.S. Clean Air Act on polluting manufacturers. It shows the relationship between environmental regulations and industrial activity, including the growth of employment, capital stock, and shipments. Greenstone (2002a) mentions that in the absence of a situation where environmental regulations are randomly assigned to plants, an experiment where similar plants face different levels of regulation could be used in their research. So, this research focuses on the US Clean Air Act and divides samples into non-attainment or attainment counties. The data used are 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 from 1972 to 1987, the first 15 years when the Clean Air Act was in force, non-attainment 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 imposed on the new non-attainment counties would bring employment, investment, and a decrease in shipment in polluting industries.

However, some literature finds a 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 factor's profitability effect, looking at where profit lies for firms. The indicators they used to denote fanatical performance are return on assets (ROA) and Tobin's q. 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 a firm, Russo and Fouts (1997) imply that environmental performance and economic performance have a positive relationship that could be moderated by industry growth. They also prove that high-growth industries are related to higher returns to environmental performance. They tested 243 firms in 1991 and 1992. Environmental regulation is denoted by independently developed environmental ratings, and firm performance is denoted by return on assets (ROA). From the resource-based view of firms, this paper analysed two kinds of policies, compliance strategy and prevention, which is an approach to source reduction and process innovation. Their result supports the "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 assessed the effects of environmental regulation on them. 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. The 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 lower permitted discharge limits for BOD and TSS, leads to higher returns on sales for chemical firms. 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. A 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 here is a voluntary environmental instrument, where firms individually decide 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 firm-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 uses 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 the 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 decides the motivation of firms' participation decisions. Expected gains and fear of high costs of compliance with future mandatory environmental regulations lead to firms being incentivized 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. The dataset used in this paper includes 4200 facilities in seven OECD countries, and the data were 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 approaches (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 the narrow version, but no evidence to support the strong version.

4.2.6 China-specific research

4.2.6.1 Empirical studies for the PHH and Neo-classical theory

In China-specific research, some researchers find evidence to support the PHH. 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 decisions 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 decisions of firms with different ownership and industries over various policy regimes. They use the removal rate of SO2, SO2 abatement divided by 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 the number of firms, but private-owned, foreign-owned, and collective-owned enterprises are more likely to enter the region with more relaxed environmental policies from 2003 to 2005 while showing a reverse pattern from 2006 to 2008.

Greaney et al. (2017) show that under stricter pollution control larger foreign firms with higher productivity that export more are less likely to relocate to new regions compared to domestic firms in China. The paper, which focuses on the Two-Control-Zone (TCZ) pollution control policy, estimated the exit rate of firms located in TCZ zones at both the city level and firm level.

Shen et al. (2019) directly prove the Pollution Haven Hypothesis at 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 the environmental efficiency of different cities in Guangdong. After PMG/ARDL regression analysis, environmental efficiency has a negative relationship with the migration of pollution-intensive industries in areas which the industries left. They proved the Pollution Haven Hypothesis by showing that polluting 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, the "Pollution Reduction Performance Assessment" was implemented by the MEP. According to the assessment, governments that fail to meet pollution reduction mandates would be punished through a reduction in rank of their government officer. So, the 11th Five-Year Plan's water pollution reduction mandates researched in this paper are a very effective environmental policy. The firm-level data used in this research contains 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 choices. For foreign polluting firms, the relationship is negative. After the implementation of the "Pollution Reduction Performance Assessment", domestic polluting firms changed their location choice from coastal provinces to western provinces.

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

Some empirical papers test the location decisions of Chinese firms using indirect measures. Guo et al. (2010) use China-US international trade to embody the CO2 emissions leak and prove 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, US emissions were reduced but global CO2 emissions increased. China-US international trade has thus increased global CO2 emissions. López et al. (2013) also developed an input-output framework to analyse whether bilateral trade between Spain and China has increased global emissions. Similar to Guo et al. (2010), they find that the Spain–China trade relationship increased global emission levels because Spain inputs more pollution-intensive goods from China. Indirectly proved by the PHH, they show that Spain's polluting industries moved to China through international trade.

By investigating FDI, some papers use capital input movement to prove the PHH indirectly. Cai et al. (2016b), Zhang and Fu (2008) and He (2006) prove the negative effect between FDI flow and China's environmental regulation stringency, using firm-level data, provincial-level data, and industrial-level data. Cai et al. (2016b) investigate whether multinational firms prefer to invest and produce in places in China with less stringent regulations. They compared firms that chose to locate in cities implementing the TCZ policy and firms that chose to locate in cities without it. 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 are from two large-scale firm-level data sets. One is two census 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 show the FDI flow in China from 1996 to 2001. Finally, they find that a one-standard-deviation increase in pollution intensity leads to an 8 % decrease in FDI flows, which shows the negative effect of environmental policy and confirms the Pollution Haven Hypothesis. Meanwhile, they find that multinational firms who are used to tougher environmental policies than China are insensitive to the toughening of Chinese environmental policy, the 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 determine whether intra-county differences in environmental regulation will affect FDI location choice in China. The result shows that FDI prefer to locate in regions with loose environmental policies.

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 are industrial-level data covering 29 Chinese provinces from 1994 to 2000. Unlike 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 in China from 2000 to 2011. The result shows that China has become a pollution haven for its foreign consumers and China's growing trade surplus leads to rising emissions in China.

4.2.6.2 Empirical studies for the PH

In research about Chinese environmental regulations, however, some literature proves environmental regulation has a favourable effect on firms. Wang et al. (2019) confirm the Porter effect 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 list of the most polluting firms from 2010 to 2015 in China. The firm-level data, including name and location, comes from the Nation Key Monitoring Enterprises (NKMEs) which are issued annually by the Ministry of Environmental Protection. Data are collected by the Environmental Protection Bureau of each province, and the emissions of these listed firms account for 65% of total pollution emissions. Using this annual firm-level data, Wang et al. (2019) obtain location information for new firms and relocation information for existing firms. They conclude that polluting firms located in the east of China invest more in provinces with stringent environmental policies, while firms in the north-eastern region have the opposite reaction.

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 proves that regulated industries innovate relatively more as environmental regulations increase in stringency. They also found that more pollution-intensive firms innovate less and industries that are less "footloose" innovate relatively more under stringent environmental policies, which means immobility factors are much more important with regard to R&D intensity than pollution factors.

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

4.2.6.3 Chinese environmental regulation and firm Productivity

In China-specific research, He et al. (2018) show the cost of stricter environmental regulation, which supports the neo-classical theory. He et al. (2018) estimate the effect of water quality regulation on firm productivity using the Geographic Regression Discontinuity (GRD) approach. They focus on the geographic location of water monitoring stations and divide firms into geographic upstream and downstream firms. As the monitoring station only captures upstream firms' emissions, environmental regulations tend to be more stringent for them than for downstream ones. They found that upstream polluting firms have a 27% reduction in TFP and a 48% reduction in emissions compared to downstream firms. This phenomenon only exists in polluting industries. They calculated that China's water pollution abatement target (2016-2020) would cause a loss of approximately one trillion Chinese Yuan in industrial output. 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 to a new version in 2003. So, the new NEQMN-SWMS is the policy this paper focuses on. Its worth noting that when investigating the relationship between environmental regulation and productivity (calculated by the Olley and Pakes (1996) method (OP), and the Levinsohn and Petrin (2003) method (LP)), this paper only used the Annual Survey of Industrial Firms (ASIF) dataset without emission data. When investigating the relationship between environmental regulation and firm emissions however, the paper used firm-level emission data from China's Environmental Survey and Reporting (ESR) database. They also present a theoretical framework to show how environmental regulation affects firm productivity negatively.

Much more literature, however, shows that Chinese environmental regulation has either no effect or a positive effect on firm productivity. Wang et al. (2018a) discuss 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 firm productivity. They found that this regulation policy led to small and heavily polluting firms closing, but had no significant effect on surviving firms' productivity results because of the ineffectiveness of the 3Rs3Ls on reducing firms' COD emissions. This paper is the first to use 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, it does the basic regression using TFP which represents productivity as a dependent variable, and the interaction of COD and whether the policy was issued are an independent variables. 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).

Wang et al. (2018a) provide two possible explanations for the basic result: the regulation policy did not successfully force firms to reduce emissions that are connected to productivity; or in line with Porter's Hypothesis, the stringent environmental policy pushed firms to find new technologies to reduce their emissions, which eventually improved their productivity. To test the first explanation, Wang et al. (2018a) 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, Wang et al. (2018a) 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 both a closed and open economy. Then they tested the model using firm-level data from 2005 to 2009. The dataset empirical analysis used comes 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 TCZ policy is used 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 effect on firm exports. But, as China is situated to the left part of the U-shape, environmental regulation harms firm exports.

At 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 enable us to 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 industry changes caused by environmental regulation are more obvious and easier to observe. The policy in this paper is China's Energy Saving Policy 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. The authors conclude that energy-saving policies initially cause reduction in energy-intensive industries' output and productivity, and then that effect is 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, find it hard to recover, and have low export rates. So, in their opinion because of capital investment and factor reallocation, Chinese environmental policy could improve industrial energy efficiency with no loss in competitiveness and no carbon leakage.

At 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 industries' competitiveness. The data they used are 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.

4.3 Specification strategy and variables

4.3.1 Specification strategy

Time and regional variations in the adoption of the TCZ policy make it possible to use the difference-in-difference approach in my research. Specifically, there are two groups of counties: the treatment group consisting of counties designated as TCZ areas in 1998, and the control group comprising non-TCZ areas. Thus, it is possible to compare firm emissions and behaviour in the 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 equation is:

$$Y_{it} = \alpha_0 + \alpha_1 TCZ_i * \ Post_t + \boldsymbol{\beta X_{it}} + \gamma_{pt} + \mu_i + \sigma_t + \varepsilon_{it} \tag{4.1}$$

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 the 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 the 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 I am interested in is α_1 which shows the average treatment effect of the TCZ policy. It is the coefficient of the interaction term between the treatment variable, TCZ_i, and the time period variable, $Post_t$. 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. (2016b). Thus, it is expected that α_1 is negative, i.e., the TCZ policy would cause firm emission reduction but also have a negative effect on firm performance.

The treatment variable, TCZ_i, in my study is a county-level one. I use the county as the smallest unit of the policy implementation area. Previous studies rely on measures of regulation that are aggregated (e.g., city-level measures, see Cai et al. (2016b)). However, the 1998 Reply listed the names of cities and counties under regulation and there would be selection bias if a regulated city that has counties outside the policy were targeted. For some cities, only counties belonging to urban areas are under-regulated. Some cities' regulated area is fuzzy, which includes lots of counties of different cities. Thus, firms in the treatment group were set as the ones 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. 2000 was chosen as the implementation year for the TCZ policy rather than 1998 because of the following reasons. First, even if the 1998 Reply was issued in 1998, the official action plan for the TCZ policy was not clear until 1999. Second, in the 1998 Reply, the official goal was that SO2 emissions in 2010 would be reduced by 10% compared to 2000. So, the government also set 2000 as the base point of comparison. Third, from 1998 to 2000, although the establishment of the two control zones restrained the rapid growth of China's SO2 pollution emissions to a certain extent, it did not help all regions to achieve the pollution reduction targets established in the 1998 Reply. According to statistics from the Ministry of Environmental Protection, only Beijing, Tianjin, Chongqing, and Guizhou reduced SO2 emissions between 1998 and 2000, while the other 23 provinces and municipalities not only failed to reduce their emissions but actually experienced relatively high emissions. Fourth, the Tenth Five-Year Plan started in 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 Sulphur Dioxide Pollution in the Two Control Areas*, which was implemented from 2000 to 2005.

4.3.2 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 the 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, 2002a; Wang et al., 2018a; He et al., 2018)). As the Chinese government targets large firms and exerts less control over small ones, He et al. (2018) show that large firms with higher emissions will have more emission reduction. Wang et al. (2018a) hold that larger firms usually have lower emission intensity. Thus, it is expected that the coefficient of *Output* is positive when using emission level indicators as the dependent variable, and negative when using SO2 intensity as the dependent variable. Large Chinese firms always have increasing productivity that is higher than average (Brandt et al., 2012). He et al. (2018) find that the TFP impacts are significant only for larger firms. It was expected that the coefficient of *Output* would be positive when using TFP and profitability indicators as the dependent variable.

gas treatment capacity is the natural log of the capacity of waste gas treatment facilities (cubic meters per hour). This variable is used to control firms' capacity for waste gas treatment. Liu et al. (2018) and He and Zhang (2018) show that pollution abatement capacity is correlated with firm behaviour and firm emission levels. Firms with Higher emissions need more abatement devices for pollution treatment, which means they are always have high pollution abatement capacity (Liu et al., 2018). It is expected that the coefficient of *gas treatment capacity* would be 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, 2002a; Greenstone et al., 2012; Wang et al., 2018a; He et al., 2018) and productivity (Syverson, 2011; Brandt et al., 2017; Greenstone et al., 2012; He et al., 2018). Firm age is often used as an indicator of firms' technology level and firms' governmental embeddedness (Sun et al., 2019a). 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 (Sun et al., 2019a). It is investigated that older firms may polluted more in their production (Greaney et al., 2017; Wang et al., 2018a; Liu et al., 2017; Sun et al., 2019a). I 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, 2019b). 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; Wang et al., 2018a) and firm productivity (Brandt et al., 2012; Syverson, 2011). It was expected that the coefficient of *export* would be positive related to TFP for two reasons. First, export is often accompanied by large R&D investments, which raise exporters' productivity levels (Syverson, 2011). Second, in line with the "learning-by-exporting" hypothesis, exporters' productivity advantage grows after entry into the export market (Van Biesebroeck, 2005; De Loecker, 2007).

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 the same 2-digit industry and the same city. This indicator is used as a control for firms' agglomeration effect in the US (Krugman, 1991; Greenstone, 2002a), China (Brandt et al., 2017; Wang et al., 2018a), 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 to share abatement technologies inside their sectors. Wang et al. (2018a) proved the negative relation between agglomeration and emission intensity. It was expected that the coefficient of *agglo* would be negative when using SO2 intensity as the dependent variable. However, the relation between emission levels and agglomeration is unclear. As with agglomeration-type productivity spillovers (see, Syverson (2011)), it is expected that the coefficient of *agglo* would be positive when using TFP as the dependent variable.

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

4.3.3 Key dependent variables

The dependent variable used here includes emission indicators, firm performance indicators, and variables used to show mechanism and channels about how the policy influences firm performance.

The ESR dataset allows us to construct firm level emission variables (Greenstone, 2002a; Greenstone et al., 2012) and emission intensity variables (List and Kunce, 2000; Rassier and Earnhart, 2015; Wang et al., 2018a; He et al., 2018). I 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. For the original database, the ESR dataset only has the information of firms' SO2 discharged amount and SO2 removed amount. The SO2 generated amount of firm i is calculated by using the SO2 discharged amount plus the SO2 removed amount. *SO2 intensity* is the rate of SO2 discharged value over gross output. It is the amount of SO2 discharged by producing one unit of output. It is expected that the coefficient of the interaction term, α_1, would be negative when using emission indicators as dependent variables, i.e., the TCZ policy results in a decline in firms' emissions.

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

TFP represents the log of total factor productivity of firm i. Firm TFP measures are constructed using the Wooldridge (2009) and Levinsohn and Petrin (2003) approaches. Specifically, the Wooldridge (2009) approach is my main measurement of TFP, and the latter one is used to test the robustness of the TCZ policy's effect. Wooldridge (2009) shows how to estimate both the first and second stage of the OP or LP procedure simultaneously, and solve the problem of the identification of the parameters in the OP and LP first stage estimation criticized by Ackerberg et al. (2006). It is expected that the coefficient of the interaction term, α_1, would be negative when using TFP as a dependent variable, i.e., the TCZ policy has a harmful effect on firm productivity. In the next section, I 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 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 are used to represent firm competitiveness (see, Rassier and Earnhart (2015); Zhao and Sun (2016)), it is expected that the coefficient of the interaction term, α_1, would be negative when using ROA and ROS as dependent variables, i.e., the TCZ policy have a negative effect on firm profitability.

In channel analysis, I use the "end of pipe" variable and the "change in process" variable as the dependent variable in equation 4.1 to denote two different pollution abatement approaches, the same approach used as Liu et al. (2018), He and Zhang

(2018), and Sun et al. (2019b). Firms regulated by environmental policies would choose to invest in "changes in process" technologies, "end-of-pipe" technologies, or both (Berman and Bui, 2001; Wang et al., 2018a).

end of pipe is the ratio of SO2 removed amount over SO2 generated amount (Liu et al., 2018; He and Zhang, 2018; Sun et al., 2019b). At the end of production but before pollutants are released into the environment, firms can use technologies or devices to reduce pollutants that have already been generated during the production process, such as scrubbers and precipitators, i.e., an indicator for "end of pipe" measurement (He and Zhang, 2018; Berman and Bui, 2001; Wang et al., 2018a). The "*end of pipe*" variable denotes firms' ability to remove pollutants. Higher *end of pipe* value means a firm removed more SO2 emissions from what they generated. Firms under environmental regulation would take more "end of pipe" measurements (He and Zhang, 2018; Sun et al., 2019b). Thus, it is expected that the coefficient of the interaction term, α_1, would be positive when using *end of pipe* as dependent variables, i.e., the TCZ policy induces firms to take more "end of pipe" measurements. 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 (Liu et al., 2018). Following Liu et al. (2018), I use the *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 boilers, and other environmental protection technologies (Berman and Bui, 2001; Wang et al., 2018a). Lower *change in process* variable means fewer pollutants per unit of output generated by firms. It is expected that the coefficient of the interaction term, α_1, would be negative when using *change in process* as dependent variables, i.e., the TCZ policy induces firms to 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 is linked directly to firms' "end of pipe" activities. I assume that regulated firms have a higher capacity for SO2 treatment facilities. The last factor used in the channel analysis is the fixed asset investment variable. Fixed asset investment is calculated by the ratio of fixed asset investment to 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 invests more in the fixed asset. I 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 in purchasing pollution abatement devices (He et al., 2018).

4.3.4 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. labour and capital. It represents growth in output which is in excess of the growth in input. In microeconomic research, production function shows the relationship between productive inputs, such as capital and labour, and output. However, the estimation of production function faces an econometric challenge in that some observed determinants of firm production are unobserved by the researcher. If the observed inputs are a function of determinants unobserved by economists, the estimation will be faced with an endogeneity problem and biased OLS estimates of the coefficients on the observed inputs. In this research, I use two approaches, the Wooldridge (2009) approach and the Levinsohn and Petrin (2003) method, i.e., LP method, to calculate firm TFP. The Wooldridge (2009) method is used in my main regression, while the LP measurement of TFP is used as a robustness check.

Wooldridge (2009) made some improvements on the basis of Olley and Pakes (1996) method (OP), and the Levinsohn and Petrin (2003) method (LP). This approach estimates both the first and second stages of the 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 methods is given to describe the TFP measurement I used.

The Wooldridge measurement is the key measurement for TFP in the basic regression. In section 4.4, the Wooldridge measurement is employed in the basic result discussion, channel analysis, and heterogeneous analysis. The LP measurement is used for robustness check. The results in the robustness check are similar to the results in basic regression.

4.3.4.1 OP measurement

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

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + w_{it} + \epsilon_{it} \tag{4.2}$$

y_{it}, k_{it}, and l_{it} are the log of output, the log of capital input, and the log of labour 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 represents 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 4.2, it is reasonable to put a constant term into the w_{it}.

There are three important assumptions in the OP method. The first is that productivity shock w_{it} evolves exogenously following a first-order Markov process. The second assumption is the moment conditions that labour is a non-dynamic input, while capital is a dynamic input. The third one is that investment is a strictly increasing function of the current productivity level. Based on these three assumptions, the estimation procedure of the 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 correlate with productivity shock w_{it}. As w_{it} is unobservable to the economist, this is a classic endogeneity problem for the identification of equation 4.2. To address that endogeneity problem, Olley and Pakes (1996) bring moment conditions to their calculation of production function, i.e., firms make their decisions to maximize profit at different times.

Olley and Pakes (1996) assume that productivity shock w_{it} evolves exogenously following a first-order Markov process.

$$p(w_{it+1}|I_{it}) = p(w_{it+1}|w_{it}) \tag{4.3}$$

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

$$E(w_{it+1}|w_{it}, ..., w_{i1}) = E(w_{it+1}|w_{it}), t = 1, 2, ..., T \tag{4.4}$$

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

$$k_{it} = K(k_{it-1}, i_{it-1}) \tag{4.5}$$

This assumption regarding moment conditions helps to solve the 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}, $\xi_{it} = w_{it} - E[w_{it}|I_{t-1}] = w_{it} - E[w_{it}|w_{it-1}]$). This orthogonality condition, k_{it} is uncorrelated with ξ_{it}, which can help to form a moment to identify capital coefficient β_k in the OP method.

So, the endogeneity problem focuses on the labour 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 the labour variable, the OP method introduces 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 the current productivity level w_{it}. The investment level in period t is restricted to productivity and capital in t, i.e.

$$i_{it} = f_t(w_{it}, k_{it}) \tag{4.6}$$

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

$$w_{it} = f_t^{-1}(i_{it}, k_{it}) \tag{4.7}$$

Substituting equation 4.7 into equation 4.2.

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + f_t^{-1}(i_{it}, k_{it}) + \epsilon_{it} \tag{4.8}$$

$$= \beta_l l_{it} + \Phi_t(i_{it}, k_{it}) + \epsilon_{it} \tag{4.9}$$

where,

$$\Phi_t(i_{it}, k_{it}) = \beta_k k_{it} + f_t^{-1}(i_{it}, k_{it}) \tag{4.10}$$

The first stage of the OP method is the estimation of equation 4.9 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},

$$w_{it} = E[w_{it}|I_{it-1}] + \xi_{it} = E[w_{it}|w_{it-1}] + \xi_{it} \tag{4.11}$$

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

$$E[\xi_{it}|I_{it-1}] = 0 \tag{4.12}$$

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 obtain,

$$E[\xi_{it}|k_{it}] = 0 \tag{4.13}$$

So the conditional mean in equation 4.12 implies that ξ_{it} and k_{it} are uncorrelated. Specifically,

$$E[\xi_{it}k_{it}] = 0 \tag{4.14}$$

To get the estimates of β_k, equation 4.10 can be rewritten as,

$$f_t^{-1}(i_{it}, k_{it}) = \Phi_t(i_{it}, k_{it}) - \beta_k k_{it} \tag{4.15}$$

So,

$$w_{it}(\beta_k) = \widehat{\Phi}_{it} - \beta_k k_{it} \tag{4.16}$$

Then regress $y_{it} - \beta_k k_{it} - \beta_l l_{it}$ on implied w_{it-1} non-parametrically, obtaining $\widehat{\Psi}(w_{it-1}(\beta_k))$. (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,

$$\xi_{it}(\beta_k) = w_{it}(\beta_k) - \widehat{\Psi}(w_{it-1}(\beta_k)) \tag{4.17}$$

Finally, using $\xi_{it}(\beta_k)$'s form equation 4.17 analogue to the moment condition of equation 4.13. In a GMM procedure, one can set equation 4.17 as close as possible to zero to get the estimates of β_k

$$\frac{1}{T}\frac{1}{N}\sum_t \sum_i \xi_{it}(\beta_k) \cdot k_{it} \tag{4.18}$$

With the $\widehat{\beta_l}$ and $\widehat{\beta_k}$, identified value of β_l and β_k, economists can calculate productivity through equation 4.2.

4.3.4.2 LP measurement

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

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + w_{it} + \epsilon_{it} \tag{4.19}$$

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.

$$m_{it} = f_t(w_{it}, k_{it}) \tag{4.20}$$

The LP method holds two-moment conditions assumptions. One is that an intermediate input choice decision is made at the same time production takes place and the same time as productivity is decided (i.e., m_{it} is a function of w_{it}). The other one is that labour 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}, obtaining,

$$w_{it} = f_t^{-1}(m_{it}, k_{it}) \tag{4.21}$$

Substituting equation 4.21 into equation 4.19,

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + f_t^{-1}(m_{it}, k_{it}) + \epsilon_{it} \tag{4.22}$$

$$= \beta_l l_{it} + \Phi_t(m_{it}, k_{it}) + \epsilon_{it} \tag{4.23}$$

where

$$\Phi_t(m_{it}, k_{it}) = \beta_k k_{it} + \beta_m m_{it} + f_t^{-1}(i_{it}, k_{it}) \tag{4.24}$$

So the first stage of the LP estimation procedure is to estimate equation 4.23 non-parametrically and get the estimate of β_l.

In the second stage of estimation, LP needs to identify both β_k and β_m given $\widehat{\beta_l}$ and $\widehat{\Phi_{it}}$ identified in the first stage. One moment condition used in LP is the 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 the 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, obtaining $\widehat{\Psi}(w_{it-1}(\beta_k, \beta_m))$.

So one can compute ξ_{it}'s by,

$$\xi_{it}(\beta_k, \beta_m) = w_{it}(\beta_k, \beta_m) - \widehat{\Psi}(w_{it-1}(\beta_k, \beta_m)) \tag{4.25}$$

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

$$E[\xi_{it}(\beta_k, \beta_m)|k_{it}, m_{it}] = 0 \tag{4.26}$$

The difference between LP and OP is that LP uses intermediate input as a proxy of productivity and introduces an additional moment condition for intermediate input.

4.3.4.3 Wooldridge measurement

Wooldridge (2009) proves how to estimate both the first and second stages of the OP or LP procedure simultaneously. He shows that the moment conditions used by LP and 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 sets of instruments across the equation. Ackerberg et al. (2006) criticize the identification of the parameters in the OP and LP first-stage estimation. They hold that labour input is also a deterministic function of unobserved productivity w_{it} and state variables k_{it}, which makes the coefficient on the labour input 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 to contain identifying information for parameters on the variable inputs, like labour input. Another benefit of joint GMM estimation is that 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).

$$w_{it} = g(k_{it}, h_{it}) \tag{4.27}$$

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

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + g(k_{it}, h_{it}) + \epsilon_{it} \tag{4.28}$$

In equation 4.28, if labour inputs are 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) makes an additional assumption:

$$E(\epsilon_{it}|l_{it}, k_{it}, h_{it}, l_{i,t-1}, k_{i,t-1}, h_{i,t-1}, ..., l_1, k_1, h_1) = 0, t = 1, 2, ..., T. \tag{4.29}$$

As with the assumption in equations 4.3 and 4.4 productivity shock, w_{it}, evolves exogenously following a 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 4.28 and 4.29 is

$$E(w_{it}|k_{it}, l_{it-1}, k_{it-1}, h_{it-1}, ..., l_1, k_1, h_1) = E(w_{it}|w_{i,t-1}) = f[g(k_{i,t-1}, h_{i,t-1})]. \tag{4.30}$$

Plugging $w_{it} == f[g(k_{i,t-1}, h_{i,t-1})] + \xi_{it}$ into equation 4.2 gives,

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + f[g(k_{i,t-1}, h_{i,t-1})] + \xi_{it} + \epsilon_{it} \tag{4.31}$$

Now, economists can specify equations 4.28 and 4.31 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).

4.3.5 Summary statistics

Table 4.1: Summary Statistics for productivity chapter

	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

Note: The numbers denote mean value. Parentheses denote standard deviations.

Table 4.1 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 amount of SO2 discharged for samples in the control group (10.06) is higher than the mean in the treatment group (9.875). For samples in high SO2 emission industries and low SO2 emission industries, the mean amount of SO2 discharged in the control group is also higher than in the treatment group, while the mean amount of SO2 discharged for high SO2 emission industries (10.62) is higher than the mean for low SO2 emission industries (9.497). The mean amount of SO2 generated in control groups is higher than the mean in treatment groups whether in the full sample or sub-group samples. Meanwhile, the mean amount of SO2 generated 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 mean SO2 intensity.

For the full sample, the mean TFP of the treatment group (7.076) is higher than the control group (6.957). In high SO2 emission industries and low SO2 emission industries, two sub-groups, the mean TFP of the treatment group was also higher than in the control group. By industry, the mean TFP for samples in high SO2 emission industries (7.209) is higher than in low SO2 emission industries (6.924). For the full sample and the sub-sample of low-emission industries, the mean ROA for samples in the control group is higher than the mean of the treatment group. However, the samples in high-emission industries have the opposite characteristics. By industry, 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 means firms in the TCZ area use more end-of-pipe devices than firms outside it. The mean "*end of pipe*" amount for samples in high SO2 emission industries (0.113) is higher than for low emission industries (0.100). For the full sample, the mean "*change in process*" amount for samples in the treatment group is lower than for samples in the control group. The same patterns are shown in high and low SO2 emission industries.

Table 4.2 indicates that, over the years, the mean amount of SO2 discharged and, generated, and its intensity fluctuated. However, all three emission variables are lower in the treatment group than in the control group each year. Figure 4.1 and Figure 4.2 indicate the mean trend for the amount of SO2 discharged and its intensity respectively. This implies that whatever the amount of SO2 discharged and whatever its SO2 intensity, there is a parallel trend in emission variables between the treatment group and the control group before 2000.

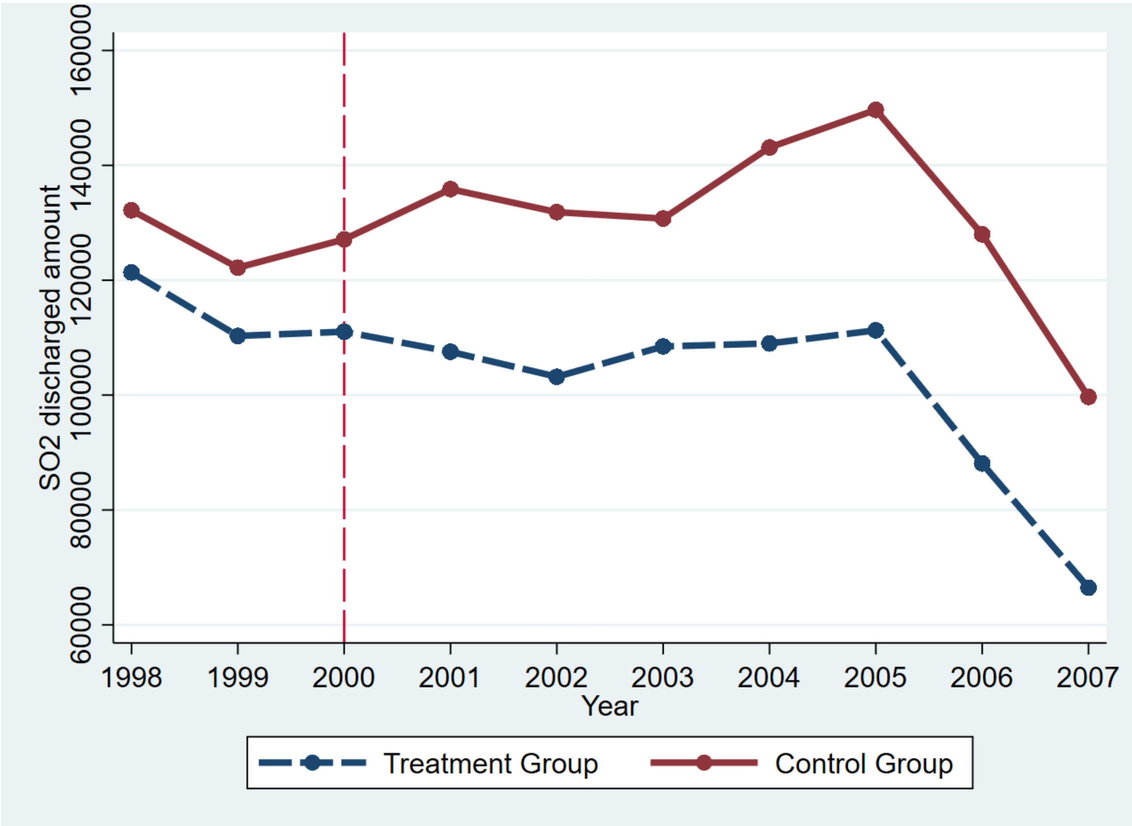


Figure 4.1: Mean trend for SO2 discharged amount

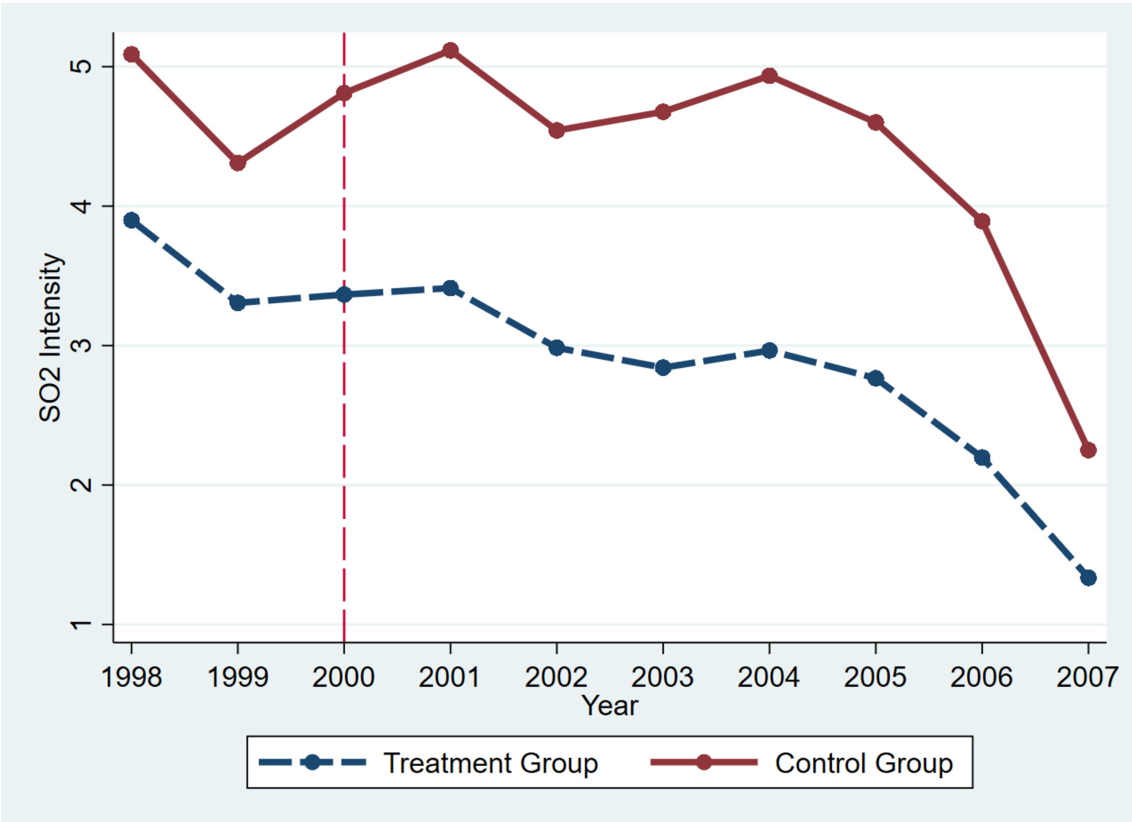


Figure 4.2: Mean trend for SO2 Intensity

Table 4.2: 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)

Note: The numbers denote mean value. Parentheses denote standard deviations.

4.4 Regression Result

I employ the difference-in-difference approach to estimate the effect of TCZ policy on firm emissions and firm performance.

The DD estimation equation is:

$$Y_{it} = \alpha_0 + \alpha_1 TCZ_i * \ Post_t + \boldsymbol{\beta X_{it}} + \gamma_{pt} + \mu_i + \sigma_t + \varepsilon_{it} \tag{4.32}$$

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 the 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 the 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 policy effect is identified by the coefficient of the interaction term, α_1. It displays the average treatment effect of the TCZ policy on firm emissions and performance. It is expected that the effect (estimated α_1) is negative, i.e., firms located in the TCZ area would experience a decline in emissions and productivity after 2000 when the policy was implemented.

4.4.1 Basic result

Table 4.3: 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. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

Table 4.3 reports the estimated effect of the TCZ policy on firm emissions. Using in turn the amount of SO2 discharged and, generated, and SO2 intensity as the proxy for firm emissions, the coefficients of $TCZ_i * Post_t$ in columns (1) to (3) are all significantly negative, consistent across all specifications. All three columns using equation 4.1 control for firm fixed effect, year fixed effect, and local economic shocks in accordance with Wang et al. (2018a). The results suggest a robust impact of the TCZ policy on firms inside the TCZ area compared to what would have happened there with no such intervention. Therefore, the TCZ policy has caused regulated firms to significantly reduce the discharge and generation of SO2 as well as the intensity of SO2 discharges. Regarding magnitudes, the result in column 1 implies that the TCZ policy has reduced firms' SO2 discharge levels by 28.9% ($e^{(-0.243)-1}$); column 2 shows that the TCZ policy decreased the amount of SO2 generated by regulated firms by 29.8% ($e^{(-0.212)-1}$); column 3 shows that regulated firms' SO2

Table 4.4: 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. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

intensity decreased by 0.767.

Most of the control variables are significantly correlated with firm emission indicators. Large firms have significantly higher amounts of SO2 discharged and generated which is in line with He et al. (2018), as bigger firms produce more than small firms. However, large firms have significantly lower SO2 intensity, consistent with the result reported by Wang et al. (2018a). Gas treatment ability is positively correlated with firm SO2 emissions. High-emission firms are always accompanied by high pollution abatement capacity (Liu et al., 2018; He and Zhang, 2018), because they need more abatement devices for pollution treatment.

Similar to the results in the existing literature, such as Greaney et al. (2017); Wang et al. (2018a); Liu et al. (2017); Sun et al. (2019b), in Table 4.3 firm age is found to be positively and significantly correlated with firm SO2 emissions. Older firms have better communication 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 (Sun et al., 2019b). This finding is consistent with the "grandfather" phenomenon, which holds that new environmental policies are often designed or implemented in such a way that older firms are exempted from tighter regulations. This phenomenon has occurred because the cost of building new sources with cleaner technology is lower than that of retrofitting existing facilities (Wang et al., 2018a). In column 3 of Table 4.3, 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 compared to the growth of emissions.

The coefficient of firms' export to sales ratio is significantly positive when using the amount of SO2 generated as dependent variables, but it is statistically insignificant when using SO2 generated or SO2 intensity as dependent variables. This result is in line with Wang et al. (2018a) which suggests a statistically insignificant effect of export ration on firm emission intensity. For the variable for controlling industry agglomeration, *agglo*, I do not find a significant correlation between industry agglomeration and the amount of SO2 discharged or generated by firms. But, similar to the result of Wang et al. (2018a), I find industry agglomeration negatively correlated with firm SO2 intensity at the 5% significance level. Firms in industries with higher agglomeration discharge produce less pollution 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 Wang et al. (2018a).

Table 4.4 reports the effect of the TCZ policy on firm performance denoted by productivity and profitability. Using equation 4.1, all three columns control for firm fixed effect, year fixed effect, and local economic shocks. In column (1) to column (3), this research uses TFP as the proxy for firm productivity and uses return on assets and return on sales as the proxy for firm profitability. 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 the TCZ area compared to what would have happened there with no such intervention. This result is in line with Neo-classical theory and existing literature such as Barbera and McConnell (1990), Greenstone et al. (2012), and 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) show the impact of the TCZ policy on firm profitability is statistically insignificant at conventional levels. Although it is statistically insignificant, I see a tendency for firms outside the TCZ area to make more profit despite not producing more.

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 large Chinese firms whose increasing productivity is always higher than the average rate. Similar to the results of existing literature, such as Ding et al. (2016) and Ding et al. (2019b), I find that older firms have higher productivity, the positive coefficient of *firm age*. This is explained as the learning-by-doing phenomenon, in which firms can improve their productivity through a long-time learning process. The ratio of export value over sales is also found to be significantly positively correlated with firm TFP, which is consistent with Brandt et al. (2012) and Syverson (2011). Syverson (2011) suggests that export is often accompanied by large R&D investments, which raise exporters' productivity levels. The positive coefficient of agglomeration is in line with Syverson (2011) who attributes 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 (2002a) as there are few observations with multi-plants in this study.

In column (2) and column (3) of Table 4.4, 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 returns on assets. While in column (3), I find that new firms have higher returns on sales than old firms. However, this paper does not find evidence suggesting a significant effect for export ratio, firm agglomeration, or gas treatment ability on firm profitability. This is inconsistent the with existing literature, where export and agglomeration have been found to be beneficial for firm productivity (Russo and Fouts, 1997).

4.4.2 Economic channels and mechanisms

How do firms respond to TCZ regulation? I examine the channels through which the TCZ policy affects firms' behaviour. In Table 4.5, I estimate the impacts of TCZ policy on several key variables, end of pipe, change in process, and SO2 treatment ability. Using the "end-of-pipe" variable and the "change-in-progress" variable, I estimate two different pollution abatement activities under environmental regulation, taking abatement devices for removing pollutants after production and improving production technologies to reduce generated pollutants during production, the same approach used by Liu et al. (2018), He and Zhang (2018), Sun et al. (2019b). Berman and Bui (2001) suggest that firms regulated by environmental policies would choose to invest in taking "changes in process" activities, "end-of-pipe" measurements, or do both.

In column (1) of Table 4.5, I focused on the "end of pipe", calculated by the

Table 4.5: Economic Channels

Dep. Var	(1) end of pipe	(2) change in process	(3) SO2 Treatment Ability (ln)
$TCZ_{it} * Post_{it}$	0.017***	-0.672***	0.133***
	(4.89)	(-2.83)	(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. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

ratio of the amount of SO2 removed to the amount of SO2 generated. 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 to increase for firms inside the TCZ area compared to what would have happened there with no such intervention. This finding implies that regulated firms adopt more "end of pipe" activities for pollutant abatement after production, which is in line with He and Zhang (2018) and Sun et al. (2019b). They removed more SO2 pollutants from the generated amount compared to the counterfactual conditions after the production process. But "end-of-pipe" activities also bring an additional cost for firms, which is harmful to firm productivity and profitability. Thus, the estimated increase of "end-of-pipe" activities for regulated firms supports the neoclassical theory of environmental economics.

In column (2) of Table 4.5, I focused on "change in process", calculated by the ratio of the amount of SO2 generated to 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 an increase in "change in process" activities for regulated firms compared to what would have happened there with no such intervention. The result suggests that regulated firms also adopt more "change in process" activities for reducing SO2 pollutants generated during production. As "change in process" activities are always accompanied by improved technologies or improved production processes, having more "change in process" activities can promote firm productivity, which confirms the Porter Hypothesis.

In column (3) of Table 4.5, I focused on firm SO2 treatment ability (Kg/h) which is directly linked 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 to increase for firms inside the TCZ area compared to what would have happened there with no such intervention. This is more evidence that the TCZ policy has forced regulated firms to invest more in devices for SO2 abatement. The TCZ policy has induced firms to take more pollutant abatement activities and also brought more additional costs.

4.4.3 Heterogeneous Analysis

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

4.4.3.1 High and low SO2 emission industries

Table 4.6: 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, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

Firms in a merged dataset are divided 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, and the Ministry of Agriculture, six industries together account for 88.5% of SO2 emissions from industrial sources, and these are defined as high-polluting industries. These six

Table 4.7: 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. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

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 4.6, I estimate the DD by firm emission type and find that high-polluting firms and low-polluting firms adopt different abatement strategies when subject to the TCZ policy, although the policy effectively reduces firm emissions for both high-polluting and low-polluting firms. In Panel A are samples from high-polluting industries, and in Panel B firms in low-polluting industries. Column (1) of Table 4.6, shows that the TCZ policy has reduced the amount of SO2 discharged by high-polluting firms by 28.4% ($e^{(-0.258)-1}$) and has reduced the amount of SO2 discharged by low-polluting firms by 29.4% ($e^{(-0.225)-1}$). The empirical p-value in column (1), used to provide evidence regarding whether the coefficient of the variable investigated in two groups has a significant difference when both are separately statistically significant, indicates that the coefficient difference of $TCZ_i * Post_t$ in two emission type groups is significant at the 10% significance level. Environmental regulation is more efficient in reducing the amount of pollutants discharged by low-polluting firms. In column (2), I find the policy significantly reduced the amount of SO2 generated by firms in both groups, but the difference in 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 the low-polluting group.

The results of column (4) and column (5) in Table 4.6 show the abatement strategy adopted by the two groups. It implies that high-polluting firms adopt both "end of pipe" activities and "change in process" activities for pollution abatement, while low-polluting firms merely adopt "end of pipe" activities. Their strategies of abatement can influence whether the TCZ policy significantly influences firm productivity and profitability. As shown in Panel A of Table 4.7, the TCZ policy does not have a significant effect on high-polluting firms' productivity and profitability, because they adopt two abatement measures, one which is harmful for firm performance and the other which is beneficial for it. Panel B of Table 4.7 shows the significant negative impact of TCZ policy on firm TFP and ROA as low-polluting firms only adopt "end of pipe" activities which increase firm production cost.

The result in Table 4.6 shows that high-polluting firms and low-polluting firms take various measures for emission reduction. One explanation is that, for high-polluting enterprises, only adopting the "end of pipe" method is not enough to effectively reduce emissions, even if "end of pipe" is the first option of firms when it comes to emission reduction. Another explanation is the "learning-by-doing" phenomenon. High-polluting firms have more opportunities and incentives to be exposed to abatement-related technologies, thus "change in process" activities are more likely to occur in high-polluting firms. Considering the result in Table 4.6 and Table 4.7 jointly, I find evidence supporting both the neo-classical theory and the Porter Hypothesis. For low-polluting firms, the TCZ policy has a negative impact on firm productivity and profitability, as they only take "end of pipe" measures that increase production cost, which supports neo-classical theories. High-polluting firms adopting "change in process" activities promotes firm productivity, supporting the Porter Hypothesis, which compensates for the productivity loss brought bout by "end of pipe" activities.

4.4.3.2 Ownership

In Table 4.8 and Table 4.9, I 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 4.8, the results in columns (1), (2), and (3) of Panel A indicate the TCZ policy has significantly reduced the amount of SO2 discharged, and generated, and its intensity by SOEs. The amount of SO2 discharged by regulated SOEs has reduced by 28.1% ($e^{(-0.271)-1}$) and the amount generated has reduced by 29% ($e^{(-0.237)-1}$). The result in columns (4) and (5) of Panel A implies that SOEs only take "end of pipe" activities to reduce their emissions rather than improving production technologies

Table 4.8: 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. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

Table 4.9: 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. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

to limit pollutants generated during production.

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

The result in Table 4.9 indicates that the TCZ policy has reduced SOEs' TFP by 34.9% ($e^{(-0.053)-1}$) and also has a deleterious impact on SOEs' return on assets, because they only take "end of pipe" measures. However, it has had an insignificant impact on private firms' productivity or profitability, which is due to private firms taking both abatement measures. On the one hand, private firms have less bargaining power than SOEs concerning the enforcement of environmental regulations such as pollution charges and fines (Wang et al., 2018a; Wang and Wheeler, 2003). To comply with environmental regulation, they would take all measures to reduce emissions. Technologies that promote "change in process" would benefit firms in the long run. On the other hand, SOEs have an 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 in China have social and political objectives other than profit maximization, which forces 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 emissions in the short run.

4.4.3.3 Large and small firms

Table 4.10: 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. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

In Table 4.10 and Table 4.11, I 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. I consider a firm which has more than 100 labourers to be a large firm, and otherwise

Table 4.11: 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. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

they are classed as small firms. As shown in Table 4.10, the results in columns (1), (2), and (3) of Panel A indicate the TCZ policy has significantly reduced the amount of SO2 discharged and generated by large firms and SO2 intensity. Regulated large firms' SO2 discharge has reduced by 28.7% ($e^{(-0.249)-1}$) and SO2 generated has reduced by 29.5% ($e^{(-0.220)-1}$). The result in columns (4) and (5) of Panel A implies that large firms only take "end of pipe" measures to reduce their emissions.

In Panel B of Table 4.10, columns (1) and (2) show that the TCZ policy did not significantly reduce large firms' emissions. However, column (3) indicates that regulated small firms have lower SO2 intensity. In columns (4) and (5), both the "end of pipe" measure and the "change in process" measure are adopted by small firms for emission abatement.

The result in Table 4.11 indicates that the TCZ policy has reduced large firms' TFP by 35.3% ($e^{(-0.041)-1}$) as they only take "end of pipe" measures. The TCZ policy has had an insignificant impact on small firms' productivity or profitability. The result of the heterogeneity analysis by firm size can be explained by 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 widely taken in policy implementation

(Hsieh and Song, 2015; He et al., 2018). (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). My heterogeneity test proved that this strategy has also been applied to the context of the TCZ policy. The policy has effectively reduced large firms' emissions and had deleterious effects on their TFP, but it has had no impact on small firms' emissions and performance.

4.4.3.4 Upstream and downstream firms

Table 4.12: 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

I 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 every two or three years, and a more detailed I-O Table (5-digit) is provided 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 corresponds to one or more 3-digit Chinese Industry Classification (CIC) sectors (see, in Table 4.12, 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) is calculated on the basis of the

Table 4.13: The impact of TCZ on firm emissions across upstream and downstream firms

Dep. Var	(1) SO2 discharged	(2) SO2 generated	(3) SO2 intensity	(4) end of pipe	(5) 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. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

Table 4.14: 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. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

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 4.12 exhibits the twenty least and most upstreams of China manufacturing industries, where a higher value of upstreams means a more upstream position. Industries with the least value of upstreamness, like food manufacturing, have output which goes directly to the end-user or consumers; while, industries with the highest value of upstreamness, like basic chemicals and chemical fibres, are producers of raw materials.

The full sample is sub-grouped according to the medium value of upstreamness. In Table 4.13 and Table 4.14, I do the estimation 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 4.13, the results in columns (1) and (2) of Panel A indicate the TCZ policy has significantly reduced the amount of SO2 discharged and generated by upstream firms by 29.3% and 30% respectively. However, the TCZ policy has had an insignificant effect on firm SO2 intensity. The result in columns (4) and (5) of Panel A implies that upstream firms only use "end of pipe" activities to reduce their emissions.

In Panel B, the results from columns (1) to (3) indicate that the TCZ policy also effectively reduced downstream firms' emissions and their intensity as SO2 discharge was reduced by 29.1% and SO2 generated was reduced by 30.3%. As shown in columns (4) and (5), both the "end of pipe" measure and the "change in process" measure are adopted by downstream firms for emission abatement. The result in Table 4.14 indicates that the TCZ policy has reduced upstream firms' TFP by 35.4% ($e^{(-0.039)-1}$) as they only implement "end of pipe" activities. In contrast, TCZ policy has had an insignificant impact on downstream firms' productivity or profitability since both "change in process" and "end of pipe" are adopted by downstream firms.

The estimation results are in line with implications from existing literature. As documented in Bas and Causa (2013), upstream industries typically have lower levels of competition because of higher monopoly power, whereas downstream industries are more competitive. There is also consensus that higher competition is associated with lower profitability or markup (e.g., Naughton (1992); Liu et al. (2019)). With higher levels of monopoly power and profitability, upstream firms tend to implement the "end of pipe" activities by increasing the production cost, rather than improving the technology, resulting in a reduction in productivity. Even though, it doesn't impose a significantly negative impact on their profitability, which may be explained by their high levels of monopoly power. In contrast, downstream firms face higher levels of competition and lower levels of profitability. Facing the compulsory environmental regulation, they may have to engage in “change in process” activities besides the “end of pipe” activities to keep themselves competitive. Adopting both activities therefore results in an insignificant effect on both productivity and profitability, since these two activities have opposing effects on productivity and profitability.

4.4.4 Economic cost caused by the TCZ policy

The baseline model estimates that the TCZ policy has caused an average reduction in SO2 discharge of 0.243 logarithmic units (as shown in column (1) of Table 4.3), equivalent to a 28.9% drop. In addition, the TCZ policy has also caused an average loss in TFP of 0.03 logarithmic units (as shown in column (1) of Table 4.4), equivalent to a 35.7% drop. To calculate the economic cost brought about by the TCZ policy, an informative counterfactual would be to determine the TFP loss connected with a given amount of emission abatement. I can directly link TFP estimates with SO2 estimates using equation 4.33 (with the same methodology as He et al. (2020)). The economic costs of SO2 abatement is calculated by equation 4.33, which displays the ratio of the policy's average treatment effect on productivity over its average treatment effect (ATE) on emissions. It displays the trade-off between the average treatment effect on TFP and the average treatment effect on emissions. It helps to translate this TFP loss into monetary value, i.e. what would happen if all of China enforced regulatory standards as stringent as those treated firms. Thus, a 10% change in SO2 discharged causes a 1.2% (0.03/0.243 ∗ 10%) change in TFP levels.

$$\frac{TFP_{ATE}}{Emission_{ATE}} \tag{4.33}$$

$$TFP_{it} = \alpha_1 Emission_{it} + \beta X_{it} + \gamma_{pt} + \mu_i + \sigma_t + \varepsilon_{it} \tag{4.34}$$

$$Labour_{it} = \alpha_1 Emission_{it} + \beta X_{it} + \gamma_{pt} + \mu_i + \sigma_t + \varepsilon_{it} \tag{4.35}$$

Another way of calculating the trade-off between emissions and TFP is estimating the TFP on emissions subject to the TCZ regulation. I keep observations in the treatment group and observations whose observable year is after 2000. Equation 4.34 is used to calculate the trade-off between emissions and firm productivity, and equation 4.35 is used to calculate the trade-off between emissions and labour loss.

Table 4.15: 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. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

Table 4.15 reports the economic cost of the TCZ policy. Column 1 shows that a 10% reduction in SO2 discharged will lead to a 0.42% reduction in firms' TFP. Column 2 shows a 10% reduction in SO2 generated brings an average 0.45% TFP loss for firms. Column 3 and 4 indicate that a 10% reduction in firms' discharge and generated values brings a decrease of 0.34% and 0.36% respectively in firms' employment.

The third way I calculate the trade-off between emissions and TFP is following the methodology of Faber (2014), which is the estimation result of equation 4.36. The advantage of this method is that it can remove fixed effects from regression. The result indicates that a 10% change in SO2 discharged will lead to a 0.55% change in firms' TFP.

$$\begin{aligned} TFP_{i,2007} - TFP_{i,1998} = \alpha(&SO2\ Discharged_{i,2007} - SO2\ Discharged_{i,1998}) \\ &+ \beta(X_{i,2007} - X_{i,1998}) \end{aligned} \tag{4.36}$$

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

4.5 Robustness test

4.5.1 Calculating TFP using the LP method

Table 4.16: 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

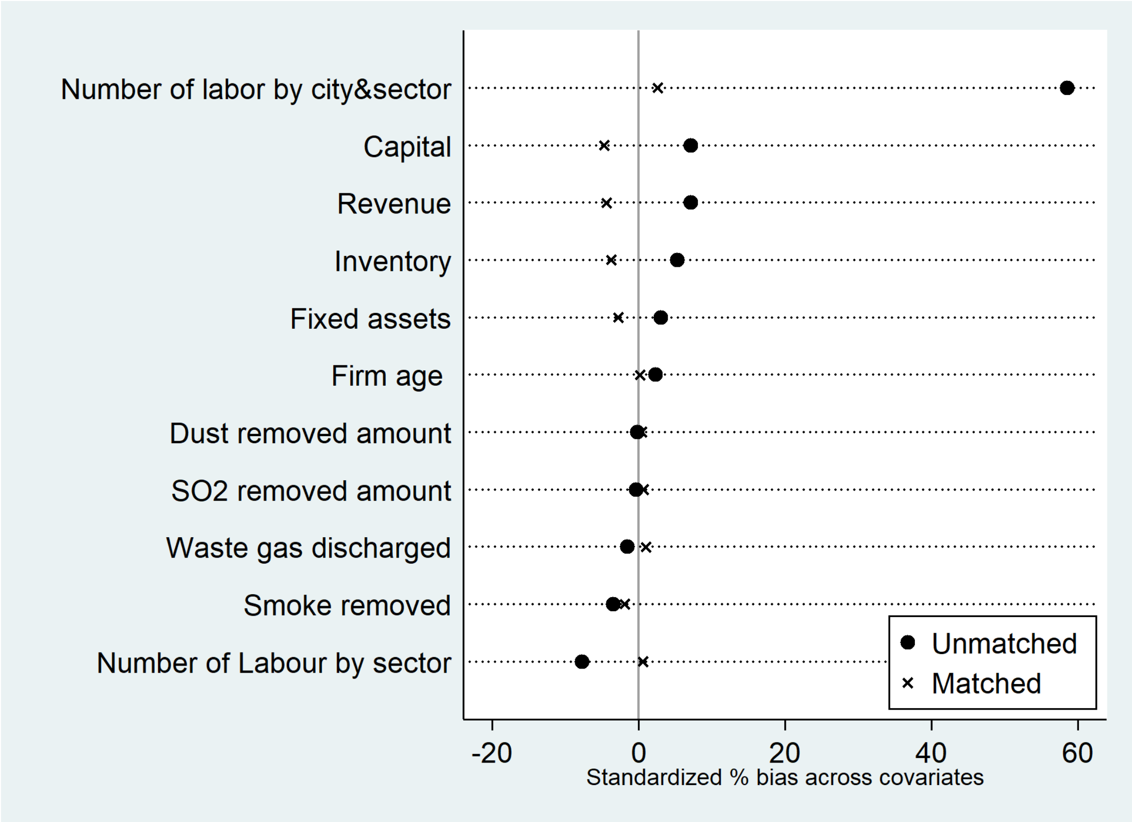
Note: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

To test the robustness of the estimation, I calculate the firm TFP using the LP method. Then, I run the basic regression and heterogeneity analysis again using this new TFP value. Table 4.16 shows the regression result using the new TFP value, which is in line with my result for basic regression and heterogeneity analysis.

4.5.2 Parallel test and robustness test using PSM approach

I conduct propensity score matching based on a set of covariates that are suggested by the basic estimation model through which policy may affect firm emissions and performance. These covariates are exactly the same as those that appear in the vast theoretical and empirical literature on productivity and emissions. Matching has gained popularity as a widely utilized method in labour, health, and development economics, and its application has extended to various other domains within the field (Levchenko et al., 2009; Wu, 2018). The basic idea in the specification involves estimating the absent counterfactual emissions for treated firms by identifying untreated firms in the data with similar covariates. In other words, the untreated firms are the 'matches' for the treated firms, exhibiting comparable covariates.

Specifically, I use kernal as the matching algorithm to match the untreated firms to treated firms using the estimated propensity scores and impose the common support restriction. Figure 4.3 shows the covariates for matching, including the number of labour of a city a sector, capital, revenue, inventory, fixed assets, amount of dust removed, amount of SO2 removed, amount of waste gas discharged, amount of smoke removed, and the number of labour of a sector. The matching also constraints to the same province, sector, and year. The result of Figure 4.3 shows the matching has built a good control group. According to the test statistics of the biases, its absolute value for all covariates is reduced after matching.



[a]

Figure 4.3: The test for variables in the Propensity score matching

[a]Note: The dotes denote the distribution before PSM. The Xs denote the distribution after PSM. After PSM, the standardized bias has been shrunk for all covariates.

The parallel test is an important test for DD regression. It examines the samples' characteristics in the treatment group and ensure that group and the control group have similar trends before policy implementation. Figure 4.4 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 significant in 1999 at 10% conventional levels. As I only have two observed years before the policy implementation, the result may not be strong enough to show that the two groups are parallel before treatment.

For further robustness tests, I use the Propensity Score Matching method (PSM) to match firms in two groups, drop observations that are not matched, and do the DD regression for samples remaining. Variables for matching include all control variables in basic regression and firms' financial information variables in the ASIF dataset. Figure 4.5 shows the coefficient of the interactions after PSM, which

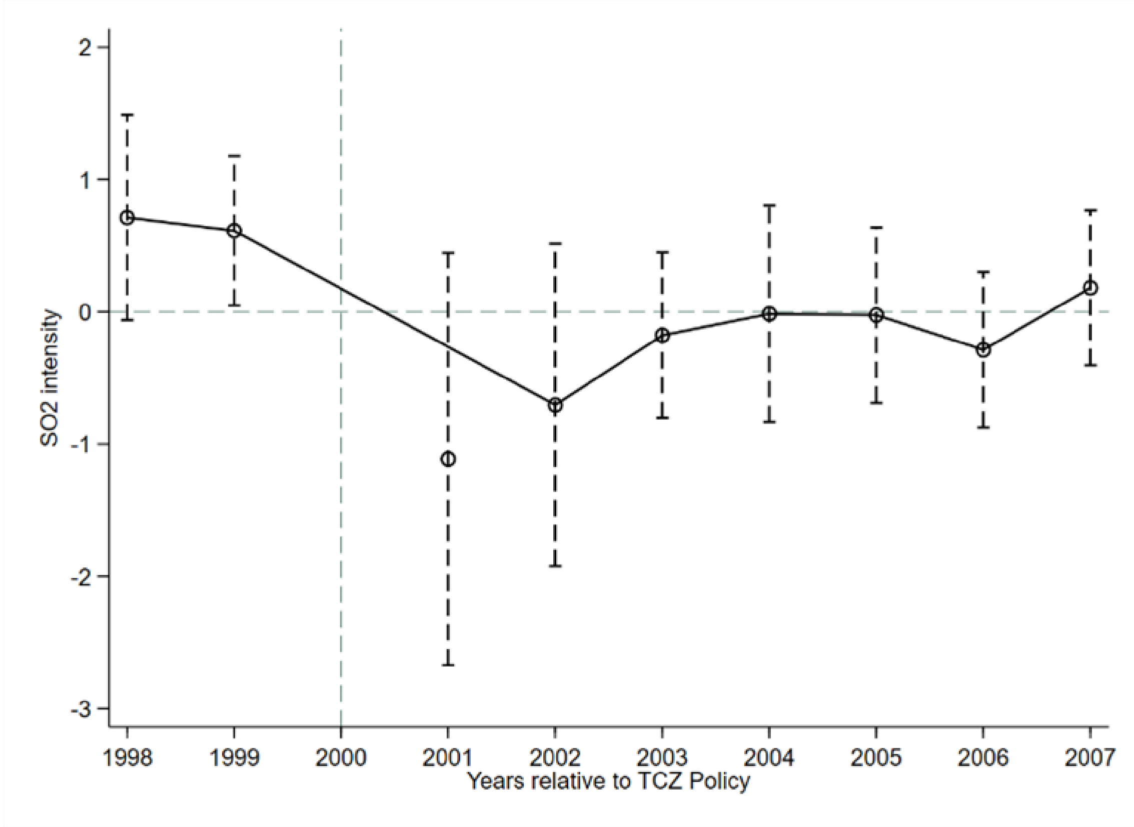


Figure 4.4: Parallel test before PSM

The dependent variable is SO2 intensity. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

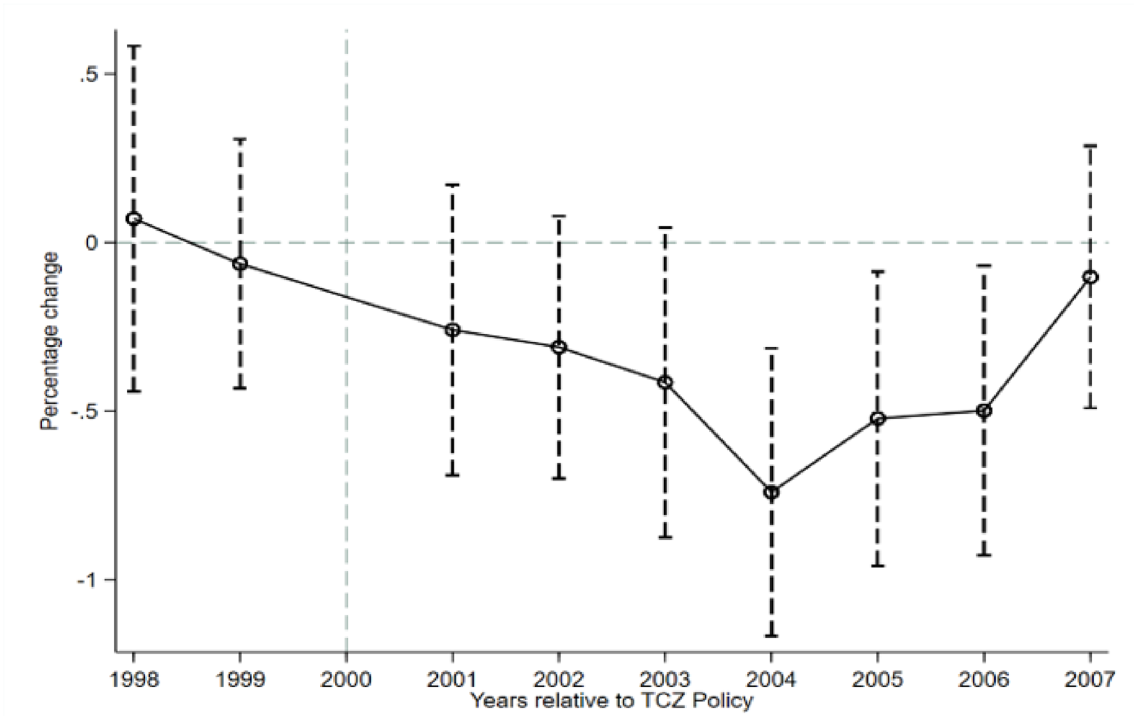


Figure 4.5: Parallel test after PSM

The dependent variable is SO2 intensity. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

implies that the two groups had parallel characteristics before 2000.

Meanwhile, Figure 4.5 displays the dynamic of policy effects. TCZ policy did not significantly reduce firm emissions in the first three years (2001, 2002, and 2003). Then regulated firms experienced a significant reduction in emissions in the following three years (2004, 2005, 2006). But the policy impact became insignificant again in the year 2007. One reason is the lagged effect of the policy implementation. The lagged effect of environmental policy on firm performance is commonly investigated in empirical analysis Huang and Liu (2019). Pu et al. (2000) shows the national initiatives of the TCZ policy, comprised of systematically planned steps. The second reason is the implementation of the 11th Five-Year Plan. It started from 2006 and included more strict environmental regulations nationally. The regulation on firm emissions extends throughout the entire country, which Reduces the disparity between treated and untreated. Thus, the policy effect in 2007 becomes insignificant as shown in Figure 4.4 and 4.5.

Then, I run the basic regression using the samples after PSM. Table 4.17 shows the result of this regression. The results in Table 4.17 are consistent with basic regressions. My findings are robust after PSM controlling most firm characteristics.

Table 4.17: DD result after PSM

Dep. Var	(1) SO2 discharged	(2) SO2 generated	(3) SO2 intensity	(4) end of pipe	(5) change in process	(6) TFP
$TCZ_{it} * Post_{it}$	-0.244*** (-10.53)	-0.209*** (-9.30)	-0.919*** (-3.88)	0.019*** (4.98)	-0.803*** (-3.06)	-0.032** (-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. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

4.5.3 Regression except observations in municipalities

As municipalities have better economic conditions, they are always chosen as the pilot cities for policies. China's four municipalities, Beijing, Shanghai, Tianjin, and Chongqing, implemented the TCZ policy in 1998 as pilot cities. I dropped the observations in these four municipalities to do a robust test for basic regression.

Table 4.18: Regression result dropping municipalities

Dep. Var	(1) SO2 discharged	(2) SO2 generated	(3) SO2 intensity	(4) end of pipe	(5) change in process	(6) 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. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

Table 4.18 indicates the regression result dropping municipalities, which is consistent with the basic result.

4.5.4 Robust test for endogeneity of self-selection

Table 4.19: Robust test for endogeneity of self-selection

Dep. Var	(1) SO2 discharged	(2) SO2 generated	(3) SO2 intensity	(4) end of pipe	(5) change in process	(6) TFP
$TCZ_{it} * Post_{it}$	-0.233***	-0.201***	-0.774***	0.018***	-0.693***	-0.026**
	(-10.63)	(-9.43)	(-3.55)	(5.03)	(-2.83)	(-2.00)
Observations	169,117	169,117	169,117	169,117	169,117	164,237
R-squared	0.043	0.040	0.011	0.051	0.009	0.168
Number of firms	49,977	49,977	49,977	49,977	49,977	49,234
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. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

Firm entry, relocation, and exit might be endogenous to policy implementation, which brings bias to the basic result. To examine the TCZ policy-induced firm productivity reduction, the unbalanced panel dataset is used for regression. Firms with higher productivity and output are accompanied by higher emissions (as shown in Table 4.4 and Table 4.16). So, new firms with high productivity might prefer to locate their plant outside the TCZ area to avoid supervision, i.e., high-productivity firms would enter non-TCZ areas. Firm relocation is another scenario endogenous to policy implementation. If firms with low productivity cannot bear the productivity loss induced by emission reduction, relocating to regions outside the TCZ area could be the choice. Meanwhile, if low-productivity firms cannot relocate to a new region, they might exit from the market.

In this part, I test the robustness of the result by dropping firms that started after 1999 and firms that changed their location during this period. Table 4.19 shows the robust result is consistent with the basic regression. The phenomenon of firm exit could make us underestimate the real effect of the TCZ policy on firm effectiveness but cannot change the negative effect of the policy.

4.6 Conclusion

With the increase in Chinese people's income levels, China is facing a dilemma that is 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 important. This is the first study to credibly estimate the impacts on Chinese firms of the TCZ policy, a national air pollutant control policy, and provide an assessment of its economic cost. Using a firm-level panel dataset for Chinese firms in the period 1998-2007, I exploit a difference-in-difference design based on the criteria of the TCZ area and find that the TCZ policy led to significant emission reduction and TFP loss for firms in the TCZ area, but had an insignificant effect on regulated firms' profitability.

I find that the TCZ policy has reduced SO2 discharge by 28.9% and TFP levels by 35.7 % for 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 that only adopt "end of pipe" measures face TFP loss as a result of the increase in production cost. The adoption of "change in process" measures can offset TFP loss brought about by "end of pipe" measures because the TCZ policy has had an insignificant effect on TFP for firms taking both two measures for abatement. The deleterious effect of the "end of pipe" is in line with Neo-classical theory on environmental economics, while the influence of "change in process" also supports the Porter Hypothesis, the opposite side of the Neo-classical theory. Thus, this research finds evidence that supports both the Neo-classical theory of environmental economics and the Porter Hypothesis. The final effect of the TCZ policy on firm performance depends on the abatement measure it adopts.

Overall, My findings highlight the negative impacts of the TCZ policy on productivity and emissions. Combining the estimates of TCZ policy on emissions and productivity, I calculate the economic cost of this air pollution control policy. I estimate that a 10% abatement in SO2 emissions can lead to a 0.42%-1.2% drop in the 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. High environmental quality improvement is thus accompanied by high economic cost, which is particularly salient for fast-growing economies such as China.

This research contributes to the literature in estimating the effect of environmental regulation on firm behaviour. My finding is consistent with the literature, such as Greenstone et al. (2012), Walker (2011), Berman and Bui (2001), and He et al. (2018), which shows 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 He et al. (2018), and is consistent with Wang et al. (2018a) who found an insignificant effect.

The identification of a trade-off between firm emissions and firm performance under environmental policy in this study holds significant policy implications. As environmental regulations become more prevalent and stringent, policymakers must carefully consider the potential impact on the economic performance of regulated firms. While reducing emissions is crucial for sustainable development and mitigating environmental degradation, the study suggests that an overly stringent regulatory approach may adversely affect the economic viability of firms. Striking the right balance between environmental conservation and economic growth is imperative. Policymakers should explore mechanisms that incentivize firms to adopt environmentally friendly practices without unduly burdening their financial performance.

In addition to revealing the trade-off between firm emissions and performance under environmental policy, the study offers insights into the effectiveness of different environmental management strategies. Firms that only adopt the "end of pipe" approach will experience the trade-off, emphasizing the limitations of such reactive strategies. On the contrary, firms that take both "end of pipe" and "change in process" approaches will seem to avoid the trade-off. This implies that environmental policies should not only encourage emission reduction but also incentivize a holistic transformation in production processes. Policymakers are urged to support and promote eco-friendly technologies and sustainable practices that go beyond mere compliance.

Chapter 5

The Effect of Environmental Regulation on Environmental Misallocation

5.1 Introduction

Rapid degradation of environmental quality and depletion of natural resources in China are creating great concern and leading to stricter and more inclusive environmental management. The Chinese national government and regional authorities have made pollution reduction a priority in the last 20 years. China's central government have introduced strong environmental regulation policies to improve the quality of air and water (Vennemo et al., 2009; Jin et al., 2016; Zheng and Kahn, 2017), such as the aggregate pollution controlling policy in the 10th Five-YearPlan, the air and water pollution reduction plan in the 11th Five-Year Plan, and further reductions in targeted pollution levels in the 12th Five-Year Plan.

This chapter examines the impact of environmental regulation policy on firms' environmental efficiency and environmental misallocation, which are indicated by marginal emissions of energy (MEPE) and their dispersion across firms in the sector respectively. Variation in marginal emissions of energy across firms within industries is evidence of frictions that prevent the optimal allocation of production in the economy, which can minimize aggregate emissions. It is imperative to understand the factors that drive environmental misallocation so that we can reallocate production to more environmentally efficient uses and reduce aggregate air pollutant emissions within industries and provinces, and over time.

The idea of environmental misallocation was first proposed by Correa et al. (2021a). Aggregate pollution is not only determined by the emissions levels of individual firms but also by how production is distributed among them (Correa et al., 2021a). Concretely, two countries with the same production technology and aggregate production could exhibit different aggregate levels of pollution when one country's firms with high environmental efficiency could be able to take more production share, whereas most of the other country's output is produced by low environmentally efficiency firms. In other words, by reallocating the production from "dirtier" firms (higher MEPE) to "cleaner" firms (low MEPE) subject to constant aggregate production, I can reduce the aggregate emission of an economy. From the perspective of minimizing aggregate emissions, the optimal allocation of production (counterfactual conditions) is equivalent to MEPE across firms in the same sector.

In this research, the marginal emission of energy (MEPE) is defined as an additional emission produced from consuming one more unit of energy. My measure of environmental efficiency relies on the assumption that firms have a production function with energy input that induces emission by-product and an emission function of which there is a fixed ratio between emission and production (Copeland and

Taylor, 2004; Wang et al., 2018a; Gowrisankaran et al., 2020). Inspired by Hsieh and Klenow (2009) and Asker et al. (2019)'s measurement of resource misallocation and Asker et al. (2014b)and Ding et al. (2019a)'s measure of marginal revenue product of capital, I develop a novel approach to measure the marginal emission of energy, the proxy for firms' environmental efficiency. MEPE dispersion denotes the environmental misallocation, which implies that the fixed aggregate output is not produced in the cleanest possible way. In an economy without green technical barriers, firm profit maximization and aggregate emission minimization imply that MEPE should be equal across firms.

Reducing environmental misallocation is important for emission reduction. It provides a possible approach to realise the environmental decoupling. In 2002, the OECD defined the term 'environmental decoupling' refers to breaking the link between "environmental bad" (like emissions) and "economic goods" (like productivity). It means the rates of increasing wealth would be greater than the rates of increasing impact. My paper proposed reducing the dispersion of environmental efficiency to realise the environmental decoupling and to realise the net zero target for carbon dioxide emissions. From macro-level data, the link between GDP growth and environmental performance is investigated through Kuznets curves (Beckerman, 1992; Holtz-Eakin and Selden, 1995; Schmalensee et al., 1998; Churchill et al., 2018) or calculate countries' decoupling elasticity (Wang and Su, 2020; Hubacek et al., 2021). But limited studies examine the environmental decoupling from micro-level data. I contribute to research on environmental decoupling from a micro-level perspective. When formulating policies, governments can decrease macro-level emissions by concentrating on narrowing the technology gap between firms.

For the link between emission and production, limited studies consider energy as a factor and by-product of production. Literature relating to resource misallocation starts from the fact that an economy's aggregate productivity and aggregate output depend not only on each firm's productivity but also on how aggregate quantities of inputs, like capital and labour, are allocated across firms (Hsieh and Klenow, 2009). Chu et al. (2019); Choi (2020); Han et al. (2020); He and Qi (2021) considers energy consumption as an input for production. The best allocation (marginal product is equalized across firms) could maximize an economy's welfare and output. Other allocations lead to lower aggregate output and therefore show a lower level of aggregate total factor productivity (TFP). However, My computation of the marginal emission of energy displays the link between production and pollution. I apply a production function with energy consumption input and firm emission as the by-product. The impact of policy distortion can be investigated through my new metric for environmental efficiency and environmental misallocation.

How environmental regulation can improve environmental efficiency is discussed in the existing literature. Firms can enhance their environmental efficiency by investing in and adopting environmentally friendly technologies(Porter, 1990; Porter and Linde, 1995). This might include the use of renewable energy sources, energy-efficient machinery, and sustainable production processes. Meanwhile, the local environmental regulatory system would improve the entry barrier for firms and eliminate technologically backward firms. Additional costs, like emission fees, brought by environmental regulation can crowd out firms with low productivity. How does environmental policy misallocate resources and production? Firm heterogeneity is an important factor in evaluating environmental policy distortion(Tombe and Winter, 2015). Firm heterogeneity under environmental policy would increase the dispersion of firm environmental efficiency, which is shown as the increased misallocation in my research. Other factors,like financial frictions (Midrigan and Xu, 2014; Grieco et al., 2022; Wu, 2018), policy distortions(Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Da Rocha and Pujolas, 2011), trade barriers (Loecker, 2011; Lileeva and Trefler, 2010), and business regulations (Leal Ordóñez, 2014) could prevent an economy from reaching the best allocation for resources.

For this study, China provides an excellent context. First, as the world's most populous country, China is a major source of pollution from manufacturing. Fewer than 1% of China's 500 cities meet the World Health Organization's air quality standards, while seven of China's cities rank among the top ten most polluted in the world (Zhang and Crooks, 2012). In the 21st century, China's air pollution problems have intensified as coal consumption has soared. Chinese coal consumption increased from less than 700 million tons in 1980 to almost 4 billion tons in 2012, illustrating the link between economic growth and air pollution (Zheng and Kahn, 2017). Resource-intensive manufacturing firms' long-term reliance on coal-burning energy has led to serious air pollution and acid rain, which caused a loss of 2% of GDP in 1995. However, the existing research on China's air quality policies focuses mainly on its impact on productivity (Huang and Liu, 2019) or FDI (Cai et al., 2016b). I thus fill the gap in the literature by exploring the role of environmental regulation on environmental misallocation in China.

Second, The Environmental Survey and Reporting Database (ESR) is the most comprehensive environmental dataset in China, which is collected and maintained by the Ministry of Environmental Protection. It is the specific data source of the Chinese Yearbook of Environmental Statistics published over the years. The sampling criteria in the ESR database is the cumulative distribution of firm emissions in each county. Polluting sources that contribute to the top 85% of total emissions in a county are monitored by the ESR database. I am therefore using a reliable dataset that has information on the most polluting companies in China.

Third, resource misallocation is widely acknowledged to be prevalent in China, generating a significant reduction in welfare (Hsieh and Klenow, 2009). Some literature concludes that the sources of resource misallocation in China are found in ownership and financial frictions (Brandt et al., 2013; Wu, 2018). The new concept of environmental misallocation is also influenced by these two factors. This study not only proposes a measurement of environmental misallocation but also examines the drivers of the observed dispersion of marginal emissions of energy.

The existing literature mainly focuses on the cost of pollution mitigation, in terms of the decrease of productivity and income (Greenstone, 2002b; Greenstone et al., 2012), labour reallocation (Walker, 2011), and FDI reduction (Cai et al., 2016b). However, little is known about the environmental efficiency effect of alleviating pollution and the link between production reallocation across firms and aggregate pollution reduction. My research on China (the world's largest emitter and producer) fills this important gap in knowledge because a unique empirical context is generated by the central government's employment of powerful political incentives to enforce environmental control in China.

Using data from 2001 to 2007, the empirical analysis finds that the environmental regulation policy has a significant impact on the marginal emission of energy and its dispersion. Compared with firms without regulation, firms that comply with the environmental policy experienced a 4% to 16% significant drop in MEPE and an 8.6% to 15.7% significant rise in MEPE dispersion. This result suggests that policies to reduce firm emissions are useful for improving their environmental efficiency but harmful for reducing environmental efficiency differences across firms. The heterogeneity effect of environmental policy on firms of various sizes or ownership contributes to increased MEPE dispersion. After reallocating production across firms in a more environmentally efficient way, aggregate emissions can be reduced by approximately 30% with constant aggregate production.

In this research marginal emission of energy denotes firms' environmental efficiency. A firm with lower MEPE has higher energy use efficiency and emits fewer pollutants with one additional unit of energy. I argue that, because environmental policy affects firms' costs and benefits (Pethig, 1976; Greenstone, 2002b; Ryan, 2012), in some instances it can trigger innovation to partially or fully offset the costs of complying with regulation (Porter, 1990; Porter and Linde, 1995). The drop in marginal emission of energy due to environmental policy shows that firms' environmental efficiency could be improved by adopting an appropriate regulation policy.

The identification of the nexus between the environmental policy and the dispersion of MEPE comes from the heterogeneity effect of regulation. Because firms with different features have different behaviours under regulation, polluting firms experience different magnitudes of environmental efficiency improvement over the period. Small firms do not have the ability to make any change, such as adapting production to meet environmental regulation as they have financial constraints (Ding et al., 2021; Ek and Wu, 2018; Hovakimian, 2011). State-owned enterprises (SOE) are not incentivized to make any changes because they have more bargaining power and are more likely to be able to afford emission fees (Wang et al., 2018a; Wang and Wheeler, 2003). Such differences can disrupt firms' decisions about investing in new environmental technology and promote their production process. The increase of MEPE dispersion due to environmental regulation represents the magnitude of environmental efficiency differences across firms in the sector that could be aggravated by policy implementation. In this sense, the impact of environmental policy on MEPE dispersion represents environmental misallocation.

In terms of environmental policy, I focus on a national policy in China, the Two Control Zone policy (TCZ), which aims at reducing sulphur dioxide in the atmosphere. The TCZ policy was proposed in 1998 and implemented from 2000 to 2010. It encompasses 380 prefecture-cities and 175 cities, which 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). From 2006 to 2010, the total SO2 emissions were reduced by 14.29% with the target being 10%. Overall, it is a large-scale environmental regulation policy achieving great success.

This research speaks to several strands of literature. First, it contributes to the literature relating to production and pollution. Air and water pollution caused by firms are issues of concern among policymakers worldwide, especially for developing countries. The existing literature focuses on the debate about whether environmental regulation hinders firm performance, in terms of productivity and competitiveness (Greenstone et al., 2012; Porter, 1990; Porter and Linde, 1995). For China-specific research, the adverse effect of environmental regulation on firm productivity is commonly accepted (He et al., 2018; Wang et al., 2018a). My study, however, from the perspective of pollution, focuses on the by-product of production instead of pollution relating to the effect of policies on production. Unlike research on reducing individual firms' emissions (Greenstone et al., 2012; He et al., 2020; Wang et al., 2018a), I suggest reducing the dispersion of environmental efficiency among firms, which may help reduce aggregate pollution with fixed production.

Second, to the best of my knowledge, my work is the first to develop this novel measure for environmental efficiency and environmental misallocation. Using a Cobb-Douglas production function with energy input, I compute the marginal emission of energy as an indicator of environmental efficiency. In the existing literature, emission intensity (emissions per unit of output value) is commonly used as a variable denoting firms' pollutant treatment ability (Schmidt and Heitzig, 2014; Wang et al., 2018a; Correa et al., 2021a; He et al., 2020). My measurement, the marginal emission of energy, can show firms' environmental technology directly as it implies whether a firm can generate fewer pollutants with one additional energy unit. Similar to the resource efficiency denoted by marginal revenue of factors (Asker et al., 2014b; Ding et al., 2019a), the MEPE measurement shows the environmental efficiency of firms.

Third, this study fills the gap relating to environmental misallocation. Existing research relating to the idea of environmental misallocation is limited. The paper most relevant to my research is Correa et al. (2021a) who pioneered this concept. By ranking firms based on their emission intensity and holding a constant total production, they compute the aggregate emission reduction in the mining sector. Because Correa et al. (2021a)'s measure of environmental misallocation need to know the production capacity of each firm, they only focus on the mining industry whose capacity is the mineral reserve. My approach, however, uses the dispersion of marginal emission of energy as an indicator of environmental misallocation, which can be applied in every sector.

5.2 Literature Review

This paper is related to three strands of literature: resource misallocation, optimal emission for firms, and energy misallocation.

5.2.1 Resource misallocation

The first strand of literature relating to my work studies resource misallocation. These studies research the role that the misallocation of resources plays in understanding income differences across countries. Poor countries produce less output per worker than rich countries, even after filling the gaps in the quantity and quality of production factors. Thus, the difference in productivity is a substantial source of the variation in living standards across countries (Restuccia and Rogerson, 2017). There are two kinds of explanations for this phenomenon. One is that frontier technologies and best practice methods do not easily diffuse to low-income countries. The other is that low-income countries cannot effectively allocate their production factors to the most efficient use, which is the idea of resource misallocation across firms.

Literature in this field starts from the fact that an economy's aggregate productivity and aggregate output depend not only on each firm's productivity but also on how aggregate quantities of inputs, like capital and labour, are allocated across firms (Hsieh and Klenow, 2009). The best allocation (marginal product is equalized across firms) could maximize an economy's welfare and output. Other allocations lead to lower aggregate output and therefore show a lower level of aggregate total factor productivity (TFP). Financial frictions (Midrigan and Xu, 2014; Grieco et al., 2022; Wu, 2018), policy distortions(Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Da Rocha and Pujolas, 2011), trade barriers (Loecker, 2011; Lileeva and Trefler, 2010), and business regulations (Leal Ordóñez, 2014) could prevent an economy from reaching the best allocation.

Restuccia and Rogerson (2008) apply a growth model with heterogeneous firms and consumers to theoretically explain the dispersion of productivity resulting from resource misallocation across firms. They prove that the allocation of aggregate resources within a country has a substantial effect on cross-country differences in per capita incomes. Non-market distortions induced by government policies are the factors bringing misallocation discussed in this paper. Their equilibrium model focuses on establishment-level taxes or subsidies to output or the use of capital or labour and policies distorting the prices faced by different producers. After calibrating the theoretical work to US data, they found empirical evidence that policy-induced reallocation of resources can lead to approximately 30% to 50% decreases in output and TFP.

Hsieh and Klenow (2009)'s theoretical discussion starts from a Cobb-Douglas (CD) production function and an output price to derive the marginal cost subject to profit maximization conditions. By solving the equilibrium allocation of resources across sectors, they derive an expression for aggregate TFP as a function of the misallocation of capital and labour factors. Firm-specific distortions are measured by the firm's revenue productivity which is the TFPR explained in Foster et al. (2008). If there are no distortions, revenue productivity would be equivalent across firms. Thus, the distortion of a factor is defined as the distortions that increase its marginal product relative to other factors. By this definition, the distortions of capital, labour, and output are all included in this model. Finally, their model of monopolistic competition with heterogeneous firms shows how the misallocation of capital and labour inputs can lower aggregate TFP.

Similar to Hsieh and Klenow (2009)'s approach, Aoki (2012) develops a multi-sector accounting framework to measure the impact of resource misallocation on aggregate productivity. Sector-specific frictions caused by taxes on inputs are the reason for resource misallocation in this equilibrium model. This model consists of three parts. It starts from industrial sector production. The firms employ the Cobb-Douglas (CD) production function which exhibits constant-return-to-scale (CRS) technology (i.e., $V_i = A_i K_i^{\alpha_i} L_i^{\alpha_i}$, where V_i is the output, K_i is the capital input, and L_i is the labour input). Based on this production function, the first-order conditions (FOC) for a firm's profit function could be computed (i.e., $\frac{\alpha_i p_i V_i}{K_i} = (1 + \tau_{Ki})p_K$ and $\frac{(1-\alpha_i)p_i V_i}{L_i} = (1 + \tau_{Li})p_L$, where τ_{Ki} and τ_{Li} are the sector's capital and labour taxes respectively). In the second part, sector production is assumed to take the CRS aggregate function, $V = V(V_1, ..., V_I) = \sum_i p_i V_i$. In the last part, resource constraints are applied. The aggregate capital and labour supply are exogenous, subject to $\sum_i K_i = K$ and $\sum_i L_i = L$, respectively. The derivation result of this equilibrium model displays the impact of taxes on resource misallocation.

Asker et al. (2014b) developed an investment model with adjustment costs to show that the dispersion of the marginal revenue product of capital (MRPK) can be explained by the dispersion of productivity. They also start from an explicit model of TFPR in the context of a profit-maximizing firm. Applying this model they displayed how the time-series process TFPR affects the cross-sectional dispersion of MRPK. The key point of this model is how optimal capital investment decision-making is influenced by capital adjustment costs. Then, the link between TFPR volatility and dispersion is investigated by applying a dynamic investment model.

Unlike other literature focusing on TFPR-related measurement of misallocation, Asker et al. (2019) shift toward the cost of production. They propose a cost-based approach to measuring the misallocation of production. The key point of this paper is to compare the observed resource cost of production to the efficient resource cost of production. They prove that the dispersion in marginal cost is proportional to dispersion in TFPR. Thus, in this paper, the equivalent marginal cost across firms is the undistorted condition. This cost-based approach allows us to decompose the aggregate misallocation measure into specific sources, which makes it possible to investigate misallocation directly (finding the evidence of misallocation induced by specific observable sources) and indirectly (evaluating the magnitude of overall misallocation in a market).

Jovanovic (2014) develops an overlapping generations model to study the effect of distortions of human capital (labour resource) on the economy's growth rate in a partnership production setting with skill complementarity. This paper studies the impacts of changes in the signal-to-noise ratio associated with young skill on and off the balanced growth path (BGP). The skill-to-noise ratio is used to denote human capital efficiency in an economy. An economy that rewards ability rather than family background or social connections is a system with a high signal-to-noise ratio. Thus, this model helps to explain why some developed countries, like the US, have outperformed other developed ones, in Europe for example, despite the US having more unequal income distribution. The author divided workers into two groups, young workers with low skills and old workers with high skills, and focused on the friction in the labour market (human capital friction). The equilibrium result proves that policy should aim to reduce friction, while taxes and transfers cannot improve allocation.

Baqaee and Farhi (2020) develop a general theory of aggregation in inefficient economies. Their general equilibrium model aggregates microeconomic shocks in economies with distortions to resource reallocation, financial frictions, and nominal rigidities. They define a new measure of aggregate TFP growth without the technological impact of factor growth. In this study, the new measure of aggregate TFP growth is decomposed into changes in technical efficiency and changes in allocative efficiency.

Based on these theoretical approaches related to resource misallocation, the existing empirical literature focuses on investigating the level of resource misallocation and its cause (Restuccia and Rogerson, 2013, 2017). The empirical literature related to resource misallocation aims to solve three questions: Is misallocation a major source of differences in productivity between countries? What are the causes of misallocation? In addition to output loss, what are the additional costs of misallocation?

A typical approach to measuring resource misallocation has been to assume that a benchmark country or economy (often the United States) is undistorted. The benchmark economy is used to measure the extent to which other economies lose from misallocation. Hsieh and Klenow (2009) is a typical study that uses this empirical approach. Hsieh and Klenow (2009) use two steps to show how the misallocation of capital and labour can lower aggregate TFP from a firm-level angle. First, dispersion in the marginal products of capital and labour is measured within 4-digit industrial sectors in China, India, and the US. Second, they choose the United States as a critical benchmark to measure the increase of aggregate manufacturing output in China and India if they were to reallocate capital and labour to equalize marginal products across firms observed in the United States. Finally, they relate the revenue productivity gaps to specific government policies, that is, state ownership of plants in China and licensing and size restrictions in India. The result shows that manufacturing TFP could increase 30-50% in China and 40-60% in India if capital and labour were reallocated to equalize marginal products to the extent observed in the US.

Restuccia and Rogerson (2008) calibrated their growth theoretical work to US data and found empirical evidence that policy-induced reallocation of resources can lead to approximately 30% to 50% decreases in output and TFP. Using a multi-sector accounting framework, Aoki (2012) finds that resource misallocation contributes to 9% of the difference in the measured aggregate productivity between Japan and the US. Using a cost-based approach, Asker et al. (2019) investigate the extent of misallocation in the global oil extraction industry and attributes part of it to the market power of OPEC countries. The results show that misallocation in the global oil industry was approximately US$ 744 billion from 1970 to 2014, where market power contributed 14.1% to 21.9 % of the misallocation.

When it comes to the causes of misallocation, Restuccia and Rogerson (2017) listed three general categories of factors that could be the potential sources. The first is statutory provisions like the tax code and regulations that vary with firm characteristics, such as the tariffs applied to specific categories of goods, employment protection measures in the labour market, and product market regulations that restrict size or limit market access. The second is discretionary provisions made by the government or other institutions (such as banks) to favour or penalize specific firms. The third, market imperfections, may also cause misallocation.

Some literature focuses on the misallocation of specific factors, like capital and labour. For capital misallocation, Midrigan and Xu (2014) estimate how financial frictions determine total factor productivity, using producer-level data. They develop a model of establishment dynamics with two channels through which financial frictions reduce TFP. The channels are the distortion of producers' entry and technology adoption decisions and capital misallocation induced by finance frictions. By parameterizing the model and estimating data from Korea and China, they find evidence that the first channel causes sizable TFP losses, while capital misallocation brings small TFP losses.

In order to explore the effect of financial frictions on capital misallocation and aggregate productivity, Moll (2014) develops a highly tractable general equilibrium model which contains heterogeneous producers facing collateral constraints. It holds that the size of steady-state productivity losses and the speed of transitions are both determined by the persistence of idiosyncratic productivity shocks. Theoretical derivation shows that in an economy with persistent productivity shocks, steady-state productivity losses are small but transitions are slow. Previous literature has developed theories about the mechanism of financial frictions inducing inefficient capital allocation which in turn translates into low aggregate productivity. But, Moll (2014) considers the accumulation of capital and wealth of entrepreneurs when they face financial constraints. He argues that self-financing has the potential to overcome financial constraints and undo capital misallocation. His result shows that if productivity shocks are relatively transitory, the efficacy of self-financing will be hampered, and financial frictions will cause large long-run productivity losses but a fast transition to a steady state.

Dispersion in value-added/capital is used as a measure of capital misallocation in David and Venkateswaran (2019). Using data for Chinese manufacturing firms they prove that adjustment costs and uncertainty explain only a modest fraction of the dispersion of capital. Using firm-level value added and investment data collected from China and the U.S., they show that unobserved heterogeneity in demand and production technologies can explain a significant portion of observed ARPK dispersion in the United States, but not in China. Size-dependent policies and/or financial imperfection can explain more ARPK dispersion in China.

On labour misallocation, Munshi and Rosenzweig (2016) focus on the dispersion of labour across urban and rural areas in India. They explain the unmatched phenomenon between large spatial wage disparities and low male migration in India. Their paper compares the distortion of labour allocation to the distortion of capital allocation arising from financial frictions explored in other literature. The structural estimates show that small improvements in formal insurance (government insurance provided for migrants rather than caste-based insurance) reduce the spatial misallocation of labour by enhancing migration significantly.

5.2.2 Optimal emission

A second strand of literature related to this research studies the optimal level of emissions in a firm or industry, which is at the core of environmental economics literature. Literature in this field either estimates pollution abatement costs or finds the optimal emission tax, which relates to a firm's optimal emissions. The first branch of the literature estimates the pollution abatement costs by using shadow prices. The shadow price of emissions (undesirable output) is the opportunity cost of reducing one additional unit of undesirable output, which is the loss of desirable output. This literature suggests that emissions should be reduced to the point that the marginal abatement costs of emissions should equal the marginal external costs (Gillingham and Stock, 2018).

Using a non-parametric approach, Faere et al. (1989) show how to adjust efficiency measures in the presence of undesirable outputs. Färe et al. (1993) apply the Shephard distance function to theoretically show how to generate shadow prices for undesirable outputs. In the empirical specification, their observations are from 30 pulp and paper mills operating in Michigan and Wisconsin. Pollutants, such as sulphur oxides, biochemical oxygen, suspended solids and particulates, are denoted as the undesirable outputs, and the shadow price for each pollutant is estimated. Their approach allows shadow prices to vary by producer, which helps producers determine the optimal emissions for their production and assists regulators in setting the penalty for a firm's emissions. The shadow price of undesirable output here is the opportunity cost of lowering them. Coggins and Swinton (1996) also apply a Shephard distance function approach to estimate the shadow price of sulphur dioxide abatement for coal-burning electric plants. Their empirical analysis uses the output distance function and finds that the average shadow price of SO2 emissions is $292.70 per ton, which is also the marginal cost of abatement for coal plants.

Several studies investigate the shadow prices of undesirable outputs for different sectors, where a distance function is commonly used. Hailu and Veeman (2000) employ a parametric input distance function to estimate pollution abatement costs for the Canadian pulp and paper industry. Their result shows that the marginal cost of abatement would be improved under pollution control. Färe et al. (2006) estimate the shadow prices and pollution costs for the agriculture industry in the US. Using Data Envelopment Analysis and Directional Distance Function, Mandal and Madheswaran (2010) measure the environmental efficiency of the cement industry in India, where carbon dioxide is considered as an undesirable output. Their empirical result shows that under environmental regulation, the cement industry has the potential to expand desirable output and contract undesirable output with the given inputs. For the power industry, Lee (2005) and Lee (2011) measure the shadow price of pollutants using the data of power plants in the U.S. and Korea respectively.

In research on China, Lee and Zhang (2012) compute the potential cost savings derived from trading emissions among 30 Chinese manufacturing industries. An input distance function is used with the shadow prices of CO2 emissions and the maximum technically obtainable CO2 emissions reduction. The empirical result shows that the shadow prices of CO2 vary across industries with an average of \$3.13 per ton and emissions can be reduced by as much as 680 million tons in the aggregate. Focusing on China's power industry, Du and Mao (2015) estimate the environmental efficiency, reduction potential and marginal abatement cost of carbon dioxide emissions. Using survey data from 2004 and 2008, they found evidence that China's CO2 emissions could have been reduced under conditions of efficient production. Zhang and Xie (2014) study the Chinese electronic information industry and use the non-radial directional distance function to estimate environmental technical efficiency and environmental regulatory costs. Their empirical analysis shows a reduced shadow price of CO2 for the electronic industry during the period 1980–2012.

Another branch of the literature discusses emission reduction policy instruments, such as emissions quotas, emissions taxes, and emissions transactions, used to achieve a firm's optimal amount of emissions. Emissions quotas (or command-and-control policies) are a commonly used instrument to mitigate environmental degradation. The upper-limit emissions and emissions quotas are specified by policymakers, whereas policymakers need to know the level of emission reduction. Naito and Ogawa (2009) employ a mixed duopoly theory to examine the effect of emissions quotas and emissions taxes. A uniform standard for each firm emission level is considered in their research. Their theoretical analysis shows that welfare is better under emissions quotas than under emissions taxes. Kato (2011) considers setting an emissions quota differently for each firm and theoretically proved that differentiated quota improved welfare.

However, emissions quotas alone are not enough to achieve each firm's optimal amount of emissions. To solve the issue of how emissions quotas can be effectively allocated among firms, policymakers always implement emissions quotas accompanied by trade in emissions or emission transaction systems. The combination of emissions quotas and emissions trade is generally considered as the cap-and-trade system. Golombek et al. (2013) investigate different ways of allocating emissions quotas (current output-based allocation and historic performance-based allocation) conditional on the total emissions target. They apply an extensive numerical equilibrium model of the Western European energy market with heterogeneous electricity producers. The empirical study proves the significantly higher welfare costs of attaining a fixed emissions quota no matter the type of allocation. Using the Boltzmann distribution instead of auctioning or grandfathering distribution, Park et al. (2012) investigate the mechanism of allocating emissions permits in different countries. Lozano et al. (2009) investigate the reallocation of emission permits using a dataset from the Swedish pulp and paper industry. They employ a data envelopment analysis (DEA) approach to reallocating existing emission permits to complete the objective of maximizing aggregated desirable production, minimizing undesirable total emissions and minimizing the consumption of input resources.

The emissions tax is another effective emissions reduction policy widely used. For instance, Hochman and Zilberman (1978) theoretically compare the performance of different environmental policies (taxes and standards) on improving social welfare with the existence of pollution externalities. Motivated by the practice of reducing air pollution from transport, S.Eskeland (1994) theoretically discusses the abatement cost of emissions reduction after the introduction of a petrol tax. In the case of Mexico City, emissions reductions would involve 24% higher abatement costs. Dissou and Karnizova (2016) develop a multi-sector business cycle model to compare the effect of carbon permits and carbon taxes on CO2 reduction with macroeconomic uncertainty. Their theoretical analysis finds evidence that in the cap regime, real variables are less volatile than in the tax regime, but from a welfare perspective, the tax regime may be preferable. When shocks occur from non-energy sectors, there is no significant difference between the cap and tax regimes. For energy industry shocks, however, the cap has lower volatility but greater welfare costs than tax.

In China-specific research, cap-and-trade schemes (a combination of emissions permits and trade) and emissions taxation are two widely discussed emissions mitigation policies in recent years. Ye et al. (2020) described in detailthe evolution of China's emissions trading system (evolving from a command-and-control policy, and emissions permits, to a market-based approach). Zhang et al. (2014) investigate the allocation of emissions quotas across provinces in China by using the Shapley Value Method. Their finding is that more emissions permits can be allocated to regions with higher GDP, higher carbon outflow and higher carbon reduction connection. Zhang and Hao (2017) developed index criteria to reallocate the emissions quota within the same industry, using an input-oriented ZSG-DEA model to examine the efficiency of reallocation. Liu and Lin (2017) propose a new cost-based nonlinear programming approach to obtain an optimal emissions quota allocation between provinces. Under a fixed national emissions reduction target, the empirical analysis shows that more emissions quotas should be allocated to the relatively developed eastern region, while the central and western regions can undertake more emissions reduction. From the perspective of firms, Cao et al. (2017) show the optimal production and carbon emission reduction level for China's manufacturing firms subject to cap-and-trade and low carbon subsidy policies respectively.

In addition to emissions quotas and emissions trade policies, emissions tax is also an effective instrument in China. Using the provincial data from 2000 to 2017 Dong et al. (2022) evaluate the emissions reduction effect of pollution fees. The empirical finding is that levying pollution fees can not only effectively mitigate emissions but also promote firms' technological innovation. Gowrisankaran et al. (2020) investigate the impact of China's discharge fee (air emissions fee especially) on firm pollution mitigation and productivity. Their research period starts from 2003, the time the regulation became a state order, continuing to 2016. By comparing firms located within 50 kilometers of a provincial border with and without fee changes, they find pollution fees caused ambient pollution and firm productivity to drop.

5.2.3 Energy misallocation

A third strand of literature related to my research studies energy misallocation across firms in an industry. Hsieh and Klenow (2009)'s approach to misallocation measurement is common in this literature. The Cobb-Douglas function, $Y_{it} = A_{it}K_{it}^{\alpha_K}L_{it}^{\alpha_L}E_{it}^{\alpha_E}$, is applied as the production function faced by heterogeneous firms, where Y_{it} is the output, K_{it}, L_{it}, E_{it} are the capital, labour, and energy factors. Energy usage, such as electricity, coal, or oil, is considered an input factor in the production function to investigate resource misallocation or TFP dispersion for all input factors.

Using firm-level data from the Korean manufacturing sector, Choi (2020) analyzes the effect of energy resource allocative efficiency on total factor productivity (TFP) and attributes the allocative inefficiency of energy markets to energy price distortions. The empirical result proves increasing intra-industry misallocation, especially in low-oil-price periods. After reallocating capital, labour, and energy resources by reshaping the energy market and capital market, aggregate TFP could be increased by 51.3 % to 71.7%. The policy implication is that government (energy) price intervention is the reason for productivity loss and allocative inefficiency in the energy market.

He and Qi (2021) measure resource misallocation with energy input for China's provinces and investigate how resources affect the economic and environmental performance of provinces. The mechanism analysis shows resource allocative efficiency affects a firm's environmental performance, which results in provincial environmental degradation. Using the panel data for 30 provinces in China from 2009 to 2016, Han et al. (2020) investigate the effect of energy misallocation on the use of renewable energy. The result shows low allocation efficiency in China. Employing provincial data in China, Chu et al. (2019) examine the impact of energy misallocation on carbon emission efficiency. By applying a spatial economic model, the empirical results show an inverted U-shaped relationship between energy misallocation and emission efficiency. From the perspective of resource misallocation, Bian et al. (2019) primarily explore the impact of market segmentation on environmental pollution. They find evidence that increasing market segmentation has led to significant misallocation of labour and capital resources, which is a major cause of environmental pollution.

Thus, the existing literature discusses resource misallocation with energy input. There is a limited number of papers relating to the misallocation of emissions across firms or reducing aggregate pollution by reallocating energy inputs or production. Correa et al. (2021b) are the most connected to my research.

Correa et al. (2021b) investigate the environmental misallocation of the international copper industry using mine-level data from different countries. They define environmental misallocation as the ratio between observed aggregate carbon dioxide (CO2) emissions and minimized aggregate emissions after reallocating production across mines subject to constant aggregate production. Environmental misallocation is based on the idea that aggregate pollution depends not only on the emission levels of individual firms but also on how production is allocated across those firms. The counterfactual condition is that firms with lower emissions efficiency produce first to their maximum capacity subject to fixed aggregate production. The result shows that optimal production allocation can reduce the copper industry's emissions by 47% and reduce production costs by 24% at the aggregate level.

In summary, the existing literature relating to resource misallocation does not consider the by-product of production. Even for research on energy misallocation, rare literature examines the link between energy consumption and emissions. As the sources of pollution, the consumption of energy input should not be disconnected from the production process. For research related to firm optional emissions, output and productivity are commonly included in the theoretical analysis, which also lacks detailed discussion on energy input factors. Existing literature commonly uses the emission intensity or the DEA method to denote environmental efficiency. However, my computation of the marginal emission of energy displays the link between production and pollution. My metric for environmental efficiency helps to fill the research gap in environmental economics.

Based on the above literature, I hypothesise that the environmental policy would improve the firm environmental efficiency but its dispersion would also be increased. First, stringent regulation would induce continuing firms to take more environmentally friendly technologies, which would improve their environmental efficiency. Second, low environmental efficiency firms would exit from the market after policy implementation. The entering firms have higher environmental efficiency than the existing firms. Firms' enter and exit behaviour increases estimated firm environmental efficiency. Meanwhile, I also hypothesise that there would be a positive relationship between the dispersion of environmental efficiency and policy implementation. Because of the heterogeneous background of firms, different firms are likely to face distinct financial constraints, bargaining power, adjustment costs, and various other factors.

5.3 Variables and Summary statistics

5.3.1 Measure of environmental efficiency and environmental misallocation

The measure of environmental efficiency relies on the assumption that firms have a production function with energy input that induces emission by-product and an emissions function in which there is a fixed ratio between emissions and production (Copeland and Taylor, 2004; Wang et al., 2018a; Gowrisankaran et al., 2020). In the spirit of Asker et al. (2014b) and Ding et al. (2019a), I developed a novel approach to denote firms' environmental efficiency, the marginal emission of energy (MEPE). Because environmental policy affects firms' costs and benefits (Pethig, 1976; Greenstone, 2002b; Ryan, 2012), it can trigger innovation to partially or fully offset the costs of complying with regulation in some instances (Porter, 1990; Porter and Linde, 1995). The drop in marginal emission of energy due to environmental policy represents that firms' environmental efficiency could be improved by introducing an appropriate regulation policy.

First, following Asker et al. (2014b) and Ding et al. (2019a), I apply a production function with energy input. A firm i, in time t, produces output Q_{it} using the Cobb-Douglas production function:

$$Q_{it}^S = A_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} E_{it}^{\alpha_E} M_{it}^{\alpha_M} \tag{5.1}$$

where K_{it} is the capital input, L_{it} is the labour input, E_{it} is the energy input (i.e., the coal consumption and petrol consumption in the dataset), M_{it} is intermediate materials.

The constant elasticity demand curve for the firm i's product is:

$$Q_{it}^{D} = B_{it} P_{it}^{-\varepsilon} \tag{5.2}$$

Market clearing assumption $Q_{it}^{S} = Q_{it}^{D}$.

$$P_{it}^{\varepsilon} A_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} E_{it}^{\alpha_E} M_{it}^{\alpha_M} = B_{it} \tag{5.3}$$

$$P_{it}^{\varepsilon-1} \cdot P_{it} \cdot Q_{it} = B_{it} \tag{5.4}$$

$$P_{it}^{\varepsilon-1} \cdot S_{it} = B_{it} \tag{5.5}$$

where S_{it} is the sales revenue of firm i at time t (Asker et al., 2014b; Ding et al., 2019a). Revenue-based productivity measures, the equation 5.9, is typically used in empirical work with microdata (Foster et al., 2008).

$$(P_{it}^{\varepsilon})^{\frac{\varepsilon-1}{\varepsilon}} \cdot S_{it} = B_{it} \tag{5.6}$$

$$(B_{it}(A_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} E_{it}^{\alpha_E} M_{it}^{\alpha_M})^{-1})^{\frac{\varepsilon-1}{\varepsilon}} \cdot S_{it} = B_{it} \tag{5.7}$$

$$S_{it} = B_{it}^{\frac{1}{\varepsilon}} A_{it}^{(1-\frac{1}{\varepsilon})} K_{it}^{\alpha_K(1-\frac{1}{\varepsilon})} L_{it}^{\alpha_L(1-\frac{1}{\varepsilon})} E_{it}^{\alpha_E(1-\frac{1}{\varepsilon})} M_{it}^{\alpha_M(1-\frac{1}{\varepsilon})} \tag{5.8}$$

So,

$$S_{it} = P_{it} Q_{it} = \Omega_{it} K_{it}^{\beta_K} L_{it}^{\beta_L} E_{it}^{\beta_E} M_{it}^{\beta_M} \tag{5.9}$$

where, $\Omega_{it} = A_{it}^{(1-1/\varepsilon)} B_{it}^{1/\varepsilon}$, and $\beta_X = \alpha_X[(1-1/\varepsilon)]$ for $X \in (K, L, E, M)$.

Then, I apply the emission functions (see, Copeland and Taylor (2004); Wang et al. (2018a); Gowrisankaran et al. (2020)) to show the connection between emissions and firm production:

$$Z_{it} = \phi_{it}(\theta)S_{it} \tag{5.10}$$

where Z_{it} is the firm's emission level observed, θ is the emission control effort of firm i. Regulations can affect firm emissions by changing θ. Following Copeland and Taylor (2004), firm emissions are a by-product of production, i.e., the emissions level observed is the fraction of the firm's output. Wang et al. (2018a) assume $\phi(\theta) = (1-\theta)^{1/\rho}$.

So, I transform equation 5.9 into equation 5.11:

$$Z_{it} = \phi_{it}(\theta)\Omega_{it}K_{it}^{\beta_K}L_{it}^{\beta_L}E_{it}^{\beta_E}M_{it}^{\beta_M} \tag{5.11}$$

$$Z_{it} = \psi_{it}K_{it}^{\beta_K}L_{it}^{\beta_L}E_{it}^{\beta_E}M_{it}^{\beta_M} \tag{5.12}$$

Finally, the marginal emission per energy consumption is computed by taking the derivatives of equation 5.12:

$$\frac{\partial Z_{it}}{\partial E_{it}} = \beta_E \frac{\psi_{it}K_{it}^{\beta_K}L_{it}^{\beta_L}E_{it}^{\beta_E}M_{it}^{\beta_M}}{E_{it}} \tag{5.13}$$

$$\frac{\partial Z_{it}}{\partial E_{it}} = \frac{\beta_E \cdot Z_{it}}{E_{it}} \tag{5.14}$$

Taking natural logarithms, I can produce

$$ln(\frac{\partial Z_{it}}{\partial E_{it}}) = ln(\beta_E) + ln(Z_{it}) - ln(E_{it}) \tag{5.15}$$

The natural logarithm of marginal emission of energy is estimated by 4 different production function estimation methods, including the Ackerberg et al. (2015) approach, the Wooldridge (2009) approach, the Olley and Pakes (1996) approach, and the Levinsohn and Petrin (2003) approach. Especially, the Ackerberg et al. (2015) approach the key method for the estimation of MEPE in the basic regression, while the others are employed in the robustness test section.

My measurement of environmental misallocation, MEPE dispersion, is inspired by Hsieh and Klenow (2009) and Asker et al. (2014b). Hsieh and Klenow (2009) focus on the observed dispersion in marginal products (in particular, the marginal revenue products of capital and labour across firms). They hold that revenue productivity should be the same across firms in the absence of capital and/or output distortions. Asker et al. (2014b) view the marginal revenue of capital (MRPK) as a static measure of capital misallocation. In the literature relating to capital misallocation, MRPK does not vary across firms within an industry unless plants face capital distortions.

The dispersion of MEPE is the indicator of environmental misallocation in this research. My measure of within-sector environmental misallocation is the dispersion (i.e., the standard deviation) of $ln(\frac{\partial Z_{it}}{\partial E_{it}})$ of firms in sector j at time t. The increase of MEPE dispersion due to environmental regulation represents the magnitude of environmental efficiency differences across firms in the sector that could be aggravated by policy implementation. The counterfactual scenario is defined as there being no difference for MEPE across firms within an industry. Within a specific sector, a firm with a higher MEPE generates more emissions after using one unit of energy for production. Higher MEPE implies the firm is suffering from its poor emissions abatement techniques. From the perspective of minimizing total emissions, I reallocated the production of firms with higher MEPE to the ones with lower MEPE. The optimal allocation of total outputs (counterfactual conditions) is equivalent to MEPE across firms in the same sector.

Environmental efficiency and environmental misallocation are the dependent variables in this research. They help us understand emission efficiency differences across firms and efficiency dispersion across regions. Under current technology, the way that aggregate production is allocated across firms and industries determines the economy's overall level of emissions. The best allocation could minimize aggregate emissions in the long run. Other allocations result in a higher level of aggregate emissions in an economy.

5.3.2 Control variables

First, a vector of control variables is used to denote the industry or province characteristics. They are government size, $GovSize_{pt}$; Inflation, $Inflation_{pt}$; provincial coal consumption intensity, $CoalInt_{pt}$; government subsidy, $Subsidy_{pt}$. Variables used to control industrial characteristics include the Herfindahl-Hirschman Index (HHI), HHI_{jt}; the ratio between SOEs' sales and the industry's aggregate sales, $SOEshare_{jt}$.

Government size ($GovSize_{p,t}$) is used to measure the extent of government intervention in the process of environmental misallocation, which is defined as the natural logarithm of total government expenditure as a share of GDP in province p at year t. Because self-interested politicians are likely to utilize political power to exercise control over firms for their own political and social objectives (Shleifer and Vishny, 2002), the friction induced by government intervention prevents firms from making optimal decisions on resource allocation. As state ownership in China's manufacturing sector is prevalent, government intervention is a key driver of resource misallocation there (Chen et al., 2011).

Inflation ($inflation_{p,t}$) is included as a measure of informational friction faced by producers and consumers (Ding et al., 2019a). It is calculated as the growth rate of the natural logarithm of the Consumer Price Index (CPI) in province p at year t. Both a more efficient allocation of resources and the informational content of the price system can be improved by low or stabilizing inflation (Friedman, 1977), whereas high inflation and relative price volatility shorten agents' horizon, disrupt the organization of markets and generate resource misallocation (Tommasi, 1999). Tobin (1972) and Akerlof et al. (1996) both hold the view that inflation is associated with the dynamics of resource allocation.

Provincial coal consumption intensity ($CoalInt_{pt}$) is used to measure the extent of coal consumption under each province's conditions, which is defined as coal consumption as a share of GDP in province p at year t.

Government subsidy ($Subsidy_{pt}$) is a measure of policy distortion, defined as the natural logarithm of total subsidized income divided by total sales income of all manufacturing firms in province p at year t. Restuccia and Rogerson (2008) hold that subsidies can distort factor prices and adversely affect resource allocation, especially in inefficient firms. This is particularly the case for China given the advantage that SOEs have over private firms. In China, SOEs can receive substantial government subsidies in the form of bank loans at subsidized rates, preferential tax treatment, market entry and many other resources (Ding et al., 2019a).

The Herfindahl-Hirschman Index (HHI) (HHI_{jt}) is a commonly accepted measure of market concentration. It shows the relative size distribution of the firms in industry j at year t. HHI is calculated by squaring the market share (a firm's sales revenue divided by the industry's aggregate sales revenue) of each firm competing in the market and then summing the resulting numbers.

The ratio between SOEs' sales and the industry's aggregate sales ($SOEshare_{jt}$) is a measure of the ownership distribution of a sector.

Second, I appliy a vector of control variables denoting firm features in the firm-level regression. This 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*.

$Output_{it}$ is the amount of firm output (10 thousand Yuan), which denotes the 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 (2002a); Wang et al. (2018a); He et al. (2018)). As the Chinese government targets large firms and exerts less control over small ones, He et al. (2018) shows that large firms with higher emissions will have more emission reduction. Wang et al. (2018a) hold that larger firms usually have lower emissions intensity. Thus, it is expected that the coefficient of *Output* will be positive when using emissions level indicators as the dependent variable, and negative when using SO2 intensity as the dependent variable. Large Chinese firms' increasing productivity is always higher than the average rate (Brandt et al., 2012). He et al. (2018) find that the TFP impacts are significant only for larger firms. I expected that the coefficient of *Output* would be positive when using TFP and profitability indicators as dependent variables.

$firmage_{it}$ is the natural log of firm age. This factor was found to be correlated with firm emissions (Greenstone, 2002b; Greenstone et al., 2012; Wang et al., 2018a; He et al., 2018) and productivity (Syverson, 2011; Brandt et al., 2017; Greenstone et al., 2012; He et al., 2018). Firm age is often used as an indicator of technology level and firms' governmental embeddedness (Sun et al., 2019a). As older firms have better communication channels with local government and long-established management systems in production and pollution control, they may not be active in improving their pollution-reducing technologies (Sun et al., 2019a). Some work has shown that older firms may pollute more in their production (Greaney et al., 2017; Wang et al., 2018a; Liu et al., 2017; Sun et al., 2019a). I expected that the coefficient of *firm age* would be 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, 2019b). It is expected that the coefficient of *firm age* will be positive when using TFP as the dependent variable.

$agglo_{it}$ 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 the same 2-digit industry and the same city. This indicator is used as a control for firms' agglomeration effect in the US (Krugman, 1991; Greenstone, 2002b), China (Brandt et al., 2017; Wang et al., 2018a), 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 to share abatement technologies inside sectors. Wang et al. (2018a) prove the negative relation between agglomeration and emission intensity. I expected that the coefficient of *agglo* would be negative when using SO2 intensity as the dependent variable. However, the relation between emission levels and agglomeration is unclear. As with agglomeration-type productivity spillovers (see, (Syverson, 2011)), it is expected that the coefficient of *agglo* will be positive when using TFP as the dependent variable.

Gas treatment capacity (GTC_{it}) is the natural log of the capacity of waste gas treatment facilities (cubic meter per hour). This variable is used to control firms' capacity for waste gas treatment. Liu et al. (2018) and He and Zhang (2018) show 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 are always accompanied by high pollution abatement capacity (Liu et al., 2018). It is expected that the coefficient of *gas treatment capacity* will be positive when using emission level indicators as the dependent variable.

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

5.3.3 Summary statistics

Table 5.1 provides a statistical description of the dataset. It illustrates the mean value, standard deviation, minimum value, and maximum value for the key variables. The mean MEPE computed by the OP method is 0.958 with a standard deviation of 1.571, a minimum value of -13.75, and a 13.32 maximum value. The mean value of

MEPE calculated by the LP method and the MEPE computed by the ACF method is 0.994 and 1.291 respectively. These two variables also have similar minimum and maximum values. Firms' average output is 19.36 with a standard derivation of 119.1. There is a huge gap between the minimum and maximum output. The mean firm age (taken logarithm) for the observations is 2.323. The average agglomeration value and gas treatment capacity is 10.71 and 6.845 respectively. About 0.59% of the observations have more than one plant.

For the sector-year variables used in my industrial level regression, Table 5.1 shows that the three misallocation proxies $\sigma(MEPE_{OP})$, $\sigma(MEPE_{LP})$, and $\sigma(MEPE_{ACF})$ have a similar average amount (1.039, 1.038, and 1.043). There is also limited difference between these three variables' standard deviation, minimum value, and maximum value. The average value of the logarithm of government size is -2.012 with a standard deviation of 0.302. The growth rate of the natural logarithm of the Consumer Price Index (CPI) has a mean value of 4.622 with a 0.0176 deviation. The mean value of the ratio of a province's coal consumption over its aggregate output is 1.706. The industry control variable, HHI, has a huge gap between the minimum and maximum value, while the difference between a maximum and a minimum for SOE share ratio is limited.

Table 5.2 shows the mean value of marginal emission of energy and the average value for the standard derivation of MEPE over the years. Column 3 indicates that, after 2003, the average MEPE value keeps decreasing over the years. As the MEPE denotes the pollutant generated with one more unit of energy consumption, the decreased average MEPE implies that firms have higher environmental efficiency over the years. Column 5, however, shows that MEPE dispersion keeps increasing from 2004 to 2006. The phenomenon of decreased mean value of MEPE with increased dispersion may imply firms' heterogeneous behaviour. Some firms chose to become cleaner and reduce their MEPE, while others fail to respond to environmental regulation or take limited actions with limited compliance to government policy.

To determine which firms have become cleaner with environmental regulation, I focus on two firm characteristics, firm size and ownership. First, the full samples were divided into two groups: big firms (more than 100 labourers) and small firms. Figure 5.1 illustrates the time evolution of MEPE dispersion of big firms over the sample period. The blue dashed line shows the MEPE dispersion for big firms in 2001; the red dot-dash line displays the MEPE dispersion for big firms in 2004; and the green solid line is the MEPE dispersion in 2006. From figure 5.1, the distribution of MEPE keeps moving to the left from 2001 to 2006. It implies that the mean MEPE in 2001 is larger than the value in 2004, and the mean MEPE in

Table 5.1: Summary statistics

Variable	Observation	Mean	Std. Dev.	Min	Max
Firm-Year variables:					
$MEPE_{OP}$	158,680	0.958	1.571	-13.75	13.32
$MEPE_{LP}$	159,438	0.994	1.555	-13.72	13.33
$MEPE_{ACF}$	156,472	1.291	1.623	-13.82	13.23
$MEPE_{Wooldrige}$	158118	0.948	1.562	-13.72	13.28
$Output$	159,669	19.36	119.1	9.99e-05	11732
$firmage$	159,459	2.323	0.945	0	7.602
$agglo$	159,669	10.71	1.489	2.944	13.91
GTC	159,669	6.845	4.272	0	20.03
$Plant$	159,669	0.00591	0.0767	0	1
Sector-Year variables:					
$\sigma(MEPE_{OP})$	7362	1.039	0.664	3.37e-07	3.617
$\sigma(MEPE_{LP})$	7479	1.038	0.667	3.37e-07	3.617
$\sigma(MEPE_{ACF})$	7198	1.043	0.667	3.37e-07	3.617
$GovSize$	9120	-2.012	0.302	-2.562	-1.106
$inflation$	9120	4.622	0.0176	4.587	4.663
$CoalInt$	9056	1.706	1.374	0.303	7.766
$Subsidy$	9120	156698	119947	7379	670165
HHI	9120	58.00	74.32	2.911	707.9
$SOEshare$	9120	0.186	0.198	0.00147	0.975

Table 5.2: Summary statistics by year

	$MEPE_{lp}$		$\sigma(MEPE_{lp})$	
Year	Observation	Mean	Observation	Mean
2001	20998	1.218	1151	0.991
2002	22382	1.090	1104	1.033
2003	22607	1.208	1127	1.092
2004	20414	1.035	1117	1.042
2005	25201	0.881	1054	1.057
2006	24422	0.917	1118	1.058
2007	23414	0.663	808	0.974
Total	159,438	0.994	7479	1.038

2004 is larger than it in 2006. The average environmental efficiency of large firms keeps increasing during the policy implementation period (from 2001 to 2006).

Figure 5.2 shows the time evolution of MEPE dispersion of small firms over the sample period. The blue dashed line shows the MEPE dispersion for small firms in 2001; the red dot-dash line displays the MEPE dispersion for small firms in 2004; and the green solid line shows the MEPE dispersion for small firms in 2006. The mean MEPE in 2001 is larger than the value in 2004, but the mean MEPE in 2004 is smaller than it in 2006. The distribution of MEPE is moving to the left first and then to the right. There is not a clear left-moving trend but a fluctuating pattern after 2004. Thus, Figure 5.1 and Figure 5.2 jointly imply that environmental regulation over this period had a more effective impact on big firms.

Second, I divided the samples into state-owned enterprises (SOEs) and non-SOEs. Figure 5.3 illustrates the time evolution of MEPE dispersion of non-SOEs over the sample period. The blue dashed line shows the MEPE dispersion for non-SOEs in 2001; the red dot-dash line displays the MEPE dispersion for non-SOEs in 2004; and the green solid line shows the MEPE dispersion for non-SOEs in 2006. The distribution of MEPE for non-SOEs keeps moving to the left from 2001 to 2006. The average environmental efficiency of non-SOEs keeps increasing during the policy implementation period.

But, for SOEs (Figure 5.4), there is not a left-moving trend after 2004. In Figure 5.4, the blue dashed line shows the MEPE dispersion for SOEs in 2001; the red dot-dash line displays the MEPE dispersion for SOEs in 2004; and the green solid line shows the MEPE dispersion for SOEs in 2006. The mean values of MEPE in 2001, 2004, and 2006 are similar to each other. The distribution of MEPE for SOEs is moving to the left first and then to the right. Thus, Figure 5.3 and Figure 5.4 jointly imply that environmental regulation over this period had an impact on non-SOEs, but did not continuously improve SOEs' pollutant treatment capacity.

Table 5.3 shows the summary statistics by different groups. Column 2 shows a decreasing trend in the mean MEPE for large firms over the years. It implies continuously increasing environmental efficiency for large firms. However, the mean MEPE for small firms in column 4 does not exhibit a clear trend. Large firms have improved their environmental efficiency during the period of policy implementation. As shown in column 6, there is also a decreasing trend in the mean MEPE for non-SOEs over the years. After the TCZ policy was implemented, the environmental efficiency for non-SOEs kept increasing. But there is a fluctuating moving trend in column 8 over the years. Thus, the TCZ policy is more effective on influencing large firms and non-SOEs.

At the same time, comparing the column 2 and 4 of Table 5.3, small firms have lower MEPE (higher environmental efficiency) than large firms before 2004. However private firms have lower MEPE (higher environmental efficiency) than SOEs over the years. Large firms are not as flexible as small firms. Their improvement takes time. Private firms are known as more productive and efficient than SOEs. For environmental efficiency, large firms have higher dispersion of MEPE than small firms over the years (shown in column 3 and 5). Private firms have a lower dispersion of MEPE than SOEs over the years (shown in columns 7 and 9).

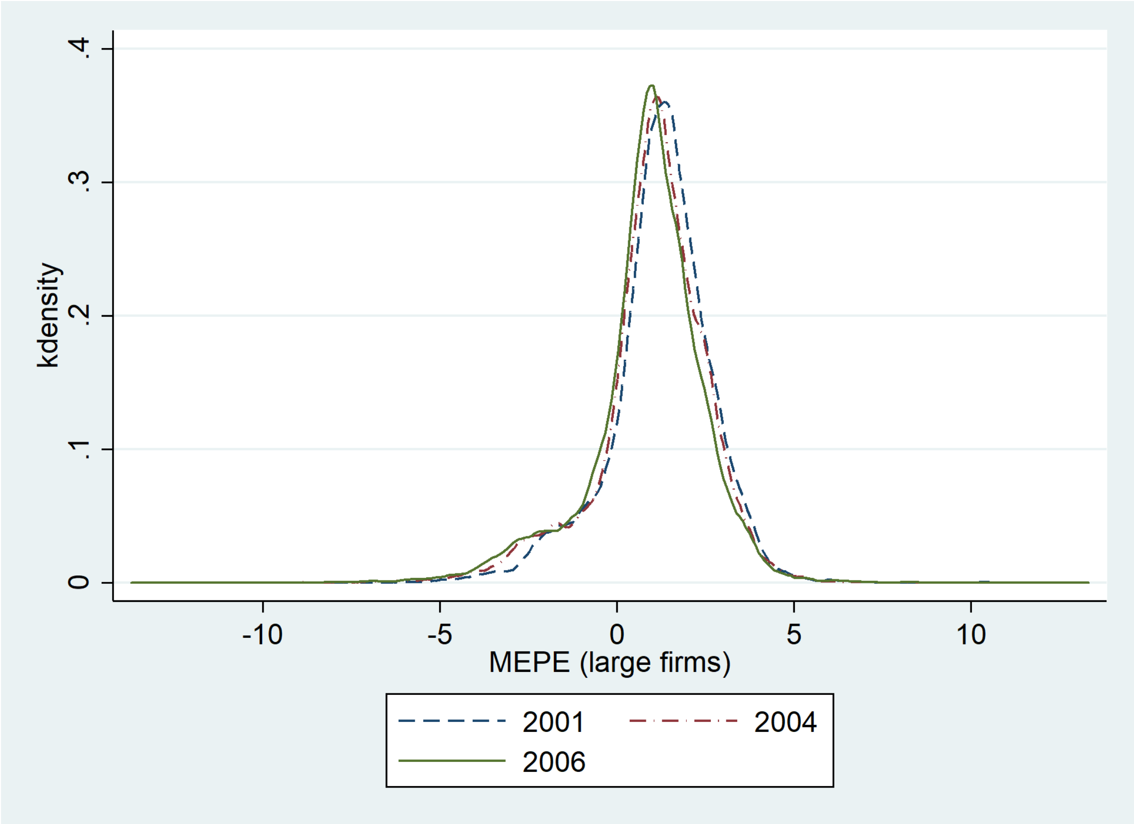


Figure 5.1: MEPE dispersion for big firms

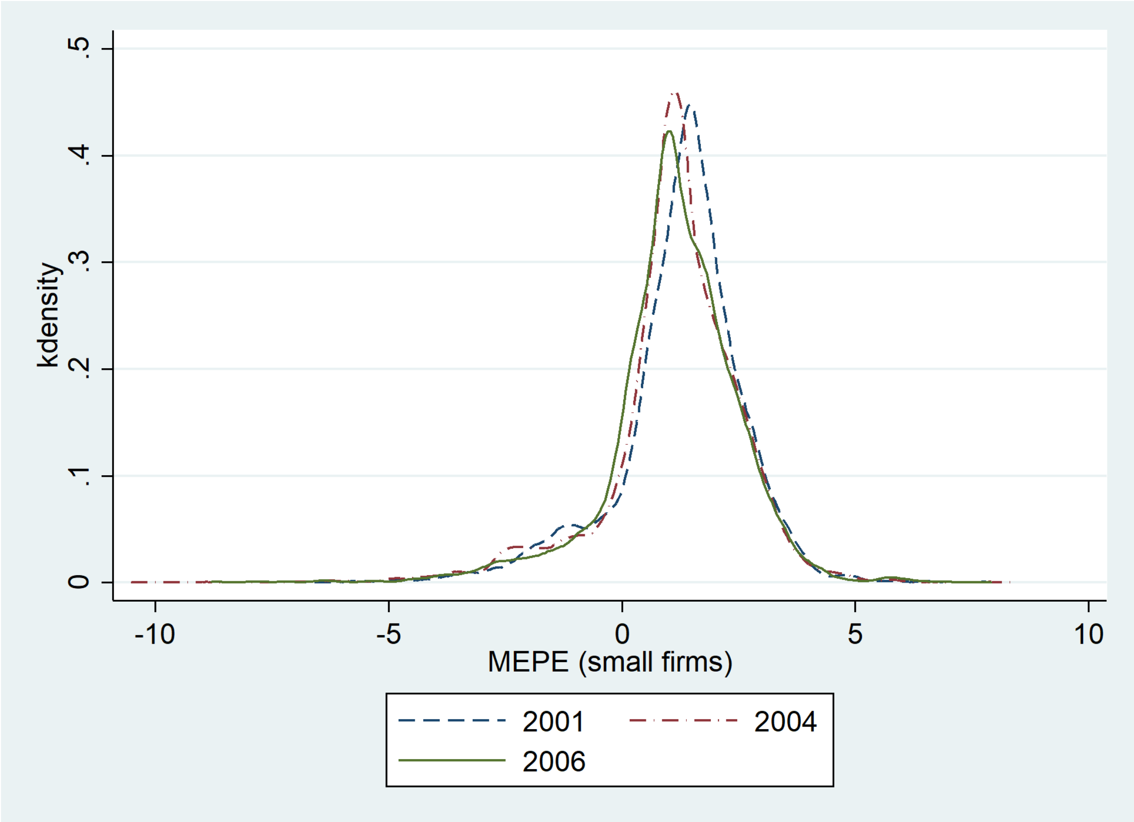


Figure 5.2: MEPE dispersion for small firms

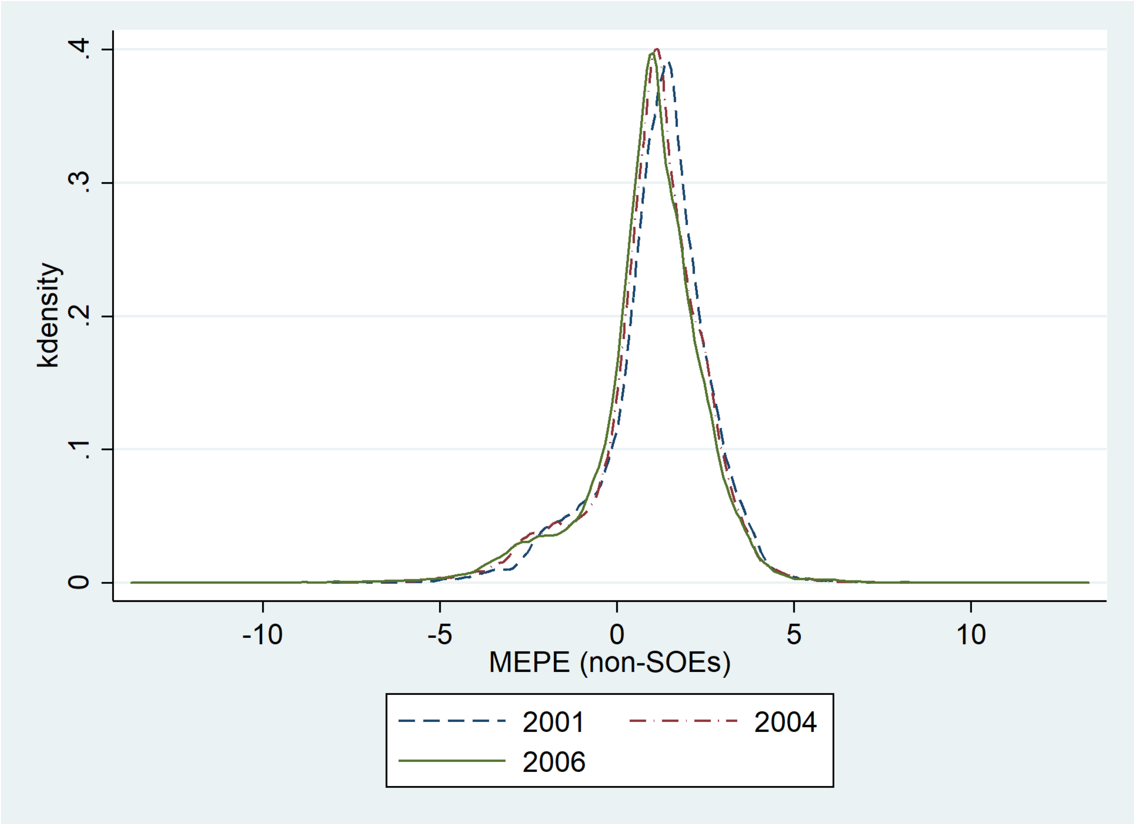


Figure 5.3: MEPE dispersion for non-SOEs

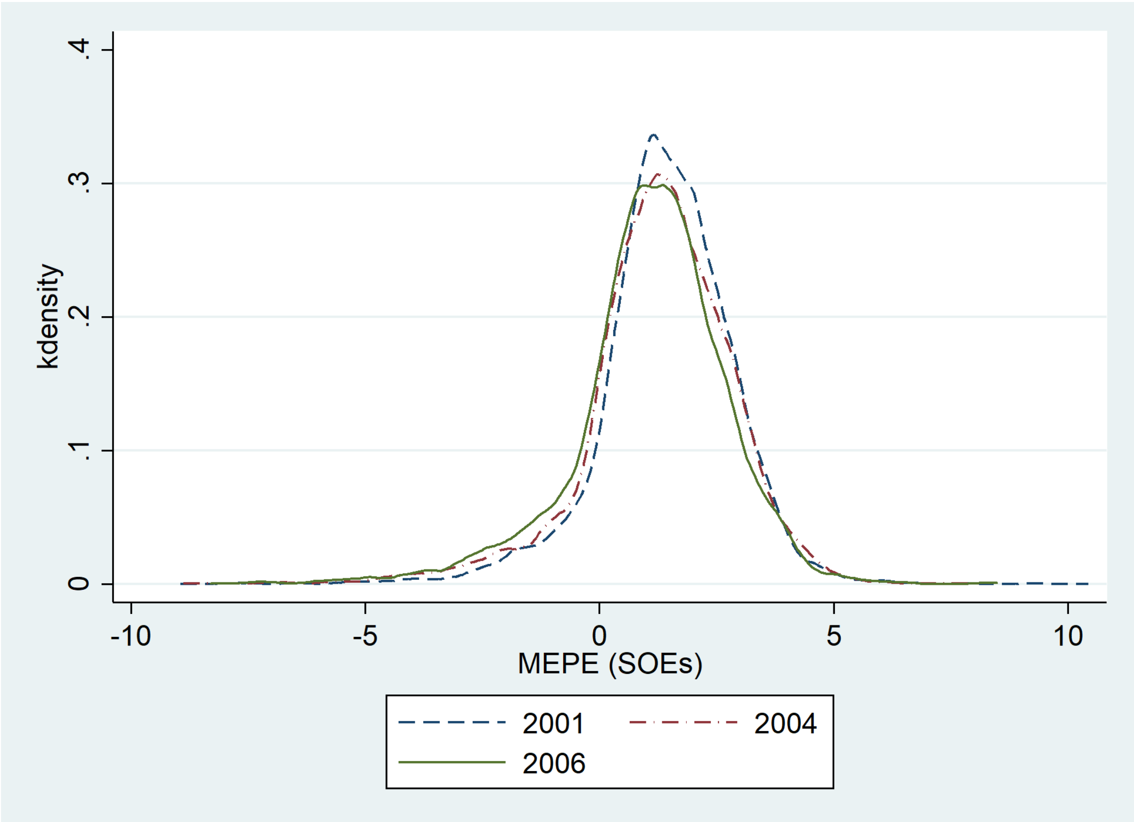


Figure 5.4: MEPE dispersion for SOEs

Table 5.3: Summary statistics by groups

$MEPE_{ACF}$	large firms		small firms		non-SOEs		SOEs	
Year	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
2001	1.53	1.60	1.47	1.48	1.44	1.57	1.78	1.58
2002	1.52	1.63	1.35	1.56	1.43	1.61	1.72	1.61
2003	1.52	1.65	1.47	1.55	1.44	1.63	1.81	1.62
2004	1.31	1.66	1.31	1.53	1.25	1.63	1.59	1.68
2005	1.15	1.63	1.21	1.41	1.18	1.57	1.39	1.70
2006	1.14	1.74	1.34	1.48	1.13	1.67	1.44	1.73
2007	0.91	1.59	1.10	1.38	0.95	1.52	1.05	1.66

5.4 Empirical strategies and estimation result

5.4.1 Basic regression: the TCZ policy's dynamic effect on firms' environmental efficiency

I start by investigating the effect of the TCZ policy on firm emissions efficiency which is denoted by MEPE. Equation 5.16, which shows the dynamic effect and heterogeneous effect of environmental regulation, is introduced to estimate the whole samples and the observations of different sub-groups. Equation 5.16 is

$$\begin{aligned} MEPE_{it} = &\alpha_{ijpt} + \beta_1 * TCZ_i * Y2002_t + \beta_2 * TCZ_i * Y2003_t + \beta_3 * TCZ_i * Y2004_t \\ &+ \beta_4 * TCZ_i * Y2005_t + \beta_5 * TCZ_i * Y2006_t + \beta_6 * TCZ_i * Y2007_t \\ &+ \gamma * Controls_{ijpt} + \mu_i + \nu_j + \gamma_p + \sigma_t + \epsilon_{ijpt} \end{aligned} \tag{5.16}$$

where, $MEPE_{it}$, is the logarithm of marginal emission per energy use; TCZ_i indicates whether firm i located in the TCZ area, i.e., $TCZ_i = 1$ if the firm i is located inside the TCZ area, $TCZ_i = 0$ otherwise; $Y2002_t$ dummy denotes the observed year in 2002, $Y2002_t = 1 \; \forall \; t = 2002$, $Y2002_t = 0$ otherwise. Similar to this, $Y2003_t$ to $Y2007_t$ denotes 2003 dummy to 2007 dummy respectively.

The sample period of this research is from 2001 to 2007. As the Chinese province-level oil price and coal price information are available from 2001, the sample period starts from one year after policy implementation. I interact the TCZ with dummies from 2002 because 2001 is chosen as the base year in regression to avoid multi-collinearity issues.

$Controls$ shows a vector of control variables denoting firm features. It includes variables denoting 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*.

μ_i are firm fixed effects, capturing firm i's time-invariant characteristics, such as geographic features, natural endowment, etc.; v_j denotes the sector fixed effects, capturing industrial j's time-invariant features; γ_p is the province fixed effect; 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.

Table 5.4: The dynamic effect of environmental policies on firms' MEPE

Dev. Var: $MEPE_{ACF}$	(1)	(2)	(3)	(4)	(5)
	Total samples	Big firms	Small firms	non-SOEs	SOEs
$TCZ * Y2002$	-0.050***	-0.043**	-0.040	-0.043**	-0.056
	(0.017)	(0.019)	(0.043)	(0.020)	(0.034)
$TCZ * Y2003$	-0.042**	-0.032	-0.001	-0.035*	-0.058
	(0.019)	(0.021)	(0.046)	(0.021)	(0.041)
$TCZ * Y2004$	-0.129***	-0.115***	-0.148***	-0.122***	-0.154***
	(0.020)	(0.023)	(0.053)	(0.023)	(0.046)
$TCZ * Y2005$	-0.109***	-0.118***	-0.012	-0.094***	-0.178***
	(0.021)	(0.024)	(0.055)	(0.024)	(0.050)
$TCZ * Y2006$	-0.166***	-0.181***	-0.058	-0.158***	-0.180***
	(0.023)	(0.027)	(0.057)	(0.026)	(0.057)
$TCZ * Y2007$	-0.105***	-0.107***	-0.070	-0.101***	-0.090
	(0.024)	(0.027)	(0.058)	(0.026)	(0.063)
$Y2002$	-0.081***	-0.085***	-0.065*	-0.094***	-0.051**
	(0.014)	(0.016)	(0.037)	(0.017)	(0.025)
$Y2003$	-0.007	-0.014	-0.024	-0.015	0.011
	(0.015)	(0.017)	(0.038)	(0.018)	(0.029)
$Y2004$	-0.107***	-0.120***	-0.059	-0.114***	-0.089***
	(0.017)	(0.018)	(0.046)	(0.020)	(0.032)
$Y2005$	-0.268***	-0.262***	-0.317***	-0.286***	-0.198***
	(0.017)	(0.019)	(0.046)	(0.020)	(0.036)
$Y2006$	-0.183***	-0.169***	-0.249***	-0.198***	-0.133***
	(0.019)	(0.022)	(0.049)	(0.022)	(0.040)
$Y2007$	-0.311***	-0.311***	-0.297***	-0.320***	-0.310***
	(0.019)	(0.022)	(0.051)	(0.022)	(0.045)
Control variables	YES	YES	YES	YES	YES
Company FE/Industry FE/Province FE	YES	YES	YES	YES	YES
R-squared	0.075	0.076	0.070	0.073	0.091
Observations	156,202	123,121	33,081	133,415	22,787

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

Table 5.4 reports the dynamic estimation result using equation 5.16. Table 5.4's Column (1) is the regression result based on the whole samples. Columns (2) and (3) are the estimation result using big firms and small firms respectively. As for firm ownership, column (4) is the regression result for non-SOEs, while column (5) is the result for state-owned enterprises (SOEs).

Column (1) of Table 5.4 indicates that firms' marginal emission of energy decreased significantly every year after TCZ implementation as the coefficients of each interaction term are negative. This implies that environmental efficiency (or emissions efficiency) is improved because firms on average generate fewer pollutants with one additional unit of energy consumption. In particular, the average MEPE was reduced by 5% and 4.2% in 2002 and 2003 respectively, while it was reduced from 10.5% to 16.6% each year from 2004 to 2007. Firms under-regulated by environmental policy experienced more environmental efficiency improvement after 2004 as the reduced point is more than twice that before 2004.

The more pronounced increase in environmental efficiency after 2004 is attributed to the implementation of the Discharge Fee policy which imposes a tax on enterprises based on the amount of pollutants they emit. Discharge fees were generally considered becoming effective after 2003 when a state order was implemented (Gowrisankaran et al., 2020). On February 28, 2003,*Administrative Measures for the Collection Standard of Pollutant Discharge Fees* (which came into force on July 1, 2003) were jointly issued by the National Development Planning Commission, the Ministry of Finance, the State Environmental Protection Administration, and the State Economic and Trade Commission. This made specific provisions for the charging standards for discharge fees.

During the research period (2001-2007), discharge fees were the same across provinces but varied over provinces from 2007 onwards. The amount of discharge fee a firm has to pay is determined by the quantity of pollutants it discharges, specifically air pollutants of sulphur dioxide (SO_2) and nitrous oxides (NO_2). In 2003, most Chinese provinces (except Xinjiang province, and Beijing which charged a higher SO2 fee in 2003) started charging fees of CNY 0.21 per kilogramme of SO_2. The discharge fee was doubled in 2004 and raised again by 50% in 2005.

In column (1) of Table 5.4, the coefficients of the year dummy denote the year effect on firms' MEPE. Except for the year 2003, the other coefficients of the year dummy are significantly negative. From 2004 in particular, the annual decrease in MEPE increases from 10.7% to 31.1%. This moving trend is consistent with the implementation of the discharge fee. Thus, environmental regulation significantly reduces a firm's marginal emissions per energy use, and stricter regulation, like the implementation of both the TCZ and discharge fee policies, can induce a more evident reduction in firm MEPE.

5.4.2 Firm size

Comparing the results of columns (2) and (3) of Table 5.4, I find evidence that the TCZ policy is more effective in reducing big firms' MEPE than small firms'. As shown in column (2), the policy significantly reduced big-size firms' MEPE every year except in 2003. However, small-size firms (column (3)) only significantly reduced their MEPE in 2004, which is a weaker dynamic effect than that of big firms. Figure 5.5 plots the coefficient and the confidence interval of Table 5.4's columns (2) and (3), displaying the more effective impact of environmental regulation on big firms than on small ones. The red line shows the coefficients estimated using big-size firms, and the blue line shows the coefficients estimated using small ones.

There are two potential reasons that help to explain why small firms are less responsive than big firms. First, due to financial constraints small firms do not have the ability to make any changes to environmental regulations. Firm size can be a proxy for the extent of asymmetric information. Due to adverse selection problems, smaller and younger firms may find it harder to raise external funds, whereas larger and older firms are more diversified and can raise funds more easily (Ding et al., 2021; Ek and Wu, 2018; Hovakimian, 2011). Financial constraints would limit small firms' ability to adapt production in a better way. Without external funds, they cannot afford the new investment relating to emissions reduction technology and fail to provide continuous investment as big firms do. Thus, financial constraints are one reason why environmental regulation is more effective for big firms than for small ones. Sufficient technology investment and equipment investment support would help small firms improve and be as environmentally efficient as big firms.

Second, the phenomenon of more effective regulation of big firms can be explained by 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 widely adopted in policy implementation (Hsieh and Song, 2015; He et al., 2018). [1] The selective control of large enterprises by local governments also contributes to the heterogeneity effect of environmental regulation.

5.4.3 Ownership

Columns (4) and (5) of Table 5.4 show that environmental regulations are more effective in reducing non-SOEs' MEPE than state-owned enterprises'. In column (4), regulation significantly reduced nonSOEs' MEPE from 2002 to 2007. But, as

[1] 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.

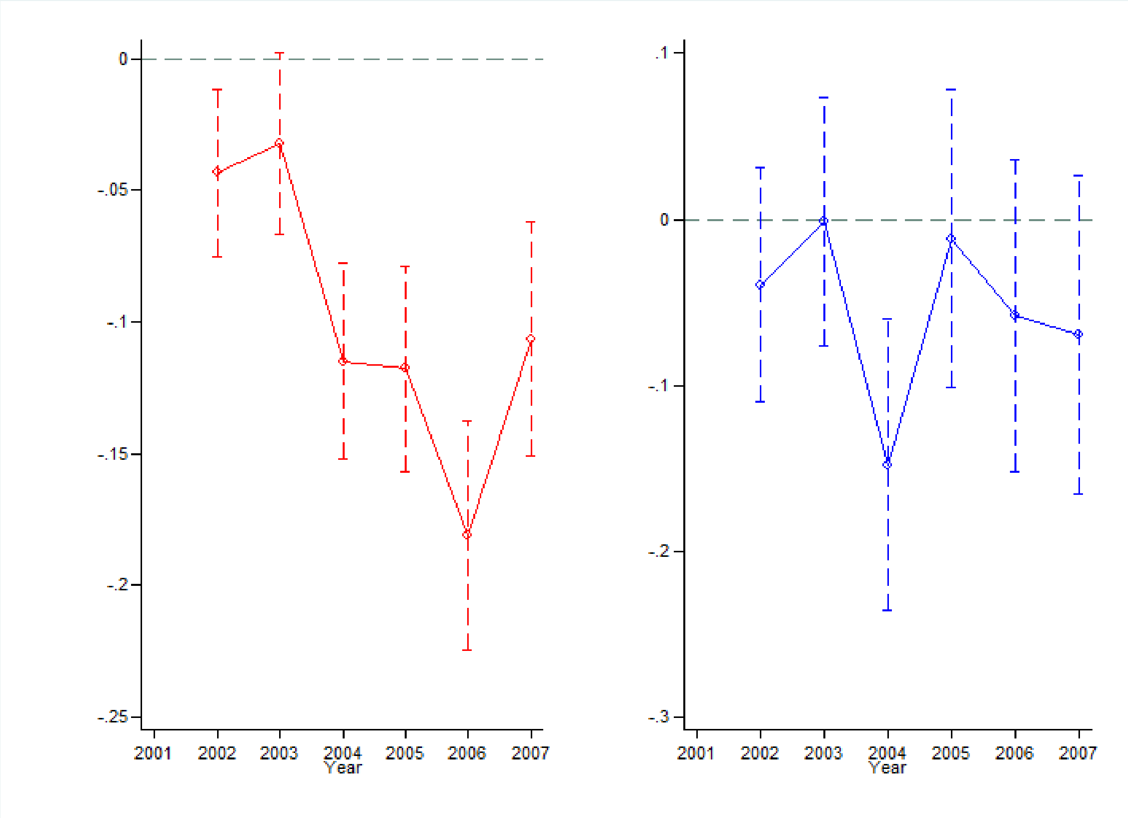


Figure 5.5: Regression result within the big firm or small firm group

Note: the red line shows the coefficient estimated using big firms, the blue line shows the coefficient estimated using small firms

shown in column (5), environmental regulation began to significantly reduce state-owned enterprises' MEPE from 2004, which is the year in which the emissions fee was levied. Before the emission fee policy was implemented (2002 and 2003), the TCZ policy alone failed to reduce state-owned firms' MEPE and could not increase their emissions efficiency. After 2004, stricter regulation (both policies relating to $SO2$ pollutants were implemented) stimulated SOEs to improve their technology and emissions efficiency. Compared with the effect of environmental regulation on non-SOEs, its impact on SOEs is much less effective and it is clear that softer regulation cannot improve SOEs' emissions efficiency successfully.

However, the magnitude of the coefficients of SOEs is higher than those of non-SOEs in 2004, 2005, and 2006. First, SOEs are not motivated to improve their technology and environmental efficiency at the beginning of policy implementation. SOEs are too big to fall and are more likely to be able to afford the emissions fee (Wang et al., 2018a; Wang and Wheeler, 2003). SOEs took three years to react to the TCZ policy. SOEs adhere more closely to their original production structure than private firms. However, after 2003, SOEs experienced more increase in environmental efficiency than private firms because they are facing less financial constraints. SOEs are more likely to secure loans from banks than private firms. High financial support induces more investment in environmental technologies.

Second, the higher improvement in SOEs' environmental efficiency is a consequence of low-productivity firms' exiting behaviour. SOEs are less effective than private and foreign-owned firms (Ding et al., 2019b; Brandt et al., 2012). With strict regulations, low-efficiency firms exit the market. After three years of screening, the remaining enterprises exhibit higher efficiency. That is another reason for the higher coefficient for the SOE group's regression.

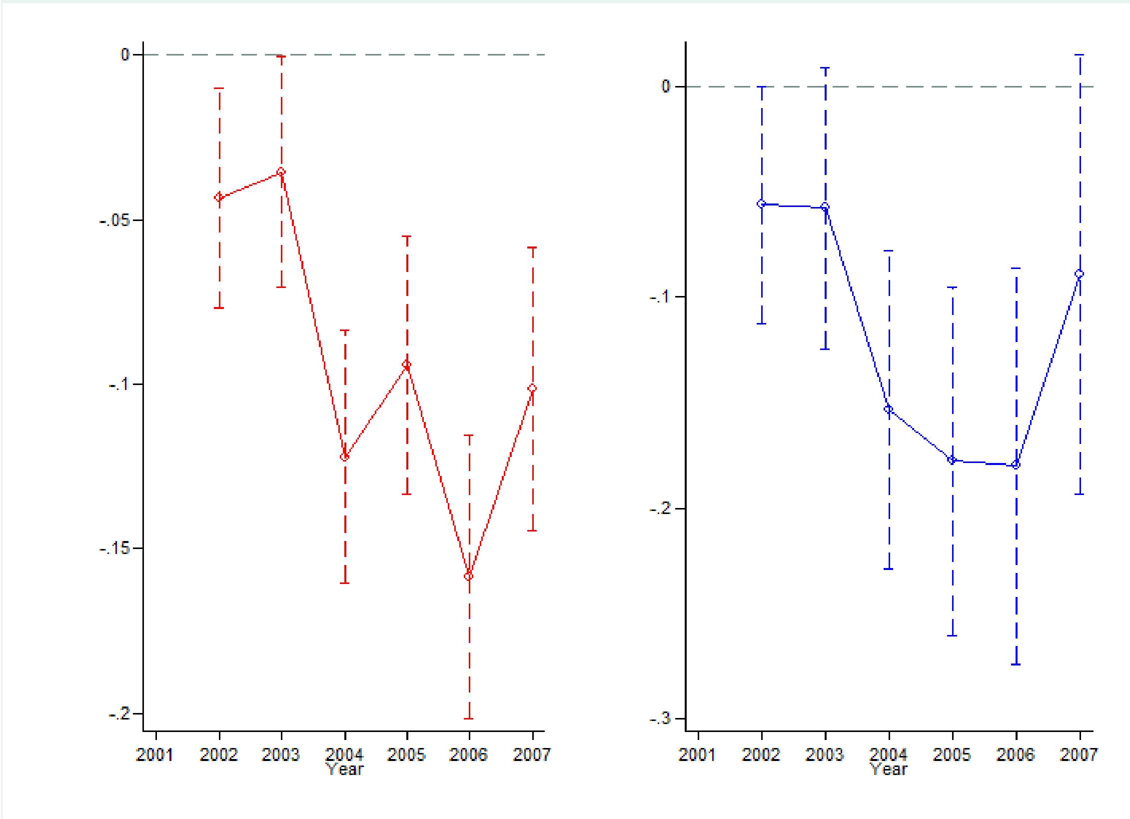


Figure 5.6: Regression result within SOEs or non-SOEs group

Note: the red line shows the coefficient estimated using SOEs, the blue line shows the coefficient estimated using non-SOEs

5.4.4 The TCZ policy's impact on environmental misallocation

In this section, the effect of the TCZ policy on MEPE dispersion is estimated. Equation 5.17 is the estimation equation, where I use the standard deviation of $MEPE$ within the same industry, same province, TCZ area, and the same year, as the dependent variable.

$$
\begin{aligned}
sd(MEPE)_{jrt} = \alpha_{jrt} &+ \beta_1 * TCZ_r * Y2002_t + \beta_2 * TCZ_r * Y2003_t \\
&+ \beta_3 * TCZ_r * Y2004_t + \beta_4 * TCZ_i * Y2005_t + \beta_5 * TCZ_r * Y2006_t \\
&+ \beta_6 * TCZ_r * Y2007_t + X_{jrt} + \nu_j + \gamma_p + \sigma_t + \epsilon_{jrt}
\end{aligned} \tag{5.17}
$$

The dependent variable, $sd(MEPE)_{jrt}$, is the standard derivation of $MEPE$ for firms within the same industry j, same region r, and same year t. I rename region r based on its province and whether a region is located in the TCZ area. For example, if only parts of a province are located in the TCZ area, then there will be two regions in this province. if the whole province is inside or outside the TCZ area, then there will only be one region in the province.

TCZ_r is a dummy denoting whether the standard deviation is computed based on firms in the TCZ region of a province.

X_{jpt} shows the vector of control variables denoting industry or province characteristics. It includes government size, $GovSize_{pt}$; Inflation, $Inflation_{pt}$; and provincial coal consumption intensity, $CoalInt_{pt}$. Variables used to control industrial characteristics include the Herfindahl-Hirschman Index (HHI), HHI_{jt}; the ratio between SOEs' sales and the industry's aggregate sales, $SOEshare_{jt}$.

Table 5.5 indicates the result of the dynamic effect of the TCZ policy on the dispersion of MEPE. From columns (1) to (4), the dependent variable, standard deviation of MEPE ($\sigma(MEPE)$), is computed applying the Ackerberg et al. (2015) approach, the Wooldridge (2009) approach, the Olley and Pakes (1996) approach, and the Levinsohn and Petrin (2003) approach respectively.

The result of Table 5.5's Column (1) shows that the TCZ policy increased environmental dispersion in most years. As a robustness check, column (2) to column (4) get consistent results. The positive effect of regulation on MEPE dispersion is getting larger (from 8.6% in 2003 to 15.7% in 2006) with more stringent regulation. Even though environmental regulation reduced firms' MEPE average (or averagely increased firms' environmental regulation), the dispersion of MEPE is getting larger. Environmental regulation results in increased environmental misallocation. As shown in the above firm-level analysis, the environmental policy has a heterogeneity effect on firms' MEPE, which finally caused the increased dispersion of MEPE.

Most of the control variables are significantly correlated with the environmental misallocation indicators. The coefficient of government size is insignificant, reflecting the fact that government intervention can not generate MEPE dispersion across firms. Inflation is found to have a positive impact on MEPE dispersion, indicating that reducing inflation could help production allocation and reduce the dispersion of MEPE. Inflation influences energy resource prices directly, as less volatile energy prices allow companies to be more flexible in the use of energy elements, which would favour the reduction of environmental misallocation. Inflation is not a commonly used control variable in papers relating to environmental economics. However, the empirical literature relating to resource misallocation, such as Ding et al. (2019a), suggests its negative effect on resource dispersion.

I find a negative effect for provincial coal consumption intensity on MEPE dispersion, suggesting the beneficial effect of agglomeration in terms of inducing pollutant mitigation technology and the spillover of these techniques. The HHI indicator, which is used to denote firm size structure for the firms in the same area and same sector, does not significantly correlate to MEPE dispersion. Market concentration is not correlated with environmental misallocation. Lastly, I find a negative effect on MEPE dispersion for the proportion of SOEs in an industry and an area. This implies that an industry with more SOEs would have less MEPS dispersion. SOEs always have more bargaining power than non-SOEs concerning the enforcement of environmental regulations such as pollution charges and fines (Wang et al., 2018a; Wang and Wheeler, 2003). To comply with environmental regulations, private firms are more likely to take all measures to reduce emissions. SOEs do not have as much motivation as private firms to improve pollutant reduction technology.

5.4.5 Quantile treatment effect of the TCZ policy

The distribution of MEPE may change in many ways that can not be revealed only by an examination of averages. The quantile treatment effect method (QTE) is useful in this research, where I am interested in understanding treatment effect heterogeneity. In this study, the average treatment effect (ATE) is useful for the discussion about whether or not being regulated by environmental policies tends to reduce firms' MEPE (or increase the dispersion of MEPE in the later content); while the quantile treatment effect (QTE) is useful for the discussion about whether regulation affects the MEPE of firms at the top of the MEPE distribution more than that of firms at the bottom of it. Thus, in addition to the average impact the environmental regulations, I also investigate their quantile treatment effect.

QTEs are defined as the difference between the quantiles (for a particular value of t) of the treated potential outcome distribution and the untreated potential outcome distribution. If observations (units) maintain their rank in the treated and

Table 5.5: The dynamic effect of environmental policies on the dispersion of MEPE

VARIABLES	(1) $\sigma(MEPE_{ACF})$	(2) $\sigma(MEPE_{Wooldrige})$	(3) $\sigma(MEPE_{OP})$	(4) $\sigma(MEPE_{LP})$
$TCZ * Y2002$	0.038	0.026	0.028	0.033
	(0.040)	(0.038)	(0.038)	(0.039)
$TCZ * Y2003$	0.086**	0.086**	0.083**	0.090**
	(0.043)	(0.041)	(0.041)	(0.042)
$TCZ * Y2004$	0.105**	0.117***	0.115***	0.114***
	(0.045)	(0.044)	(0.043)	(0.044)
$TCZ * Y2005$	0.069	0.070	0.066	0.075*
	(0.045)	(0.044)	(0.044)	(0.044)
$TCZ * Y2006$	0.157***	0.146***	0.142***	0.144***
	(0.047)	(0.046)	(0.046)	(0.046)
$TCZ * Y2007$	0.111**	0.125**	0.125**	0.127**
	(0.051)	(0.050)	(0.050)	(0.050)
$GovSize$	-0.112	-0.030	-0.016	-0.052
	(0.131)	(0.132)	(0.132)	(0.131)
$Inflation$	0.018*	0.019*	0.019**	0.016*
	(0.010)	(0.010)	(0.010)	(0.009)
$CoalInt$	-0.061**	-0.063**	-0.061**	-0.055**
	(0.027)	(0.027)	(0.027)	(0.027)
HHI	-0.002	-0.007	-0.008	0.001
	(0.022)	(0.022)	(0.021)	(0.022)
$SOEshare$	-0.039***	-0.040***	-0.039***	-0.040***
	(0.014)	(0.014)	(0.014)	(0.014)
Constant	0.813***	1.004***	1.040***	0.903***
	(0.308)	(0.306)	(0.305)	(0.306)
Province FE/Year FE	Yes	Yes	Yes	Yes
R-squared	0.011	0.012	0.011	0.010
Observations	7,034	7,118	7,196	7,313

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

untreated distributions and the QTE is increasing in τ (the τ-th quantile), then the QTE equals to the quantiles of the treatment effect. For $\tau \in [0, 1]$

$$QTE(\tau) = F_{Y_1}^{-1}(\tau) - F_{Y_0}^{-1}(\tau) \tag{5.18}$$

where F_{Y_1} is the distribution function for the treated potential outcome, and F_{Y_0} is the distribution function for the untreated potential outcome.

In the above section, on average, I find that environmental regulation has reduced firms' MEPE. Figure 5.7 shows the quantile treatment effect of environmental regulation on firms' MEPE. The quantile treatment effect is estimated by the Recentered influence functions (RIFs) regression. The horizontal line shows the distribution of the outcome (MEPE). The vertical line shows the treatment effect for each quantile. Each point represents the average treatment effect from 2002 to 2007 in different quantiles. The negative effect in most years implies improved environmental efficiency. At the low end of the distribution of MEPE, the effect of complying with environmental regulation has much more impact on reducing MEPE. The top 20% of firms have reduced more MEPE than the average level, while the bottom 10% of firms did not significantly reduce their MEPE after regulation.

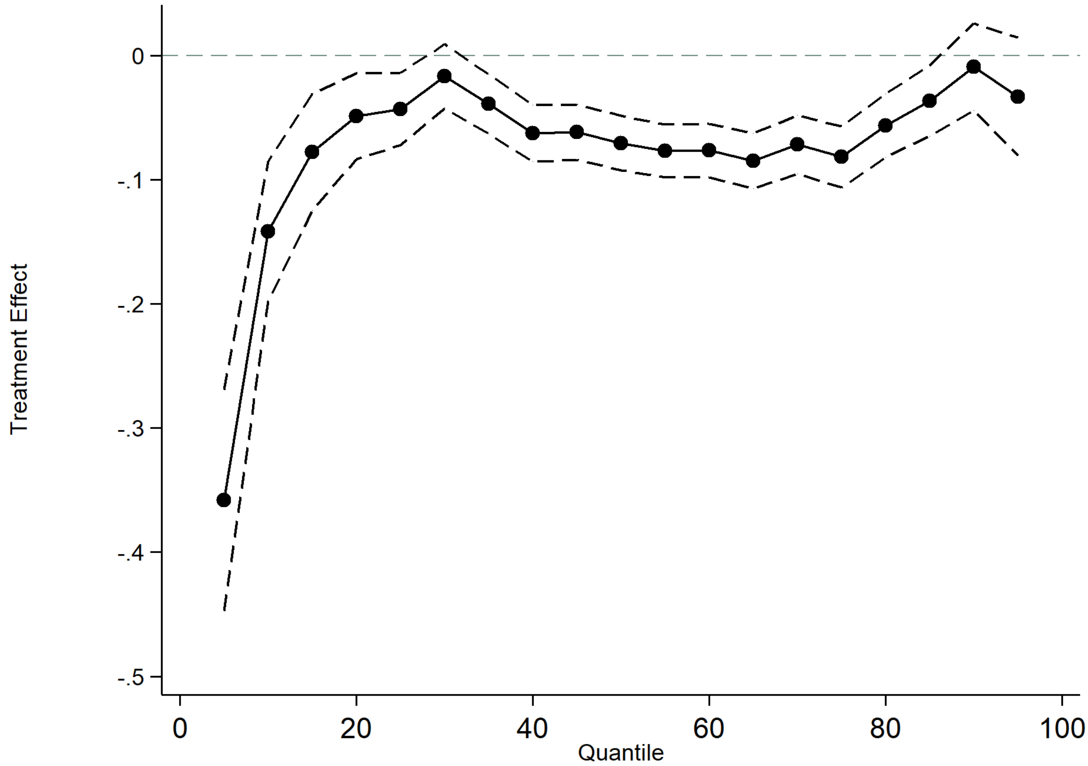


Figure 5.7: Quantile treatment effect for firm-level regression

Note: The quantile treatment effect is estimated by the Recentered influence functions (RIFs) regression. The horizontal line shows the distribution of the outcome (MEPE). The vertical line shows the treatment effect for each quantile. Each point represents the average treatment effect from 2002 to 2007 in different quantiles.

There is much heterogeneity in the quantile treatment effect of environmental regulation on the dispersion of MEPE. As shown in Figure 5.8, at the low end of the distribution of MEPE dispersion, the effect of environmental regulation on the dispersion of MEPE appears to be negative. For example, at the 10th percentile, the logarithm of dispersion of MEPE is estimated to be 0.045 points lower following the regulation than it would have been without any regulation. It implies that the TCZ policy can reduce environmental misallocation in the top 10% of regions that have lower original MEPE dispersion.

However, in the middle and upper parts of the MEPE dispersion distribution, environmental regulation appears to increase dispersion. In 45% to 85% of the distribution, the TCZ policy increased these observations' MEPE dispersion. Thus the positive effect of the TCZ policy on environmental misallocation is mainly contributed from the observations from 25 to 85 quantile.

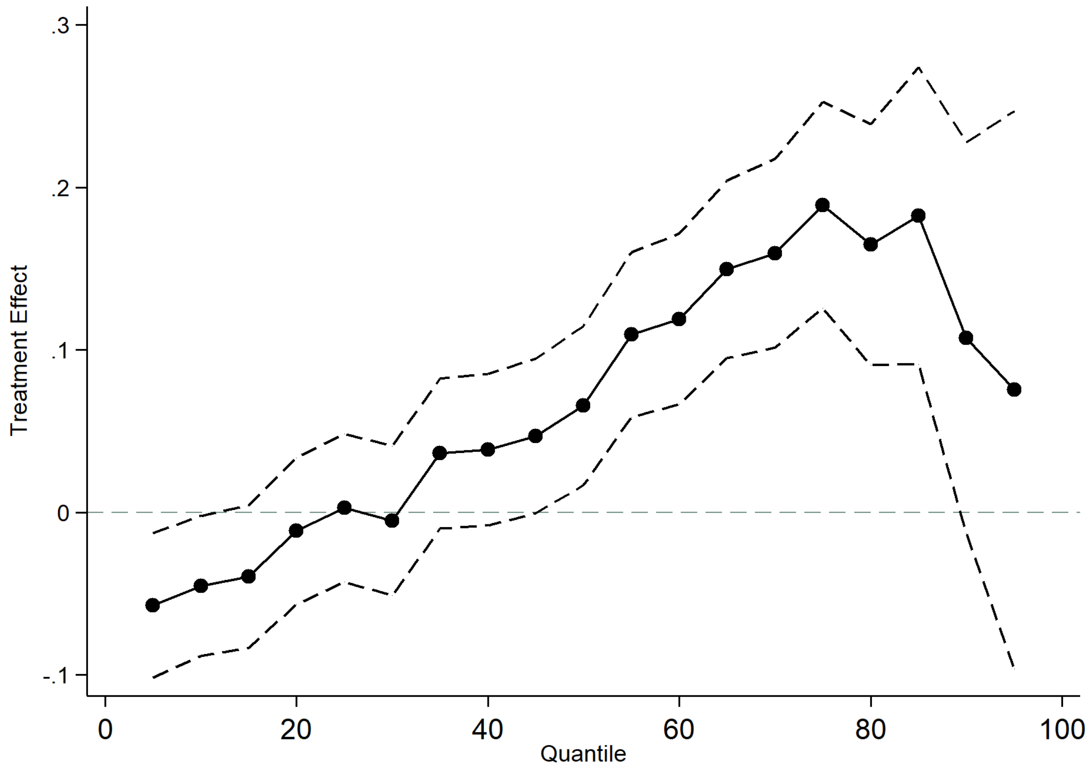


Figure 5.8: Quantile treatment effect for industrial level regression

Note: The quantile treatment effect is estimated by the Recentered influence functions (RIFs) regression. The horizontal line shows the distribution of the outcome (MEPE). The vertical line shows the treatment effect for each quantile. Each point represents the average treatment effect from 2002 to 2007 in different quantiles.

5.4.6 Aggregate emissions reduction with a better allocation

Under optimal (counterfactual) conditions, in this study all firms in a sector would have the same marginal emission of energy with aggregate emission minimization and firm profit maximization assumptions. However, I do not know firms' constant MEPE under optimal conditions. Thus, I considered a better allocation condition inspired by Asker et al. (2019) and Correa et al. (2021a) in which the production amount is reallocated across firms with aggregate production output fixed.

To investigate aggregate emissions reduction under better allocation conditions, I proceed with the following steps. First, I re-rank firms in the same sector (2-digit) in ascending order based on the firm's MEPE. Second, a firm's production capacity at year t is assumed to be 1.1 times its real output. Third, keeping the aggregate production of a sector fixed, I let the No.1 firm (by ranking) produce to maximum capacity first. Then, the No.2 firm produces to its capacity. Letting the aggregate output equal the original one, firms with lower environmental efficiency would be shut down. Finally, each firm's emissions can be calculated by using their MEPE and the new production. The new aggregate emissions under better allocation are the sum of each existing firm's emissions.

Table 5.6 shows the aggregate emissions for real and better allocation conditions in each year. It implies that aggregate emissions can be reduced by approximately 30% under better allocation conditions.

Table 5.6: Aggregate emission reduction with better allocation

Year	Real emission	Better allocation	Percentage reduction
2001	8.98	6.25	30.4%
2002	10.2	6.97	31.7%
2003	12.8	8.38	34.5%
2004	13.3	9.24	30.5%
2005	18.2	13.0	28.6%
2006	8.77	6.31	28.1%
2007	7.29	5.31	27.2%

Note: the unite is million ton.

5.5 Robustness test

5.5.1 Computing MEPE with various approaches

I use another three approaches to computing the MEPE again: the Wooldridge (2009) approach, the Olley and Pakes (1996) approach, and the Levinsohn and Petrin (2003) approach. Applying these three approaches, I examine the robustness of the environmental misallocation measurement. The result in Table 5.7 is consistent with column (1) of Table 5.4. Regulation significantly reduced firms' MEPE in 2002, 2004, and 2006. The result in Table 5.8 is consistent with columns (2) and (3) of Table 5.4. The environmental policy has a more effective impact on big firms than on small ones. The result in Table 5.9 is consistent with the result in columns (4) and (5) of Table 5.4.

Table 5.7: The effect of TCZ policy on firm MEPE estimated on whole samples

Dev. Var	(1) $MEPE_{Wooldrige}$	(2) $MEPE_{OP}$	(3) $MEPE_{LP}$
$TCZ * Y2002$	-0.050***	-0.050***	-0.050***
	(0.017)	(0.017)	(0.017)
$TCZ * Y2003$	-0.043**	-0.043**	-0.043**
	(0.018)	(0.018)	(0.018)
$TCZ * Y2004$	-0.134***	-0.133***	-0.131***
	(0.020)	(0.020)	(0.020)
$TCZ * Y2005$	-0.113***	-0.114***	-0.113***
	(0.021)	(0.021)	(0.021)
$TCZ * Y2006$	-0.168***	-0.170***	-0.170***
	(0.023)	(0.023)	(0.023)
$TCZ * Y2007$	-0.105***	-0.102***	-0.105***
	(0.023)	(0.023)	(0.023)
Control variables	YES	YES	YES
Company FE/Industry FE/Province FE/Year FE	YES	YES	YES
R-squared	0.041	0.042	0.042
Observations	157,913	158,408	159,166

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

5.5.2 Considering the effect of emissions fees

As the discharge fee on sulphur dioxide was levied, environmental regulation became more stringent for firms in the TCZ area after 2004. In this section, I identify the joint effect of the TCZ policy and discharge fee implementation on MEPE and MEPE dispersion. Equation 5.19 is used to estimate the impact of stricter environ-

Table 5.8: The effect of TCZ policy on MEPE across firm size

	(1)	(2)	(3)	(4)	(5)	(6)
		Big firms			Small firms	
Dev. Var	$MEPE_{Wooldrige}$	$MEPE_{OP}$	$MEPE_{LP}$	$MEPE_{Wooldrige}$	$MEPE_{OP}$	$MEPE_{LP}$
$TCZ * Y2002$	-0.044**	-0.044**	-0.044**	-0.039	-0.039	-0.041
	(0.019)	(0.019)	(0.019)	(0.043)	(0.043)	(0.043)
$TCZ * Y2003$	-0.035*	-0.034	-0.033	-0.001	-0.002	-0.005
	(0.021)	(0.021)	(0.021)	(0.045)	(0.045)	(0.045)
$TCZ * Y2004$	-0.119***	-0.118***	-0.117***	-0.162***	-0.163***	-0.154***
	(0.023)	(0.023)	(0.022)	(0.053)	(0.053)	(0.053)
$TCZ * Y2005$	-0.122***	-0.122***	-0.121***	-0.020	-0.021	-0.016
	(0.024)	(0.024)	(0.024)	(0.055)	(0.054)	(0.054)
$TCZ * Y2006$	-0.182***	-0.184***	-0.184***	-0.065	-0.063	-0.062
	(0.026)	(0.026)	(0.026)	(0.057)	(0.057)	(0.057)
$TCZ * Y2007$	-0.106***	-0.102***	-0.106***	-0.072	-0.073	-0.072
	(0.027)	(0.027)	(0.027)	(0.058)	(0.058)	(0.058)
Control variables	YES	YES	YES	YES	YES	YES
Company FE/Industry FE/Province FE/Year FE	YES	YES	YES	YES	YES	YES
R-squared	0.041	0.043	0.041	0.041	0.041	0.045
Observations	124,663	125,051	125,728	33,250	33,357	33,438

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

Table 5.9: The effect of TCZ policy on MEPE across ownership

	(1)	(2)	(3)	(4)	(5)	(6)
		non-SOEs			SOEs	
Dev. Var	$MEPE_{Wooldrige}$	$MEPE_{OP}$	$MEPE_{LP}$	$MEPE_{Wooldrige}$	$MEPE_{OP}$	$MEPE_{LP}$
$TCZ * Y2002$	-0.042**	-0.042**	-0.044**	-0.057*	-0.056*	-0.055
	(0.020)	(0.020)	(0.020)	(0.034)	(0.034)	(0.034)
$TCZ * Y2003$	-0.034	-0.035	-0.037*	-0.070*	-0.068*	-0.059
	(0.021)	(0.021)	(0.021)	(0.041)	(0.041)	(0.040)
$TCZ * Y2004$	-0.126***	-0.125***	-0.125***	-0.161***	-0.161***	-0.152***
	(0.023)	(0.023)	(0.023)	(0.046)	(0.046)	(0.045)
$TCZ * Y2005$	-0.097***	-0.097***	-0.099***	-0.185***	-0.186***	-0.177***
	(0.024)	(0.024)	(0.024)	(0.051)	(0.050)	(0.050)
$TCZ * Y2006$	-0.160***	-0.161***	-0.161***	-0.181***	-0.186***	-0.187***
	(0.026)	(0.026)	(0.026)	(0.057)	(0.057)	(0.057)
$TCZ * Y2007$	-0.099***	-0.097***	-0.101***	-0.103*	-0.098	-0.093
	(0.026)	(0.026)	(0.026)	(0.062)	(0.061)	(0.063)
Control variables	YES	YES	YES	YES	YES	YES
Company FE/Industry FE/Province FE/Year FE	YES	YES	YES	YES	YES	YES
R-squared	0.040	0.042	0.041	0.046	0.047	0.048
Observations	135,178	135,550	136,048	22,735	22,858	23,118

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

mental regulation on firm MEPE. The logarithm of marginal emission per energy use, $MEPE_{it}$, is the dependent variable. Whether a firm is complying with the dual-regulation is denoted by an interaction term ($TCZ_i * A2004_t$) between the TCZ dummy and a time dummy representing the time after 2004. Equation 5.19 is

$$MEPE_{it} = \alpha_{it} + \beta * TCZ_i * A2004_t + \gamma * Controls_{it} + \mu_i + \nu_j + \gamma_p + \sigma_t + \epsilon_{ijpt} \tag{5.19}$$

where, TCZ_i indicates whether firm i is located in TCZ area, i.e., $TCZ_i = 1$ if the firm i is located inside the TCZ area, $TCZ_i = 0$ otherwise; $A2004_t$ denotes the observed year after 2004, $A2004_t = 1 \ \forall \ t \geq 2004$, $A2004_t = 0$ otherwise.

$$\begin{aligned} MEPE_{it} = {} & \alpha_{ijpt} + \beta * TCZ_i * A2004_t * BigFirm + \gamma * Controls_{ijpt} + \mu_i \\ & + \nu_j + \gamma_p + \sigma_t + \epsilon_{ijpt} \end{aligned} \tag{5.20}$$

$$\begin{aligned} MEPE_{it} = {} & \alpha_{ijpt} + \beta * TCZ_i * A2004_t * nonSOE + \gamma * Controls_{ijpt} + \mu_i + \\ & \nu_j + \gamma_p + \sigma_t + \epsilon_{ijpt} \end{aligned} \tag{5.21}$$

Column (1) of Table 5.10 shows the estimation result of equation 5.19. The significantly negative coefficient of the interaction term, β, is what I am interested in. It indicates that compared with the firms without dual regulation, the firms complying with the TCZ policy and discharge fee policy reduced their MEPE by 33.5% $((e^{(-0.094)-1}))$. The reduced marginal emission per energy usage brought about by stricter regulation implies that environmental policies improved firms' environmental efficiency. With 1 unit of energy consumption, regulated firms generated fewer emissions than firms without regulation.

In column (2) of Table 5.10, the $BigFirm$ dummy is used to denote the firm size feature. It is considered that a firm with more than 100 labourers is a large firm ($BigFirm = 1$), otherwise it is small firms ($BigFirm = 0$). Under-regulated big firms reduced more MEPE than regulated small firms. Compared with small firms, big firms reduced their MEPE by 36.3% $((e^{(-0.063+0.049)-1}))$. Environmental regulation is more effective for big firms than small ones. In column (3), I employed another dummy, $nonSOE$, to denote firm ownership. It represents two groups of observations with different ownership, where $nonSOE = 0$ denotes state-owned firms and $nonSOE = 0$ otherwise.

Table 5.10: Dual regulation effect and firm heterogeneity effect

Dev. Var:	(1) $MEPE_{ACF}$	(2) $\sigma(MEPE_{ACF})$	(3) $MEPE_{ACF}$	(4) $MEPE_{ACF}$
$TCZ * A2004$	-0.094***	0.069**	-0.041	-0.112***
	(0.014)	(0.028)	(0.028)	(0.033)
$TCZ * A2004 * BigFirm$			-0.063**	
			(0.030)	
$TCZ * BigFirm$			0.049**	
			(0.019)	
$A2004 * BigFirm$			0.031	
			(0.024)	
$TCZ * A2004 * nonSOE$				0.022
				(0.037)
$TCZ * nonSOE$				0.082
				(0.094)
$A2004 * nonSOE$				-0.011
				(0.027)
Control variables	YES	YES	YES	YES
Company FE/Industry FE/Province FE/Year FE	YES	YES	YES	YES
R-squared	0.075	0.009	0.075	0.075
Observations	156,202	7,034	156,202	156,202

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The control variables include SO2 discharged amount, firm output, firm age, firm export amount, the number of labour by city and sector, waste gas discharged amount, and Plant dummy.

5.6 Conclusion

With the increase in Chinese people's income level, China is facing a dilemma that is 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 important. I have developed a novel approach to measure firms' environmental efficiency and the marginal emission of energy. The dispersion of marginal emission of energy is the proxy for environmental misallocation. I find that the environmental regulation policy has a significant impact on marginal emission per energy use and its dispersion.

Compared with firms without regulation, firms complying with the environmental policy averagely experienced a 4% to 16% drop in MEPE and an 8.6% to 15.7% rise in MEPE dispersion. The drop in marginal emission of energy due to the environmental policy shows that firms' environmental efficiency could be improved by adopting an appropriate regulation policy. The increase of MEPE dispersion due to environmental regulation represents the magnitude of environmental efficiency differences across firms in the sector that could be aggravated by policy implementation. In this sense, the impact of environmental policy on MEPE dispersion represents environmental misallocation.

To explain why environmental regulation brings more environmental misallocation, my heterogeneity analysis indicates that environmental regulations have a more effective impact on big firms and private firms than on small firms and SOEs. Because of financial constraints and difference in bargaining power, big firms and private firms are more willing and able to improve their environmental efficiency. Finally, aggregate emissions can be reduced by approximately 30% under better allocation conditions.

In developing countries, especially, air and water pollution from firms is of concern to policymakers. This research provides a perspective on emissions mitigation. While increasing the environmental efficiency of businesses, policymakers should also take into account the environmental technical gap that is widening as a result of environmental control regulations.

Chapter 6

Emission decomposition with entry and exit on China's polluting enterprises

6.1 Introduction

The challenge of explaining the decline in industry-level emissions intensity persists. The reduction could stem from adaptations in production techniques or investments in abatement by existing firms. It might also result from the reallocation of resources within industries towards less emissions-intensive firms, or from the exit of emissions-intense incumbents and the entry of comparatively cleaner firms. Identifying the mechanism accountable for the environmental improvement is crucial. Recognizing whether the reduction in emissions is primarily due to the closure of polluting firms or a decrease in emissions intensity at existing firms allows us to pinpoint potential factors behind the cleanup. If the environmental improvement is predominantly driven by the closure of polluting firms, enhanced environmental performance may be linked to disruption in the manufacturing industry (Holladay and LaPlue, 2021). The cleanup may raise concerns about market power within industries if it is driven by the reallocation within the industry towards the cleanest firms. Additionally, the involvement of various market powers in environmental improvement complicates assessments of the effectiveness of environmental regulations. The significance of firm selection or the reallocation of market shares in observed shifts in emissions implies that a precise analysis of the environmental impacts of policy changes must account for these effects (Holladay and LaPlue, 2021).

Aggregate emission changes over time are not only affected by shifts in the distribution of firm-level emissions (within-firm effect) but also by composition changes between firms, which are induced by shifts in market share between firms (between-firm effect), entries of new firms, and exit of incumbents. Decomposition methods are useful tools to shed light on the underlying causes of aggregate emission movements. In this chapter, I explored how various decompositions of aggregate emissions can capture their key microeconomic sources, such as the reallocation of resources between firms. My aggregate emission decomposition method is inspired by the commonly used shift-share decomposition method applied in literature on productivity or labour productivity.

In the analysis, I follow the dynamic decomposition method proposed by Melitz and Polanec (2015). Dynamic decomposition can measure the contributions of entry and exit and track individual firms over time. The upside of this approach is that it is more directly related to theoretical models of firm productivity heterogeneity because it is developed on moments of the distribution of productivity and market share. Theoretical models have been proposed to analyze the patterns of market share reallocation between firms and how they affect aggregate productivity (Hsieh and Klenow, 2009; Asker et al., 2014a).

The goal of this chapter is to decompose the gap of the weighted average reduction in emission between the TCZ area and non-TCZ area into survivors, entry, and exit channels. An economy in transition with very large emissions changes has been selected as an empirical case study: aggregate sulphur dioxide (SO2) discharged amount in China's TCZ area reduced by over 10% from 2000 to 2010 (*Report of the Ministry of Environmental Protection of the People's Republic of China, 2011*). It is therefore possible to decompose the substantial SO2 pollutant change into four components (emission distribution shifts among survivors, market share reallocations among survivors, entry, and exit). By comparing emissions reduction between in-TCZ and out-TCZ, I propose a difference-in-difference framework decomposition.

There are several reasons why I use DID framework decompositions for emissions growth. First, the difference-in-difference framework decomposition makes up for the deficiency in panel data analysis. The DID regression using panel data misses information on entering firms and exiting firms, as it can not display the channels of entrants and exiters on firm emissions. In the decomposition analysis, I decompose the weighted average emissions changes into the survival channel, entrance channel, and exit channel, and further break down the survival channel into the within-firm component and the cross-firm component. These key channels influencing aggregate emissions can only be investigated through decomposition analysis rather than panel regression analysis.

Second, the DID regression using panel data gives equal weight to each producer. In particular, equal weight analysis can not display differences in population and competition for various moments. Our DID framework decomposition complements the previous panel data regression analysis. The result uncovers findings that cannot be observed by panel regression. The entering and exiting firms have different average environmental efficiency, which makes the net exit become a key contribution to emissions changes. When using the amount of SO2 generated as a proxy of emissions, I find results opposite to the panel regression analysis. Whether in the TCZ area or outside it, the growth of the weighted average SO2 generated amount has been positive over the years. The contribution of the surviving firms is in particular the key driver that pulls up the average generated pollutant. The negative effect of the TCZ policy results from the positive growth of the weighted average SO2 generated amount in the TCZ area being smaller than growth out of the TCZ area.

Third, I am not only interested in aggregate emissions movements with the decomposed before and after the policy implementation, but also interested in decomposing the gap between the in-TCZ area's aggregate emissions reduction and the out-TCZ area's aggregate emissions reduction into the contributions of survive, entry and exit. The TCZ policy geographically divides China's counties into two groups, in-TCZ area and out-TCZ area, which have different aggregate air pollutant (SO2) changes. Using the DID framework decomposition can help us investigate simultaneously the dynamic effect of policy and the conditions without policy.

Data in decomposition analysis needs to be able to detect firms' entry and exit behaviour. Census-based data sets have been used in many previous studies of productivity decomposition (Fagerberg, 2000; Foster et al., 2001; Melitz and Polanec, 2015). The data sets may cover (nearly) all firms in the entire country (Hyytinen, 2016). Instead of using the merged dataset presented in my first and second chapters, the ESR dataset's observations are plants that contribute to the top 85% of total emissions in a county. The sampling criteria in the ESR database is the cumulative distribution of firm emissions in each county. As I only use the ESR database in the study, the decomposed channels can display the contribution of entering firms or exiting firms no matter whether they are entering/exiting from the market or the dataset. Entering/exiting from the market or the dataset gives the same signal that a firm has missed/reached the emissions criteria. Another option would be to use the NBS manufacturing dataset but that is not a good choice because it only includes firms whose annual sales are over 5 million CNY.

This study makes a major contribution to research on the impact of environmental policy on aggregate emissions movements. First, as we know, this is the first study to undertake a difference-in-difference framework decomposition analysis of aggregate emissions changes. In the field of environmental economics, panel data analysis is commonly used to investigate the average reduction of emissions (see, Porter and Linde (1995); Greenstone (2002a); Cai et al. (2016a); Wang et al. (2018b); He et al. (2020)). However, our decomposition method with weighted average emissions helps to uncover the channels that contribute to aggregate emissions mitigation. In particular population differences across moments and competition between firms are investigated through the information on firms' shift shares.

Second, I extend dynamic decomposition into a difference-in-difference framework. The dynamic decomposition methods proposed by Fagerberg (2000), Foster et al. (2001), and Melitz and Polanec (2015) all decompose aggregate productivity growth in two moments. But in our scenario, there is an evident difference in emission growth between in-TCZ and out-TCZ areas. I am more interested in the gap between the two groups' emissions growth. I am not only investigating dynamic decomposition for emission changes within the in-TCZ area and out-TCZ area but also developing decomposition for the gap in emissions movements.

6.2 Literature Review

In this section, I review some aggregate productivity growth decomposition methods, which are used to investigate the influence of resource reallocation on the aggregate economy. How inputs, like workers and capital, are smoothly relocated between firms is crucial to aggregate productivity growth (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008, 2013; Syverson, 2011). A law or regulation affecting economic activity can sometimes promote or interfere with such resource reallocation in the macro-economy. I will introduce two categories of aggregate productivity growth decomposition methods: one is the reduced form decomposition method and the other is the structural decomposition method.

The use of productivity measurement and share weight differs in various ways. In the empirical analysis of existing literature, labour productivity and total factor productivity are widely used to denote firm performance (Fagerberg, 2000; Foster et al., 2001; Melitz and Polanec, 2015; Decker et al., 2017). Some research uses inputs share, while others choose output shares as weights (Fagerberg, 2000; Foster et al., 2001; Melitz and Polanec, 2015; Decker et al., 2017). Measuring firm-level productivity in levels or in logarithms is another methodological difference (Van Biesebroeck, 2008; Melitz and Polanec, 2015)

First, reduced-form decomposition methods are based on a simple two-period exposition (Baily et al., 1992; Haltiwanger, 1997; Foster et al., 2001; Melitz and Polanec, 2015). In these productivity decompositions, aggregate productivity P_t in period t is defined as a share-weighted average of firm i's productivity p_{it}, i.e., $P_t = \sum_i w_{it}p_{it}$ (where the market shares w_{it} of firm i in period t sum to 1). Aggregate productivity growth ($\Delta P = P_{t1} - P_{t0}$) from period t_1 to t_0 is the object of interest in related papers. An analysis of aggregate productivity growth can be facilitated by using productivity decomposition methods proposed in the existing literature, which classify the contribution for ΔP from each firm into three components by firms' activity status: (1) surviving/continuing firms (active in both periods); (2) entering firms (only active in the second period $t1$); and (3) exiting firms (only active in the first period $t0$). Baily et al. (1992), Haltiwanger (1997), Griliches and Regev (1995), Foster et al. (2001) and Melitz and Polanec (2015) all use shift-share decomposition methods in reduced form.

Baily et al. (1992) is the first study exploring what microeconomic sources of industrial productivity growth can be captured through various decompositions. Their seminal contribution tracks the productivity p_{it} changes and market share w_{it} changes of firms over time. Surviving firms, entering firms, and exiting firms are then categorized into three contributions of aggregate productivity change, $\Delta P = w_{i,t1}p_{i,t1} - w_{i,t0}p_{i,t0}$. For the surviving firms' contribution, the change in weighted productivity for survivors is further decomposed into two categories: a sum of the productivity changes with constant firms' shares (within-firm component) and a sum of the share changes with constant firm productivity (between-firm component). Baily et al. (1992)'s aggregate productivity growth decomposition method is :

$$
\begin{aligned}
\Delta P &= \underbrace{\sum_{i\in S}(w_{i,t1}p_{i,t1} - w_{i,t0}p_{i,t0})}_{Survive} + \underbrace{\sum_{i\in E} w_{i,t1}p_{i,t1}}_{Enter} - \underbrace{\sum_{i\in X} w_{i,t0}p_{i,t0}}_{Exit} \\
&= \underbrace{\sum_{i\in S} w_{i,t0}(p_{i,t1} - p_{i,t0})}_{Within} + \underbrace{\sum_{i\in S}(w_{i,t1} - w_{i,t0})p_{i,t0}}_{Between} + \underbrace{\sum_{i\in E} w_{i,t1}p_{i,t1}}_{Enter} - \underbrace{\sum_{i\in X} w_{i,t0}p_{i,t0}}_{Exit}
\end{aligned} \tag{6.1}
$$

where S is a set of indexes for surviving firms, E is a set of indexes for entering firms, X is a set of indexes for exiting firms. The first line of equation 6.1 decomposes the aggregate productivity growth ΔP into three components: the first term is the contribution of surviving firms, the second term is the contribution of entering firms, and the third term is the contribution of exiting firms. According to Baily et al. (1992), firm share and productivity are tracked over time. The second line of equation 6.1 breaks down the contribution of surviving firms into two subcomponents: within-firm subcomponents (the first term) and between-firm subcomponents (the second term). The within-firm effect attempts to capture productivity improvements within companies that have survived. The between-firm subcomponent captures the contribution of market share changes between firms that survive.

Haltiwanger (1997) made a modification for the Baily et al. (1992)'s method. In Haltiwanger (1997)'s decomposition process, a deviation term related to firm productivity was proposed to decompose the same change into components indexed by relative firm productivity. The relative firm productivity of firm i at period t is $\hat{p}_{it} = p_{it} - K_t$, where K_t is the reference value at time t that serves as a benchmark. Comparing with Baily et al. (1992)'s decomposition in equation 6.1, Haltiwanger (1997) suggests using the covariance terms between productivity change and share change at the second period to capture the " market share effect" across firms. Haltiwanger (1997)'s aggregate productivity growth decomposition method is :

$$\Delta P = \underbrace{\sum_{i \in S} w_{i,t0}(p_{i,t1} - p_{i,t0})}_{Within} + \underbrace{\sum_{i \in S}(w_{i,t1} - w_{i,t0})p_{i,t0}}_{Between} + \underbrace{\sum_{i \in S}(w_{i,t1} - w_{i,t0})(p_{i,t1} - p_{i,t0})}_{Covariance} + \underbrace{\sum_{i \in E} w_{i,t1}p_{i,t1}}_{Enter} - \underbrace{\sum_{i \in X} w_{i,t0}p_{i,t0}}_{Exit} \tag{6.2}$$

where the first three terms are the subcomponents of the contribution of surviving firms. The third term denotes the cross-firm subcomponents.

Based on Baily et al. (1992)'s seminal contribution, Griliches and Regev (1995) and Foster et al. (2001) developed another two reduced-form decomposition approaches. They decompose aggregate productivity growth by micro-channels, including (i) productivity changes at the individual firm level (within-firm effect), (ii) shifts in market share between firms (between-firm effect), (iii) entries of new firms, and (iv) exits of incumbent firms. The decompositions method of Griliches and Regev (1995) and Foster et al. (2001) track share and productivity changes over time in the same way as Baily et al. (1992). The difference though, is the introduction of a reference average productivity level as the benchmark (Griliches and Regev, 1995; Foster et al., 2001). The aggregate productivity growth ΔP is written as a difference with respect to the reference productivity level, $\Delta P = \sum_i [w_{i,t1}(p_{i,t1} - P_{REF}) - w_{i,t0}(p_{i,t0} - P_{REF})]$. Using this reference productivity level, the contributions of entrants and exiters are evaluated relative to surviving firms.

Griliches and Regev (1995) modify the decomposition method of Baily et al. (1992) and propose a reference productivity level, which is the average aggregate productivity level between the two moments, $P_{REF} = \overline{P} = (P_{t1} + P_{t0})/2$. The decomposition method of Griliches and Regev (1995) is thus:

$$\Delta P = \sum_{i \in S}[w_{i,t1}(p_{i,t1} - \overline{P}) - w_{i,t0}(p_{i,t0} - \overline{P})] + \sum_{i \in E} w_{i,t1}(p_{i,t1} - \overline{P}) - \sum_{i \in X} w_{i,t0}(p_{i,t0} - \overline{P}) \tag{6.3}$$

Equation 6.3 separates out the contributions of surviving firms, entering firms, and exiting firms to aggregate productivity growth. Unlike Baily et al. (1992)'s decomposition with the positive contribution of entry and negative contribution of exit, Griliches and Regev (1995)'s decomposition proposes the contribution of entrants and exiters to aggregate productivity movements can be positive or negative, depending on a firm's productivity to the reference level. This shows the importance of the reference productivity level $\overline{P}$ on the measured contributions of entry and exit relative to surviving firms (Melitz and Polanec, 2015).

Foster et al. (2001) apply the first moment's aggregate productivity, P_{t0}, as the reference productivity level in decomposition, i.e., $P_{REF} = P_{t0}$. Their decomposition is given by:

$$
\begin{aligned}
\Delta P =& \sum_{i \in S}[w_{i,t1}(p_{i,t1} - P_{t0}) - w_{i,t0}(p_{i,t0} - P_{t0})] + \sum_{i \in E} w_{i,t1}(p_{i,t1} - \Phi_{t0}) - \sum_{i \in X} w_{i,t0}(p_{i,t0} - P_{t0}) \\
=& \sum_{i \in S} w_{i,t0}(p_{i,t1} - p_{i,t0}) + \sum_{i \in S}(w_{i,t1} - w_{i,t0})(p_{i,t0} - P_{t0}) + \sum_{i \in S}(w_{i,t1} - w_{i,t0})(p_{i,t1} - p_{i,t0}) \\
&+ \sum_{i \in E} w_{i,t1}(p_{i,t1} - \Phi_{t0}) - \sum_{i \in X} w_{i,t0}(p_{i,t0} - P_{t0})
\end{aligned}
\tag{6.4}
$$

The first line of Equation 6.4 also breaks down productivity growth into three components, surviving, entering, and exiting. The second line of equation 6.4 shows that in addition to decomposing the contribution of within-firm and between-firm components, Foster et al. (2001) also split the cross-firm component, which is the covariance between changes in market share and changes in productivity. Just like the Griliches and Regev (1995) decomposition, in Foster et al. (2001)'s method the contributions of entry and exit can be either positive or negative.

The decomposition of Olley and Pakes (1996) is another widely used approach. They propose a static decomposition method, which decomposes aggregate productivity in each period separately rather than following firms over time. The Olley and Pakes (1996) decomposition shows how the weighted average of firm productivity is decomposed into the unweighted average of firms' productivity and a covariance-like term between market shares (i.e. output or input) and productivity. Decomposition in time t is written as:

$$
\begin{aligned}
P_t &= \overline{p}_t + \sum_i (w_{it} - \overline{w}_t)(p_{it} - \overline{p}_t) \\
&= \overline{p}_t + cov(w_{it}, p_{it})
\end{aligned}
\tag{6.5}
$$

where $\overline{p}_t = \frac{1}{n_t}\sum_{i=1}^{n_t} p_{it}$ is the unweighted firm productivity mean, $\overline{w}_t = 1/n_t$ is the mean market share. The second term of the equation is called the Olley-Pakes covariance, which increases with the correlation between market share and productivity. This is a slight abuse of notation since the *cov* operator would normally be multiplied by $1/Nt$. The larger Olley-Pakes covariance means that the higher share of output goes to more productive firms and further implies higher industry productivity. It is important to interpret the difference between the Olley-Pakes covariance and the covariance in Haltiwanger (1997) and Foster et al. (2001) (the covariance in equations 6.2 and 6.4). The Olley-Pakes covariance is measured in the cross-sectional distribution of market shares and productivity, which increases with the correlation between market shares and productivity for an industry at a specific time t. But the covariance in the methods of Haltiwanger (1997) and Foster et al. (2001) capture the same firm's covariance of market share shifts and productivity changes, i.e., the intertemporal covariance between market share and productivity for firm i.

When applying the Olley and Pakes (1996) decomposition in a dynamic scenario, aggregate productivity growth ΔP is given by the growth of the unweighted productivity mean $\Delta \overline{p}$ and the change in covariance term Δcov. The growth of the unweighted productivity mean captures shifts in productivity distribution, which implies firms' self-improvement. Meanwhile, change in the Olley-Pakes covariance captures the market share reallocation between firms. It is often used in studies of firm-level productivity and industry dynamics and can provide valuable insights into the factors that drive changes in productivity over time.

Melitz and Polanec (2015) propose a dynamic extension of the Olley-Pakes decomposition extending it to accommodate firm entry and exit. Basing themselves on Olley and Pakes (1996)'s approach, Melitz and Polanec (2015)'s approach also denotes the shifts in productivity distributions and reallocations in market share and captures the separate contributions of entrants, exiters, and survivors to aggregate productivity changes, just like other dynamic decomposition approaches.

Melitz and Polanec (2015) divide firms into three groups, entrants, exiters, and survivors (i.e., $g \in (E, X, S)$). For computation, they introduce the aggregate market share of a group g of firms as $w_{gt} = \sum_{i \in g} w_{it}$. w_E is the aggregate market share for entering firms, w_X is the aggregate market share for exiting firms, and w_S is the aggregate market share for surviving firms. Then, each group's aggregate (average) productivity is written by $P_{gt} = \sum_{i \in g}(w_{it}/w_{gt} p_{it})$. P_E is the weighted average productivity for entering firms, P_X is the weighted average productivity for exiting firms, and P_S is the weighted average productivity for surviving firms. Then, the aggregate productivity in year t is:

$$P_{t0} = w_{S,t0} P_{S,t0} + w_{X,t0} P_{X,t0} \tag{6.6}$$

$$P_{t1} = w_{S,t1} P_{S,t1} + w_{E,t1} p_{E,t1} \tag{6.7}$$

For each period, aggregate productivity is a function of the aggregate market share of a group and the aggregate productivity of a group. Based on the aggregate productivity shown in equations 6.6 and 6.7, aggregate productivity growth ΔP can be written by equation 6.8 with the substitution of Olley-Pakes decomposition. Equation 6.8 is the decomposition of aggregate productivity proposed by Melitz and Polanec (2015):

$$\Delta P = \underbrace{(P_{S,t1} - P_{S,t0})}_{Survive} + \underbrace{w_{E,t1}(P_{E,t1} - P_{S,t1})}_{Enter} + \underbrace{w_{X,t0}(P_{S,t0} - P_{X,t0})}_{Exit} \tag{6.8}$$

The three terms in equation 6.8 denote the contribution of surviving firms, entering firms, and exiting firms respectively.

The decomposition approaches proposed by Baily et al. (1992), Haltiwanger (1997), Griliches and Regev (1995), Foster et al. (2001), Olley and Pakes (1996), and Melitz and Polanec (2015) are the reduced form decomposition methods. They have advantages in explaining aggregate productivity growth through resource reallocation from low-productive firms to high-productive firms. These methods are easy to conduct, which makes them commonly used to research across sectors and periods. The straightforward deduction of these methods makes them easy to extend (Collard-Wexler and De Loecker, 2015; Nishiwaki and Kwon, 2013). In this research, I extend the basic idea of decomposition into a difference-in-difference framework and employ the emissions variable instead of productivity to denote firm performance.

In addition to the reduced-form decomposition method, Lentz and Mortensen (2008) develop a new formula for aggregate productivity growth decomposition using an endogenous model. Each decomposed component in this method is displayed by a structural model whose structural parameters are estimated through firm-level panel data.

Lentz and Mortensen (2008)'s structural decomposition method is based on a "quality ladder" framework, which assumes only one consumption good that is produced from many intermediate input goods in the economy. Each intermediate input is made by only one firm which is called the incumbent firm. R&D investment in improving intermediate goods quality is the point of the quality ladder model. A firm that successfully improves the quality of an intermediate good can drive out the existing producer, which brings an entering firm and an exiting firm to the economy. The market share of products produced by high-innovation firms keeps increasing, which creates the stationary equilibrium that the quality of goods is the same across firms.

The formula of Lentz and Mortensen (2008)'s structural decomposition method decomposes aggregate productivity growth into three components: the contribution of the entry and exit effect, the contribution of the selection effect, and the contribution of the within effect. To be specific, the selection effect implies the market share reallocates from low to highly innovative firms, and the within effect indicates technical efficiency improvement within each firm.

6.3 DID framework decomposition in the emissions context

Inspired by the decomposition approach of Baily et al. (1992) and Melitz and Polanec (2015), I propose a difference-in-difference framework decomposition for the weighted average emission within an area, which breaks down the gap in aggregate emission growth inside and outside the TCZ area into surviving firms component, entering firms component, and exiting firms component. The weighted average emission Φ_t^A in area A at period t is the environmental variable I am interested in:

$$\Phi_t^A = \sum_{i\in(A)} w_{i,t}\varphi_{i,t} \qquad where \qquad \sum_{i\in(A,t)} w_{i,t} = 1$$

In this research, the TCZ policy creates two areas in China, the TCZ area and the non-TCZ area ($A \in$(in-TCZ, out-TCZ)). Only firms located in the TCZ area need to follow the environmental policy. All firms are categorized into two groups based on their geographic location. I employ the amount of sulphur dioxide (SO_2) discharged and (SO_2) generated as the proxy of firm i's emissions level at period t, $\varphi_{i,t}$. Then, Φ_t^A is used to denote the weighted average sulphur dioxide (SO_2) discharged/generated at period t. $w_{i,t}$ is the market share (wight) for firm i in area A at period t. It is the ratio of firm i's output to the group's aggregate output. The sum of firms' market share within an area A at time t equals to 1, $\sum_{i\in(A,t)} w_{it} = 1$. In contrast to the paper relating to productivity growth, the lower the weighted average emission Φ_t^A the better the air conditions of an economy. Environmental policies, improved firm environmental efficiency, and better reallocation would reduce the weighted average emissions.

Table 6.1: Difference-in-difference framework

Group	Before 2000, $t0$	After 2000, $t1$
In TCZ	Un-regulated	**Regulated**
Out TCZ	Un-regulated	Un-regulated

Two moments are considered in the analysis, one year before the policy implementation ($t0$) and one year after it ($t1$). In this study, I choose the base year 1998 as the period before policy implementation (i.e., $t0$ represents the year 1998). $t1$ represents a year after TCZ policy implementation (the year 2001, 2002, to, 2007). The weighted average emission growth at $t1$ is the weighted average emission at $t1$ relative to the value at $t0$. In addition to the time dimension, there is a geographic dimension in the research, which is inside or outside the TCZ area. As shown in Table 6.1, the difference-in-difference framework contains four blocks, which means the TCZ policy splits the population into four groups. In this scenario, the weighted average emissions and market share need to be separately computed in each group. The weighted average emission for each block is denoted by Φ_{t0}^{in}, Φ_{t0}^{out}, Φ_{t1}^{in}, Φ_{t1}^{out}. The market share for each block is $w_{i,t0}^{in}$, $w_{i,t0}^{out}$, $w_{i,t1}^{in}$, $w_{i,t1}^{out}$. Table 6.2 further shows components for the weighted average emissions in area A at time t. In the second line of Table 6.2, the weighted average emissions in the TCZ area in 1998 are composed of the contribution of survivors and exiters. I take the same definition of an entrant and an exiter as (Melitz and Polanec, 2015). A firm that enters the market has its market share increase from zero; similarly, a firm that exits has its market share decrease to zero.

Table 6.2: Channels' Contribution to each scenario

	Surviving firms	Entering firms	Exiting firms
In TCZ, $t0$	$\sum_{i\in(S,In)}(w_{i,t0}^{in}\varphi_{i,t0}^{in})$	- - -	$\sum_{i\in(X,In)}(w_{i,t0}^{in}\varphi_{i,t0}^{in})$
In TCZ, $t1$	$\sum_{i\in(S,In)}(w_{i,t1}^{in}\varphi_{i,t1}^{in})$	$\sum_{i\in(E,In)}(w_{i,t1}^{in}\varphi_{i,t1}^{in})$	- - -
Out TCZ, $t0$	$\sum_{i\in(S,Out)}(w_{i,t0}^{out}\varphi_{i,t0}^{out})$	- - -	$\sum_{i\in(X,Out)}(w_{i,t0}^{out}\varphi_{i,t0}^{out})$
Out TCZ, $t1$	$\sum_{i\in(S,Out)}(w_{i,t1}^{out}\varphi_{i,t1}^{out})$	$\sum_{i\in(E,Out)}(w_{i,t1}^{out}\varphi_{i,t1}^{out})$	- - -

With the notations in Table 6.2, the weighted average emission growth for area A is given by:

$$
\begin{aligned}
\Phi_{t1}^{A} - \Phi_{t0}^{A} &= \sum_{i\in(A)} w_{i,t1}^{A}\varphi_{i,t1}^{A} - \sum_{i\in(A)} w_{i,t0}^{A}\varphi_{i,t0}^{A} \\
&= \underbrace{\sum_{i\in(S,A)} (w_{i,t1}^{A}\varphi_{i,t1}^{A} - w_{i,t0}^{A}\varphi_{i,t0}^{A})}_{Surviving firms} + \underbrace{\sum_{i\in(E,A)} w_{i,t1}^{A}\varphi_{i,t1}^{A}}_{Entering firms} \\
&\quad \underbrace{- \sum_{i\in(X,A)} w_{i,t0}^{A}\varphi_{i,t0}^{A}}_{Exiting firms}
\end{aligned}
\tag{6.9}
$$

Equation 6.9 shows the decomposition of the weighted average emissions growth. In the second line of equation 6.9, the weighted average emissions are broken down into three components: the contribution of surviving firms, entering firms and exiting firms. If the value of the contribution of surviving firms, $\sum_{i\in(S,A)}(w_{i,t1}^{A}\varphi_{i,t1}^{A} - w_{i,t0}^{A}\varphi_{i,t0}^{A})$ is negative, surviving firms' average emission at period $t1$ will be lower than that at $t0$, which implies they contribute to the improvement of air quality. If this value is positive, then the surviving firms' production activities aggravate pollution. Since the stringent regulation of the TCZ policy, the value of the contribution of surviving firms is supposed to be negative in the TCZ area. The value of the entering firms component $\sum_{i\in(E,A)} w_{i,t1}^{A}\varphi_{i,t1}^{A}$ is always positive and the value of the exiting firms component $-\sum_{i\in(X,A)} w_{i,t0}^{A}\varphi_{i,t0}^{A}$ is always negative. But it doesn't mean that entering firms increase average emissions or exiting firms reduce them. The mathematical sign is used to distinguish market entry activities and market exit activities. The mathematical sign of net entry, $\sum_{i\in(E,A)} w_{i,t1}^{A}\varphi_{i,t1}^{A} - \sum_{i\in(X,A)} w_{i,t0}^{A}\varphi_{i,t0}^{A}$, can display the environmental efficiency gap between entering firms and exiting firms. The negative value of the contribution of net entry implies that entering firms are cleaner than exiting firms.

Finally, the difference between the weighted average emissions growth inside the TCZ area and the weighted average emissions growth outside the TCZ area is what I am interested in. To get this difference which displays the effect of the TCZ policy on weighted average emissions, I propose a DID framework decomposition that is equation 6.10. By adding equation 6.9 to equation 6.10, I get the difference-in-difference framework decomposition with three components, surviving firms' contribution, entering firms' contribution, and exiting firms' contribution.

Table 6.3 shows the difference-in-difference framework decomposition approach for the weighted average emissions. The first line of Table 6.3 is the decomposition of average emissions for firms inside the TCZ area, which is calculated based on Equation 6.9. The second line of Table 6.3 is the decomposition of average emissions for firms outside the TCZ area, which is also calculated based on Equation 6.9. The third line of Table 6.3 is the DID framework decomposition for weighted average emissions, which is computed based on Equation 6.10. Subtracting the first line value from the second line value gives the result in the third line.

For the contribution of surviving firms in the DID framework decomposition (the second column of the third line of Table 6.3), its value should be negative, indicating the effective impact of the TCZ policy on surviving firms' pollution reduction. But it contains two scenarios. The first scenario is that average emissions growth inside the TCZ area (column 2 of the first line) and outside it (column 2 of the second line) are both negative. The TCZ policy's spillover effect brings environmental efficiency improvement for firms outside the TCZ area, which is the reason for the negative average emissions growth outside the TCZ area. But as the direct effect of the TCZ policy on target cities is more evident than its spillover effect, the absolute value of average emissions growth inside the TCZ area would be larger, which results in the negative contribution of surviving firms in the DID framework decomposition. The second scenario is that the negative average emissions growth inside the TCZ area is negative but the value outside the TCZ area is positive. Without environmental regulation, surviving firms outside the TCZ area would not reduce their average emissions.

$$[\Phi^{in}_{After} - \Phi^{in}_{Before}] - [\Phi^{out}_{After} - \Phi^{out}_{Before}] \tag{6.10}$$

6.4 Stylized facts

I use two firm-level databases, the Annual Survey of Industrial Firms Database (ASIF) and the Environmental Survey and Reporting Database (ESR), covering the whole of China's polluting sector for the 1998-2007 period. From 2000 to 2007, 157 cities are monitored by the Two Control Zone policy, which led to large declines in the SO2 emissions of firms in the TCZ area. There are two before-treatment years and 7 post-treatment years in our research period (1998-2007). Thus, I can employ the DID framework decomposition method on emissions variables.

Table 6.4 reports the number of firms with different behaviour over the years. I am using the same definition of entering and exiting firms as Griliches and Regev (1995); Foster et al. (2001); Melitz and Polanec (2015). An entering firm has its market share increase from zero; equally, an existing firm's market share decreases to zero. As the time span increases the number of surviving firms decreases a lot. There were 28.7% survivors in 2001 relative to 1998, while the rate decreased to 8.4%. There is thus a huge gap between surviving firms in 2001 and in 2007.

Table 6.3: Difference-in-difference framework decomposition

	Surviving firms	Entering firms	Exiting firms	Total (in static)
$\Phi^{in}_{t1} - \Phi^{in}_{t0}$	$\sum_{i\in(S,in)}(w^{in}_{i,t1}\varphi^{in}_{i,t1}) -$ $\sum_{i\in(S,in)}(w^{in}_{i,t0}\varphi^{in}_{i,t0})$	$\sum_{i\in(E,in)}(w^{in}_{i,t1}\varphi^{in}_{i,t1})$	$-[\sum_{i\in(X,in)}(w^{in}_{i,t0}\varphi^{in}_{i,t0})]$	$[\sum_{i\in(S,in)}(w^{in}_{i,t1}\varphi^{in}_{i,t1}) - \sum_{i\in(S,in)}(w^{in}_{i,t0}\varphi^{in}_{i,t0})] +$ $[\sum_{i\in(E,in)}(w^{in}_{i,t1}\varphi^{in}_{i,t1})] - [\sum_{i\in(X,in)}(w^{in}_{i,t0}\varphi^{in}_{i,t0})]$
$\Phi^{out}_{t1} - \Phi^{out}_{t0}$	$\sum_{i\in(S,out)}(w^{out}_{i,t1}\varphi^{out}_{i,t1}) -$ $\sum_{i\in(S,out)}(w^{out}_{i,t0}\varphi^{out}_{i,t0})$	$\sum_{i\in(E,out)}(w^{out}_{i,t1}\varphi^{out}_{i,t1})$	$-[\sum_{i\in(X,out)}(w^{out}_{i,t0}\varphi^{out}_{i,t0})]$	$[\sum_{i\in(S,out)}(w^{out}_{i,t1}\varphi^{out}_{i,t1}) - \sum_{i\in(S,out)}(w^{out}_{i,t0}\varphi^{out}_{i,t0}] +$ $[\sum_{i\in(E,out)}(w^{out}_{i,t1}\varphi^{out}_{i,t1})] - [\sum_{i\in(X,out)}(w^{out}_{i,t0}\varphi^{out}_{i,t0})]$
$[\Phi^{in}_{t1} - \Phi^{in}_{t0}] -$ $[\Phi^{out}_{t1} - \Phi^{out}_{t0}]$	$[\sum_{i\in(S,in)}(w^{in}_{i,t1}\varphi^{in}_{i,t1}) -$ $\sum_{i\in(S,in)}(w^{in}_{i,t0}\varphi^{in}_{i,t0})] -$ $[\sum_{i\in(S,out)}(w^{out}_{i,t1}\varphi^{out}_{i,t1}) -$ $\sum_{i\in(S,out)}(w^{out}_{i,t0}\varphi^{out}_{i,t0})]$	$\sum_{i\in(E,in)}(w^{in}_{i,t1}\varphi^{in}_{i,t1})-$ $\sum_{i\in(E,out)}(w^{out}_{i,t1}\varphi^{out}_{i,t1})$	$-[\sum_{i\in(X,in)}(w^{in}_{i,t0}\varphi^{in}_{i,t0})]+$ $[\sum_{i\in(X,out)}(w^{out}_{i,t0}\varphi^{out}_{i,t0})]$	$[\sum_{i\in(S,in)}(w^{in}_{i,t1}\varphi^{in}_{i,t1}) - \sum_{i\in(S,in)}(w^{in}_{i,t0}\varphi^{in}_{i,t0})] +$ $[\sum_{i\in(E,in)}(w^{in}_{i,t1}\varphi^{in}_{i,t1})] - [\sum_{i\in(X,n)}(w^{in}_{i,t0}\varphi^{in}_{i,t0})] -$ $[\sum_{i\in(S,out)}(w^{out}_{i,t1}\varphi^{out}_{i,t1}) - \sum_{i\in(S,out)}(w^{out}_{i,t0}\varphi^{out}_{i,t0}] -$ $[\sum_{i\in(E,out)}(w^{out}_{i,t1}\varphi^{out}_{i,t1})] + [\sum_{i\in(X,out)}(w^{out}_{i,t0}\varphi^{out}_{i,t0})]$

Two reasons can help to explain this gap. First, China's fast economic growth crowded out the firms with low productivity, and the stringent environmental policy knocked out the firms with low environmental efficiency. Second, because of data limitations, I was not able to target continuing firms that underwent a name change while maintaining their existing structure and operations. As shown in Table 6.4, the number of entering and exiting firms keeps rising from 2001 to 2007, while the number of entering firms is always larger than the number exiting.

From Figure 6.1 to Figure 6.6, firm characteristics are shown in a grid level (50km*50km) China map. Figure 6.1 displays the geographic distribution for firm density. Each grid denotes the number of firms in the local area. It shows that more firms existed in 2007 (shown in more green and orange cells). Meanwhile, observed firms have agglomerated to China's eastern coastal cities. However, I cannot find evidence that firms agglomerated to cities outside the TCZ area.

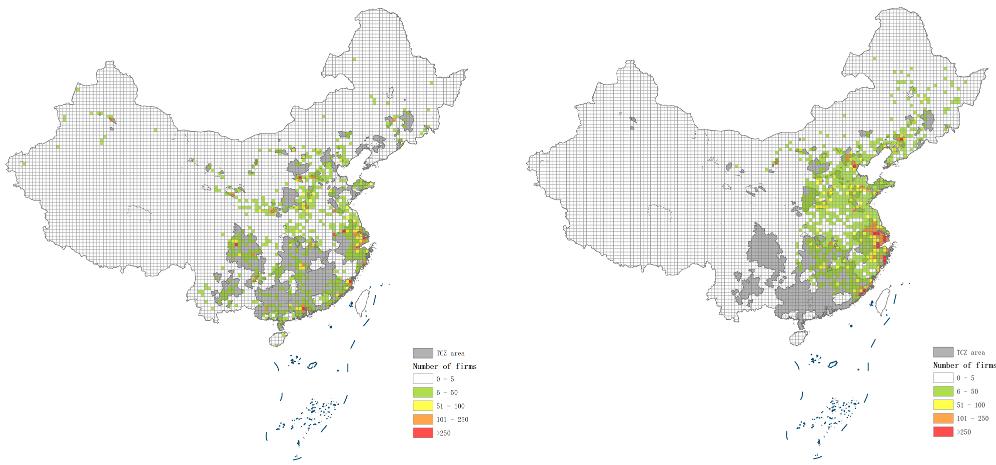
Figure 6.2 is the geographic distribution for average SO2 discharged. The decreased trend in average SO2 discharged is clear. In 2007, there was no grid that had more than 5,000,000 tons of emissions (no red grid); there are fewer orange grids in Figure 6.2a; and there are more green cells in Figure 6.2b. The in-TCZ area has more grids (green grids) with low average SO2 discharged than the out-TCZ area in 2007.

Figure 6.3 shows the geographic distribution for average SO2 generated, which does not display a similar moving trend to Figure 6.2. In 2007, fewer grids (red grids) with more than 5 million tons of emissions are shown, but more (yellow grids) with 50,000 to 500,000 tons of emissions are shown. Figures 6.2 and 6.3 show the reduced average SO2 discharged and the mostly unchanged average SO2 generated.

Figure 6.4 shows the geographic distribution of the average output of firms. It is apparent that the average output has significantly increased from 1998 to 2007. More orange grids and yellow grids exist in 2007. Since firms have agglomerated to China's eastern coastal cities, that area contains the most grids with high average output (yellow grids). Figure 6.5 is the geographic distribution for average SO2 intensity. It is evident that SO2 intensity has declined significantly, implying improved emissions efficiency during the production process. In 2007, most green grids were inside the TCZ area and there were few grids (orange and red grids) with high emissions in the TCZ area.

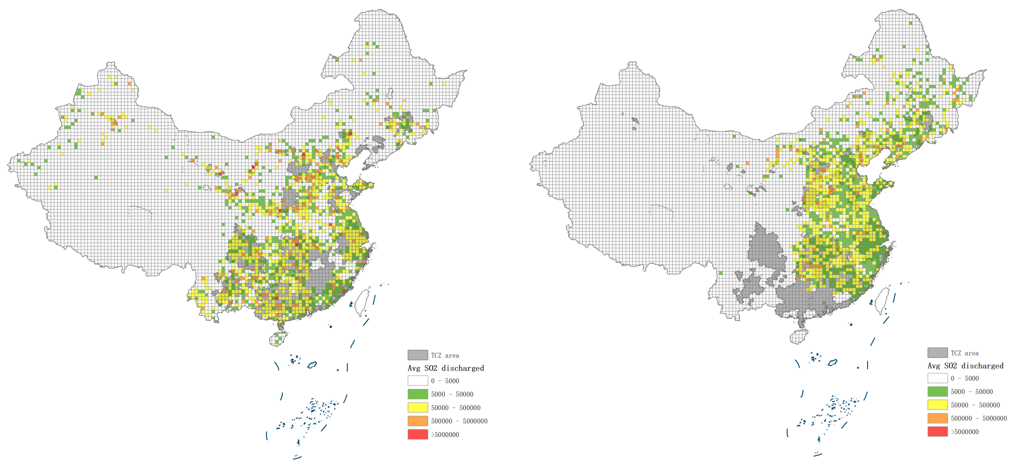
Table 6.4: Number of firms relative to 1998 ($t0$)

Year	Number of firms	Surviving firms	Entering firms	Exiting firms
1998	41,277	—	—	—
2001	46,824	13,447	33,377	27,830
2002	47,477	11,555	35,922	29,722
2003	46,034	9,747	36,287	31,530
2004	46,091	8,352	37,739	32,925
2005	44,865	6,783	38,082	34,494
2006	44,264	5,414	38,850	35,863
2007	45,702	3,838	41,864	37,439



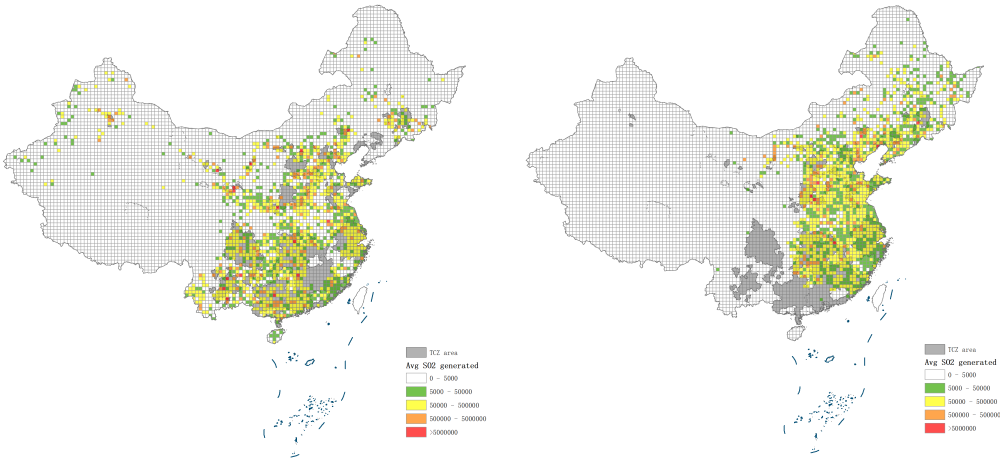
(a) Firm density in 1998 (b) Firm density in 2007

Figure 6.1: The geographic distribution for firm density



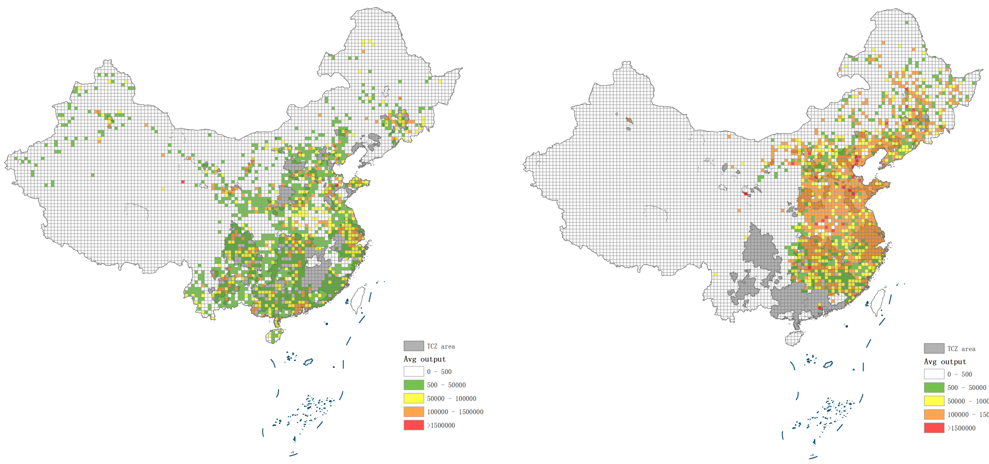
(a) Average SO2 discharged amount in 1998 (b) Average SO2 discharged amount in 2007

Figure 6.2: The geographic distribution for average SO2 discharged amount



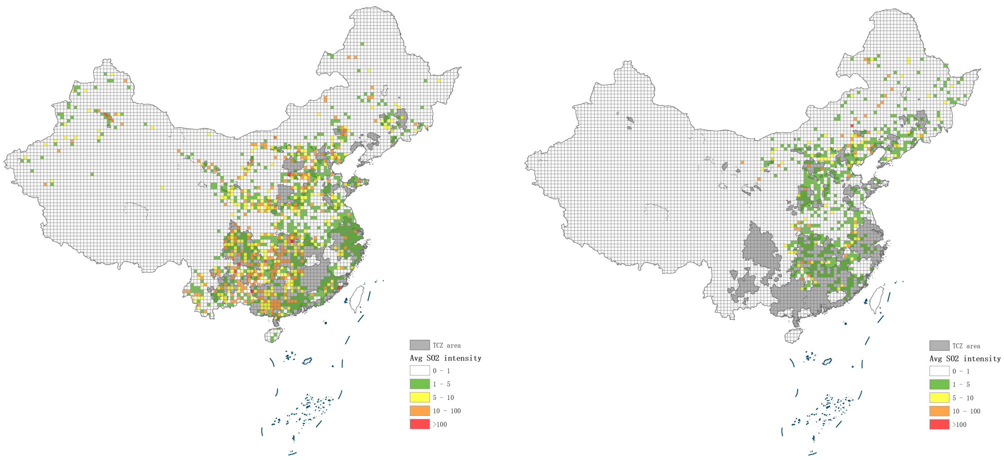
(a) Average SO2 generated amount in 1998 (b) [Average SO2 generated amount in 2007

Figure 6.3: The geographic distribution for average SO2 generated amount



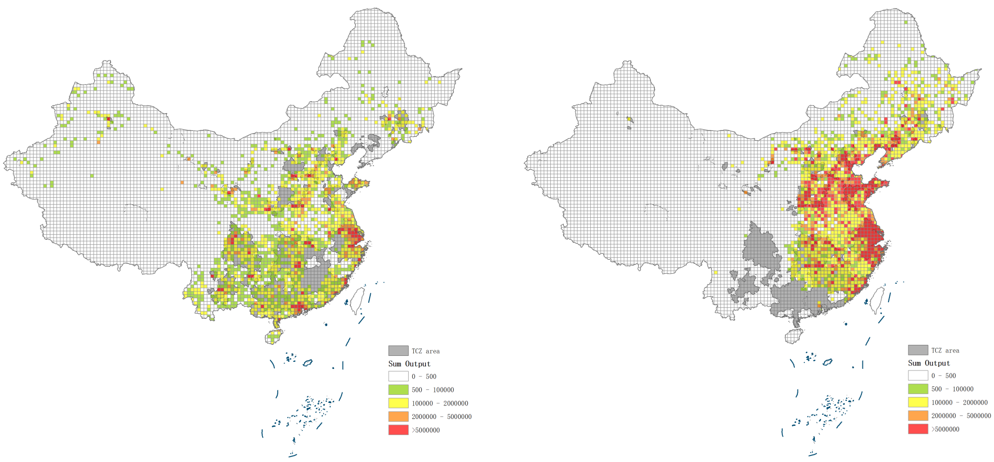
(a) Average output in 1998 (b) Average output in 2007

Figure 6.4: The geographic distribution for average output



(a) Average SO2 intensity in 1998 (b) Average SO2 intensity in 2007

Figure 6.5: The geographic distribution for average SO2 intensity



(a) Sum of output in 1998 (b) Sum of output in 2007

Figure 6.6: The geographic distribution for Sum of output

6.5 Empirical application: Chinese polluting enterprises 1998–2007

I report the DID framework decomposition with entry and exit in Table 6.5. It includes the emission reduction contributions of surviving firms, along with those from entering and exiting firms, in order to focus on the differences associated with entry and exit. The top panel is based on SO2 discharged measured with output shares and the bottom panel is based on SO2 generated measured with output weight. $t0$ is one year before the treatment. In this research, I choose $t0 = 1998$, i.e., the base year for comparison. As the TCZ policy started in the middle of 2000, I choose to report the decomposition result from 2001. A lagged year can help to display the policy's significant effect on firm emission reductions. I report decompositions between 1998 and all subsequent years from 2001 to 2007 to illustrate how the weighted average emissions are affected by environmental policy and the length of the time span.

For either decomposition for in-TCZ (columns 2-6) or decomposition for out-TCZ (columns 7-11), column (6) and column (11) are the total contributions of surviving, entering, and exiting firms to the total weighted average emissions change. For the DID framework decomposition (columns 12-16), the contributions of surviving, entering, and exiting firms sum to the total weighted average emission change listed in the far-right column. As I compare the contributions of survivors, entrants, and exits across the in-TCZ and the out-TCZ tables, I can verify the DID framework decomposition that I previously explained in equation 6.9. All emissions changes are reported as log percentages (or log points), which can be interpreted as percentage point changes.

6.5.1 Decompositions for SO2 discharged

Consider first the case of SO2 discharged amount in the top panel of Table 6.5. Columns 2 to 4 report the underlying weighted average emission changes for all three groups of firms in the TCZ area across all time spans.

For the in-TCZ table, as shown in column 6, the growth of the weighted average SO2 discharged is negative from 2002, which indicates the reduced weighted average emissions caused by regulation over the years. The decomposition reports a positive contribution of entry and a negative contribution of exit. In all sample years, the entrants' weighted average SO2 discharged is above the overall weighted

Table 6.5: Contributions of the channels to emission changes

	Aggregate Emission Change Relative to 1998														
	In-TCZ, $t1-t0$					Out-TCZ, $t1-t0$					DID				
Year ($t1$)	Surviving	Entering	Exiting	Net exit	Total	Surviving	Entering	Exiting	Net exit	Total	Surviving	Entering	Exiting	Net exit	Total
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
SO2 Discharged Amount—Output Share Weight															
2001	0.02	14.26	-14.23	0.03	0.06	-0.22	13.66	-14.41	-0.75	-0.97	0.23	0.61	0.18	0.79	1.03
2002	-0.54	14.47	-14.75	-0.28	-0.82	-0.18	13.87	-14.47	-0.6	-0.78	-0.36	0.60	-0.29	0.31	-0.04
2003	-0.40	14.56	-14.83	-0.27	-0.66	-0.23	14.18	-14.42	-0.24	-0.47	-0.17	0.38	-0.40	-0.02	-0.19
2004	-0.35	14.80	-14.84	-0.04	-0.38	-0.32	14.28	-14.16	0.12	-0.20	-0.02	0.52	-0.68	-0.16	-0.18
2005	-0.30	14.90	-14.91	-0.01	-0.31	-0.20	14.69	-14.49	0.2	0.00	-0.10	0.21	-0.42	-0.21	-0.31
2006	-0.21	14.52	-15.27	-0.75	-0.96	0.03	14.01	-14.79	-0.78	-0.74	-0.24	0.51	-0.48	0.03	-0.21
2007	-0.11	14.57	-15.20	-0.63	-0.75	0.31	13.64	-14.48	-0.84	-0.53	-0.42	0.92	-0.73	0.19	-0.23
SO2 generated Amount—Output Share Weight															
2001	0.31	15.04	-14.57	0.47	0.78	0.02	14.67	-13.33	1.34	1.36	0.29	0.37	-1.24	-0.87	-0.57
2002	0.01	15.40	-15.14	0.26	0.27	0.13	14.78	-13.38	1.4	1.53	-0.13	0.63	-1.75	-1.12	-1.25
2003	0.26	15.66	-14.99	0.67	0.92	0.08	14.97	-13.09	1.88	1.95	0.18	0.69	-1.90	-1.21	-1.03
2004	0.49	15.87	-15.13	0.74	1.23	0.20	15.05	-13.12	1.93	2.13	0.30	0.82	-2.01	-1.19	-0.89
2005	0.37	16.13	-15.20	0.93	1.30	0.39	15.39	-13.64	1.75	2.14	-0.02	0.74	-1.56	-0.82	-0.85
2006	1.16	15.93	-15.43	0.5	1.67	0.22	15.34	-13.68	1.66	1.89	0.93	0.60	-1.75	-1.15	-0.22
2007	0.86	16.54	-15.41	1.13	1.99	0.75	14.03	-13.85	0.18	0.93	0.11	2.51	-1.56	0.95	1.06

Note: The base year is 1998, i.e., $t_0 = 1998$. All changes are reported as log percentages (or log points), which be interpreted as percentage point changes.

emission level Φ^{in}_{After}: their presence pulls the weighted average SO2 discharged level upward. On the contrary, exiting firms pull the weighted average SO2 discharged level downward.

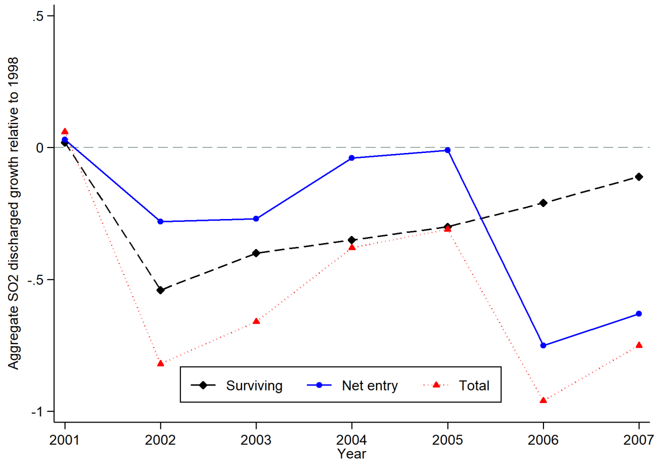
The contribution of net exit (combined contribution of entrants and exits, column 5) remains negative in any given year, which is attributed to the reduced total weighted average emission in column 6. There is a negative contribution of net exit because, in any given year, entrants have a weighted average SO2 discharged, $\sum_{i\in(En,In)}(s^{in}_{i,t1}\varphi^{in}_{i,t1})$, whose absolute value is below the absolute value of weighted average emissions of exiting firms ($[\sum_{i\in(Ex,In)}(s^{in}_{i,t0}\varphi^{in}_{i,t0})]$). This result uncovers the finding that cannot be observed by panel regression: in the TCZ area, exiting firms' environmental efficiency is on average lower than that of entering firms, which contributes to the reduced aggregate emissions level.

As the time span increases, we see that the contributions of survivors for the decompositions steadily decrease, down to 0.11 percentage points. This shows that continuing firms with a longer life are big firms with more bargaining power, who contribute less to emissions reduction. Concurrently, the weighted average SO2 discharged of exiting firms has been steadily growing over the years, up to 15.20. Although both survivors and the net exit contribute to reduced weighted average emissions, the contribution of survivors is larger than that of the net exit before 2005, while the reverse occurred in 2006 and 2007. Weighted average emissions change is primarily driven by surviving firms rather than by net exit before 2005. But with the time span increase, net exit contributes more to aggregate emissions reduction. In addition to the TCZ policy, China implemented "the 11th Five-Year Plan" from 2006 to 2010, which sets out targets for energy conservation and emissions reduction. More firms with low environmental efficiency have been forced to exit the market because of the 11th Five-Year Plan, which is another reason for the reversed condition.

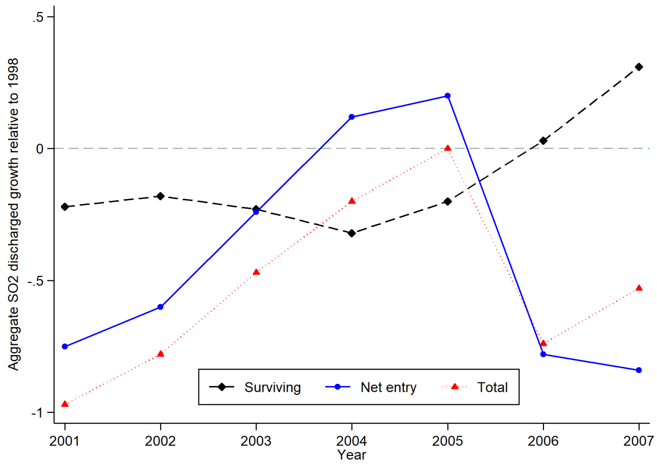
In the out-TCZ table (columns 7-11), however, the contributions of survivors for the decompositions transformed from negative to positive in 2006. In the area without environmental regulations, continuing firms are less likely to reduce weighted average emissions. Similar to the result for the in-TCZ table, a positive contribution of entry and a negative contribution of exit is reported. However, the results do not report a neat moving trend similar to the contribution of entry and exit. The contribution of the net effect of entry and exit (column 10) shows a fluctuating pattern. Overall, the out-TCZ area did not experience a pattern as the in-TCZ area did, because of weak regulation but the total effect is negative.

Columns 12-16 of Table 6.5 are the DID framework decomposition for emissions variables proposed in this research. As the in-TCZ and out-TCZ firms all experience negative growth in the weighted average SO2 amount, I can compute the difference between them and decompose it into the contribution of channels (survivors, entrants, exits). Column 16 reports the difference between the weighted average SO2 discharged growth for the in-TCZ area and the out-TCZ area, which indicates that there is a negative effect of the TCZ policy on weighted average emissions subject to the firms in the control group. As the time span increases, we see that the total effect steadily decreased to -0.41 in 2005. In the first five years of implementation the TCZ policy widened the gap between the in-TCZ area's emissions reduction and the out-TCZ area's emissions mitigation. The national scale 11th Five-Year Plan, however, helped shrink the gap in 2006 and 2007, by -0.21 and -0.23 respectively. It helped to improve air quality nationally and eliminate the spatial spillover effect caused by polluting firms' relocation to out-TCZ areas.

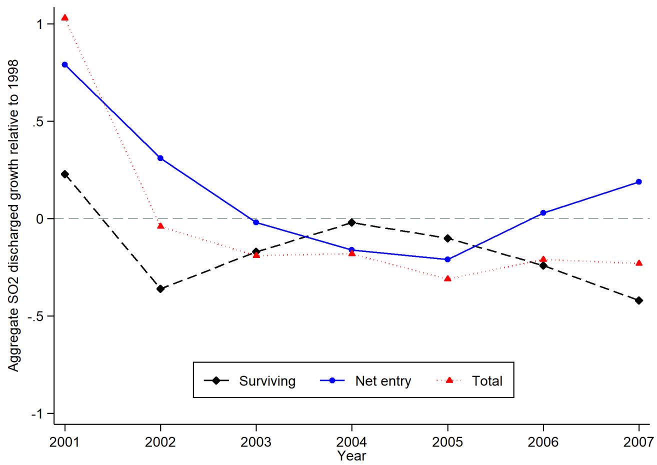
Similar to the interpretation of DID panel regression, column 16 is the pure effect of environmental policy. The contribution of survivors, entrants, and exits is presented in columns 12-14. There is a slightly negative net effect of survivors and exit and a positive effect of entry. The entering firms for in-TCZ areas have higher average SO2 discharged than those in out-TCZ areas. Even with more stringent regulations, polluting firms are still willing to start up in TCZ areas. Panel regression analysis with a conclusion of averagely reduced emission fails to display the behaviour of entering firms facing regulations. But, at the same time, exiting firms in the in-TCZ group have a higher weighted average SO2 discharged drop than that of the out-TCZ group. For the contribution of surviving firms, the effect is negative over the years as shown in column 12. The results are striking: the difference between weighted average SO2 discharged growth for the in-TCZ area and the out-TCZ area is primarily driven by the gap in the surviving firms channel across the two groups rather than by the net exit channel.



(a) In-TCZ area



(b) Out-TCZ area



(c) DID Framework

Figure 6.7: The decomposition of SO2 discharged amount relative to 1998

6.5.2 Decompositions for the SO2 generated amount

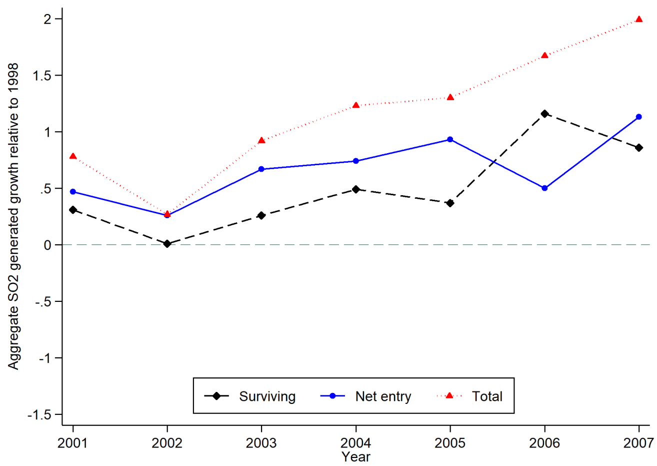
We look now at SO2 generated in the bottom panel of Table 6.5. Columns (2) to (6) report changes in weighted average SO2 generated for all three groups of firms in the TCZ area across all time spans, (the in-TCZ panel). These results show an opposite pattern to the changes in SO2 discharged (displayed in the top panel) and different findings from the panel regression. As shown in column (6), the growth of weighted average SO2 generated is positive over the years. As the time span increases, we see that the growth rate steadily increases from 2002, up to 1.99 percentage points in 2007. The decomposition reports a positive contribution of survivors and entrants and a negative contribution of exit. The entrants pull the weighted average SO2 generated level upwards but exiting firms pull it downwards. In all sample years, the contribution of survivors is positive. Even facing strict regulation, surviving firms keep increasing average generated SO2.

The contribution of net exit remains positive in any given year, which is attributed to the increased total weighted average SO2 generated in column (6). Net exit makes a positive contribution because entrants have a weighted average of SO2 generated, $\sum_{i\in(En,In)}(s^{in}_{i,t1}\varphi^{in}_{i,t1})$, whose absolute value is above the absolute value of the weighted average generated SO2 of exiting firms $([\sum_{i\in(Ex,In)}(s^{in}_{i,t0}\varphi^{in}_{i,t0})])$. The results imply that exiting firms' environmental efficiency is averagely lower than that of entering firms in the TCZ area when SO2 generated is used to denote emissions.

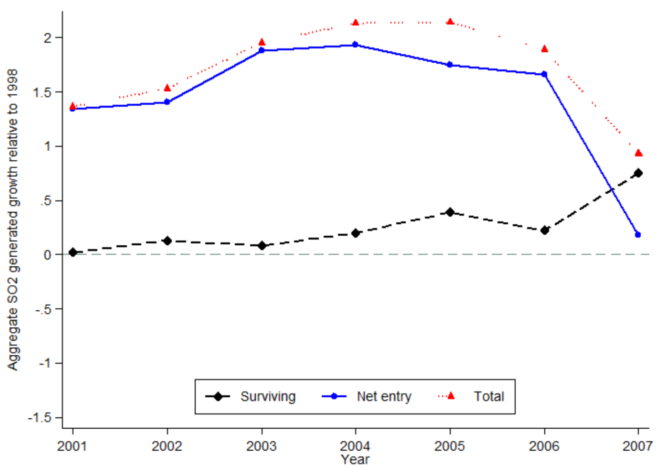
The striking finding is that weighted average SO2 generated is increasing even under strict regulations. (In the DID panel regression analysis in Chapter 1, each firm has the same weight, which empirically reports the reduced average SO2 generated influenced by the TCZ policy). Both survivors and net exit contribute to increased weighted average SO2 generated, and net exit contributes more than survivors in most years. In particular, the contributions of entering firms for decompositions steadily increase. When I consider output weight, a firm with higher output and more market share generates more pollutants. Although the amount of SO2 generated has increased over the years, SO2 discharged shows a decreasing trend because of improved ability to treat the pollutant SO2. In the out-TCZ panel (columns 7-11), the positive contribution of survivors and net exit are the reason for the increased weighted average SO2 generated shown in column (11), which is a similar pattern to the in-TCZ area.

I am interested in the difference between the growth of the weighted average SO2 generated for the in-TCZ area and the out-TCZ area, which is shown in the DID framework decomposition (columns 12-16). Since the growth of average SO2 generated for the in-TCZ area (column 6) is higher than that for the out-TCZ area (column 11), the effect of environmental policy on the weighted average SO2 generated is negative as shown in column (16). The contribution of survivors to the DID framework decompositions is positive in most years. However, the contribution of net exit to the DID framework decompositions has been negative over the years. The reduced average SO2 generated is driven by the net exit effect difference between in-TCZ and out-TCZ groups.

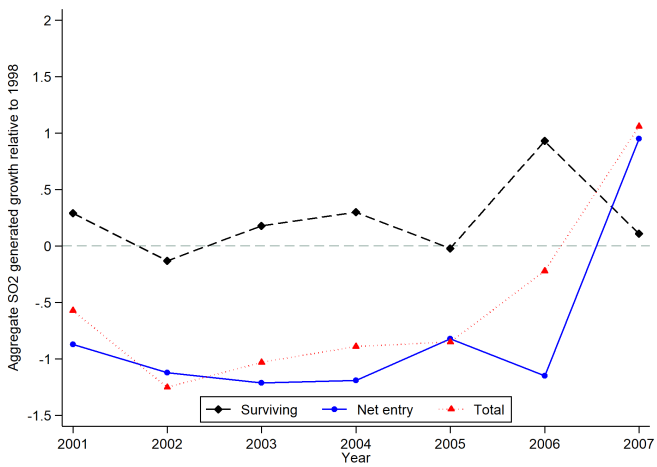
In the panel regression analysis of Chapter 1, I find evidence that the TCZ policy averagely reduced firms' discharge and generation of SO2. Through the empirical analysis with the decomposition approach, I find that the TCZ policy can successfully reduce regulated firms' weighted average SO2 discharged but fails to mitigate their weighted average SO2 generated. On the contrary, the weighted average SO2 generated increased during the sample periods. From the decompositions for the weighted average SO2 discharged, I find that the channels of survivors and net exit both contributed to emissions reduction. Surviving firms in the TCZ area have larger negative growth in discharged SO2 than those out of the TCZ area, which is the driver for reducing discharged pollutants. For the decompositions for the weighted average SO2 generated, the contribution of net exit is the driver of its reduction. The negative effect of net exit (column 15) results from the positive growth of weighted average SO2 generated in the TCZ area being smaller than growth out of the TCZ area. For firms located inside the TCZ area or outside it, the growth of weighted average SO2 generated remained positive during the sample periods.



(a) In-TCZ area



(b) Out-TCZ area



(c) DID Framework

Figure 6.8: The decomposition of SO2 generated amount relative to 1998

6.5.3 Within-firm and Cross-firm components

In this section, I use the Melitz and Polanec (2015) approach to split the contribution of surviving firms into two compositions, the within-firm subcomponent and the the cross-firm subcomponent. The change in weighted average emissions for surviving firms can then be decomposed into a sum of emissions changes holding the firms' shares constant (within-firm component) and the covariance between changes in market share and changes in productivity (cross-firm component). Melitz and Polanec (2015)'s decomposition approach considers market share reallocation across firms between two periods, which can be used for my further decomposition of the contribution of surviving firms.

6.5.3.1 Basic model setup

First, I start from the static decomposition method proposed by Olley and Pakes (1996) which provides a natural way of decomposing weighted average productivity into the mean market share and a covariance term. In equation 6.11, the weighted average emissions for surviving firms at period t is decomposed into two terms, unweighted average emissions and a covariance term between market share and firm emissions.

$$\begin{aligned}\Phi_{S,t} =& \sum_{i \in S} w'_{i,t}\varphi_{i,t} \\ =& \overline{\varphi}_{S,t} + cov_{S,t}\end{aligned} \tag{6.11}$$

where $\overline{\varphi}_{S,t} = \frac{1}{n_t}\sum_{i=1,i\in(S,A)}^{n_t} \varphi_{it}$ is the unweighted firm emission, and $cov_{S,t} = \sum_{i\in(S,A)}(w'_{i,t} - \overline{w'}_t)(\varphi_{it} - \overline{\varphi}_{S,t})$. Firm i's market share within the subset of surviving firms (in/out of the TCZ area) is given by: $w'_{(i,t)} = \frac{w_{(i,t)}}{w_{(S,t)}}$ (where $w_{(S,t)} = \sum_{i\in(S,A)} w_{(i,t)}$). For surviving firms in/out of the TCZ area, their market share sum to 1, $\sum_{i\in(S,A)} w'_{(i,t)} = 1$. The first term $\overline{\varphi}_{S,t}$ shows the unweighted average emission level for surviving firms inside or outside the TCZ area. The higher $\overline{\varphi}_{S,t}$ means a higher average emission level. The second term $cov_{S,t}$ is the Olley-Pakes covariance, which increases with the correlation between market share and emissions. The larger the covariance the higher the share of output that goes to more polluting firms, implying larger local emissions. Conversely, the smaller the covariance the higher the share of output going to cleaner firms, which indicates a cleaner economy. After the environmental policy was implemented, I supposed resources would be reallocated to firms with fewer emissions, which is an economy with lower covariance term $cov_{S,t}$.

Second, a dynamic scenario displaying the weighted average emission growth $\Delta\Phi$ for surviving firms is needed. Following Melitz and Polanec (2015)'s approach, for firms in (or out of) the TCZ area, surviving firms' weighted average emissions growth is given by:

$$\begin{aligned}
\Delta\Phi_S &= \Phi_{(S,t1)} - \Phi_{(S,t0)} \\
&= \sum_{i\in S} w'_{(i,t1)}\varphi_{(i,t1)} - \sum_{i\in S} w'_{(i,t0)}\varphi_{(i,t0)} \\
&= \overline{\varphi}_{(S,t1)} + cov_{(S,t1)} - \overline{\varphi}_{(S,t0)} - cov_{(S,t0)} \\
&= \underbrace{\Delta\overline{\varphi}_S}_{Within} + \underbrace{\Delta cov_S}_{Cross}
\end{aligned} \tag{6.12}$$

Equation 6.12 breaks down the contribution of surviving firms for weighted average emissions growth (inside or outside the TCZ area) into two subcomponents, within-firm subcomponents and cross-firm subcomponents. This is an intertemporal difference that only considers firms within the same area. In the fourth line of equation 6.12, the first term, $\Delta\overline{\varphi}_S$, denotes the within-firm subcomponent in Melitz and Polanec (2015), which captures the contribution of emissions reductions within surviving firms. The second term, Δcov_S, represents the cross-firm subcomponent in Melitz and Polanec (2015), which is the covariance between share changes and emissions changes. The fourth line of equation 6.11 means that the changes in emission over time $\Delta\Phi_S$ are given by the shifts in the emissions distribution $\Delta\overline{\varphi}_S$ and another component capturing market share reallocations via the change in covariance Δcov_S.

The within-firm subcomponent, $\Delta\overline{\varphi}_S$, is calculated by the unweighted mean change in the emissions of surviving firms, $\overline{\varphi}_{(S,t1)} - \overline{\varphi}_{(S,t0)}$. It is induced by the shift in the distribution of firm emissions. The decline of unweighted average emissions captures the shifts in emissions distribution, which implies firms' self-improvement. Thus, if the within-firm subcomponent, $\Delta\overline{\varphi}_S$, is negative, then it implies firms inside or outside the TCZ area have become cleaner over the years. If the term is positive, average emissions will increase from $t0$ to $t1$, which means a dirtier economy.

The cross-firm subcomponent, Δcov_S, is computed by the covariance change between market share and emissions for surviving firms inside or outside the TCZ area, $\Delta cov_S = cov_{(S,t1)} - cov_{(S,t0)}$. The change in the Olley-Pakes covariance captures market share reallocation between firms. As described above, the larger the covariance the higher the share of output going to dirtier firms. Thus, if the cross-firm subcomponent, Δcov_S, is negative, it denotes a good change because dirtier firms have a larger market share at time $t0$ but a smaller market share at time $t1$. The production of an economy has been reallocated to cleaner firms during this period. If the term is positive, an environmentally bad change has occurred.

I suppose the growth of unweighted average emissions $\Delta\overline{\varphi}_S$ for the in-TCZ area is negative, which indicates reduced average firm emission under environmental regulation. Reduced unweighted average emissions are induced by the firm's self-improvement in environmental efficiency under policy regulation. However, the growth of unweighted average emissions $\Delta\overline{\varphi}_S$ for the out-TCZ area could be positive or negative. It is negative because spillover effect of an environmental policy can influence the firms in nearby cities and finally reduce unweighted average emissions outside the TCZ area.

The change in covariance Δcov_S for the in-TCZ area is also supposed to be negative, i.e., the covariance at period $t1$, $cov_{(S,t1)}$, is smaller than the covariance at period $t0$, $cov_{(S,t0)}$. Since the introduction of stringent regulation, market share is reallocated to firms with lower emissions which are the cleaner firms. The change in covariance Δcov_S for the out-TCZ area could be positive or negative. The TCZ policy's spillover effect can influence firms outside the TCZ area and make the covariance value negative. Meanwhile, firms with higher emissions are always large firms or SOEs. They have more bargaining power and may not be willing to reduce their production. Thus, for the out-TCZ area, large firms with higher emissions can gain more market share over the years, which induces the positive cross-firm effect.

In summary, the within-firm component denotes firms' self-improvement in pollutant treatment, and the cross-firm component indicates how market share is reallocated across firms. I suppose that firms in the TCZ area not only reduce their emissions (negative within-firm subcomponent) but also reallocate market share to cleaner firms with fewer emissions (negative cross-firm subcomponent).

Third, DID framework decomposition is created for the analysis. Equation 6.13 is the DID framework decomposition for the contribution of surviving firms. The difference in surviving firms' weighted average emissions growth between the in-TCZ and out-TCZ areas is given by $\Delta\Phi_S^{in} - \Delta\Phi_S^{out}$. Equation 6.13 breaks down the difference in emissions growth into within-firm subcomponents and cross-firm subcomponents. This DID framework decomposition not only considers intertemporal average emission growth for firms within the same TCZ area but also considers the regional difference induced by the TCZ policy. The DID framework decomposition of surviving firms' contribution is given by:

$$\Delta\Phi_S^{in} - \Delta\Phi_S^{out} = \underbrace{\Delta\overline{\varphi}_S^{in} - \Delta\overline{\varphi}_S^{out}}_{Within} + \underbrace{\Delta cov_S^{in} - \Delta cov_S^{out}}_{Cross} \tag{6.13}$$

where $(\Delta\overline{\varphi}_S^{in} - \Delta\overline{\varphi}_S^{out})$ is the difference between the unweighted mean emissions growth for the in-TCZ area and the growth for the out-TCZ area, which denotes the within-firm effect of the DID framework decomposition. $(\Delta cov_S^{in} - \Delta cov_S^{out})$ is the gap between the covariance change for the in-TCZ area and the covariance change for the out-TCZ area, which denotes the cross-firm effect of the DID framework decomposition.

The within-firm subcomponent, $\Delta\overline{\varphi}_S^{in} - \Delta\overline{\varphi}_S^{out}$, is induced by the shift in the distribution of firm emissions. Since the TCZ policy motivates firms' self-improvement significantly, the within-firm subcomponent of the DID framework decomposition, $\Delta\overline{\varphi}_S^{in} - \Delta\overline{\varphi}_S^{out}$, is supposed to be negative. It implies two scenarios that could happen. In the first scenario, $\Delta\overline{\varphi}_S^{in}$ is negative denoting a cleaner improvement inside the TCZ area; and $\Delta\overline{\varphi}_S^{out}$ is positive indicating a dirtier change outside the TCZ area due to a lack of environmental regulation. In the second scenario, $\Delta\overline{\varphi}_S^{in}$ and $\Delta\overline{\varphi}_S^{out}$ are both negative but $\Delta\overline{\varphi}_S^{in}$ has a larger absolute value. The spillover effect of the TCZ policy's on firms located in nearby cities results in reduced unweighted average emissions outside the TCZ area (i.e., negative $\Delta\overline{\varphi}_S^{out}$). But the policy's direct influences on firms inside the TCZ area should be more effective than its spillover effect on firms outside the TCZ area, which explains the negative value of $\Delta\overline{\varphi}_S^{in} - \Delta\overline{\varphi}_S^{out}$. Thus, the negative term of $(\Delta\overline{\varphi}_S^{in} - \Delta\overline{\varphi}_S^{out})$ denotes that firms inside the TCZ area have better self-improvement relative to firms outside the TCZ area, which could be a result of the pure effect of the TCZ policy or its relatively more effective impact on the TCZ area.

The cross-firm subcomponent, $\Delta cov_S^{in} - \Delta cov_S^{out}$, captures market share reallocation between firms. If the cross-firm subcomponent is negative, it denotes a larger market share outside the TCZ area at period $t0$ has been reallocated to cleaner firms inside the TCZ area at period $t1$, which implies the TCZ policy's effect on relocating production to cleaner firms. Production has been reallocated to cleaner firms in the TCZ area during this period. The negative cross-firm subcomponent also denotes two scenarios. One scenario is that the negative Δcov_S^{in} induced by the TCZ policy's reallocation effect is accompanied by the positive Δcov_S^{out} resulting from dirtier firms with large production outside the TCZ area facing fewer financial constraints and having more bargaining power. In the second scenario, the TCZ policy's spillover effect could lead to the negative Δcov_S^{out}. But the final cross-firm effect, $\Delta cov_S^{in} - \Delta cov_S^{out}$, is negative, which indicates a better reallocation to cleaner firms.

6.5.3.2 Decomposition results for surviving contribution

The within- and cross-firm components for surviving firms are separately reported in Table 6.6. The top panel is based on amounts of SO2 discharged measured with output shares and the bottom panel is based on SO2 generated measured with output weight. Columns (2) and (3) report the underlying weighted average emission changes for surviving firms in the TCZ area across all time spans. Columns (4) and (5) report the weighted average emissions changes for surviving firms out of the TCZ area. The last two columns are the DID framework decomposition for surviving firms' contributions.

The interpretation starts from SO2 discharged in the top panel of Table 6.6. For the in-TCZ group, as shown in column (2), the growth of unweighted average SO2 discharged is negative over the years, which indicates reduced firm emissions holding firms' shares constant. Since 2003, the absolute value of the within-firm subcomponent has kept increasing (from 0.41 percentage points in 2003 to 1.46 percentage points in 2007). In column (3), a negative contribution of the cross-firm subcomponent is reported. However, the results do not report a neat moving trend similar to the contribution of the within-firm subcomponent. For surviving firms in the TCZ area, within- and cross-firm subcomponents both contribute to the reduction of weighted average emissions. But it is primarily driven by the within-firm subcomponents, which indicates that the reduced firm emissions holding the firms' shares constant are the key reason leading to the negative contribution of surviving firms rather than market share reallocations (the results in Table 6.5 column 2).

For the out-TCZ panel (columns 4 and 5), when considering the market share changes in this section, I obtained an opposite finding compared with the result in Table 6.5. The contribution of within- and cross-firm subcomponents for surviving firms out of the TCZ area remains positive in any given year. This finding is additional proof of the TCZ policy's negative effect on surviving firms' weighted and unweighted average emissions.

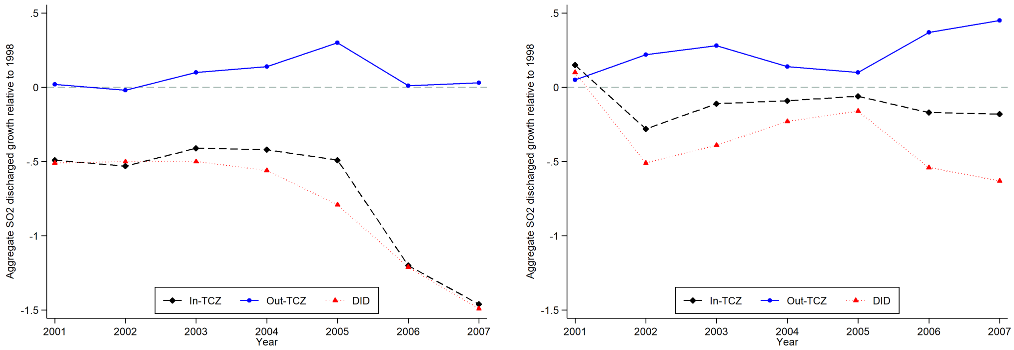
Considering the DID results, column (6) of the top panel of Table 6.6 indicates that there is a negative effect of the TCZ policy on the unweighted mean change in the emissions of survivors subject to the firms in the control group. Meanwhile, column (7) shows a similar pattern for cross-firm components. To be specific, the within-firm subcomponent has been negative over the years as shown in column (6). The within-firm contribution keeps decreasing, which proves the policy is widening the unweighted average emissions gap between firms in and out of the TCZ area.

I investigate the case of SO2 generated in the bottom panel of Table 6.6. Both in-TCZ and out-TCZ surviving firms' contributions have been decomposed into a positive within-firm subcomponent and a positive cross-firm subcomponent. For the in-TCZ panel (columns 2 and 3), the cross-firm subcomponent is the key driver of the positive contribution of surviving firms. Market share reallocation instead of the increased unweighted average SO2 generated is the reason for the positive surviving contribution. The TCZ area's surviving firms with higher amounts of SO2-generated took more market share after the policy was implemented. This effect keeps increasing as the cross-firm subcomponent has increased from 0.15 percentage points in 2002 to 1.2 percentage points in 2006. A similar pattern has emerged in the out-TCZ area (columns 4 and 5). Thus, the negative contribution of surviving firms in the DID frame decomposition is contributed by the negative within- and cross-firm subcomponents (columns 6 and 7), which is induced by the lower within- and cross-firm subcomponents for the in-TCZ area than that for the out-TCZ area.

Table 6.6: Contributions of within-firm emissions reduction and between-firm reallocations

	In-TCZ, $t1 - t0$		Out-TCZ, $t1 - t0$		DID	
Year ($t1$)	Within	Cross	Within	Cross	Within	Cross
(1)	(2)	(3)	(4)	(5)	(6)	(7)
			SO2 Discharged amount—Output Share Weight			
2001	-0.49	0.15	0.02	0.05	-0.51	0.10
2002	-0.53	-0.28	-0.02	0.22	-0.50	-0.51
2003	-0.41	-0.11	0.10	0.28	-0.50	-0.39
2004	-0.42	-0.09	0.14	0.14	-0.56	-0.23
2005	-0.49	-0.06	0.30	0.10	-0.79	-0.16
2006	-1.20	-0.17	0.01	0.37	-1.21	-0.54
2007	-1.46	-0.18	0.03	0.45	-1.49	-0.63
			SO2 generated amount—Output Share Weight			
2001	-0.01	0.43	0.11	0.37	-0.13	0.06
2002	-0.01	0.15	0.17	0.65	-0.17	-0.50
2003	0.13	0.36	0.23	0.69	-0.10	-0.34
2004	0.25	0.51	0.35	0.76	-0.10	-0.25
2005	0.24	0.62	0.54	0.78	-0.30	-0.16
2006	0.20	1.20	0.23	0.64	-0.03	0.56
2007	0.25	0.76	0.59	0.95	-0.34	-0.19

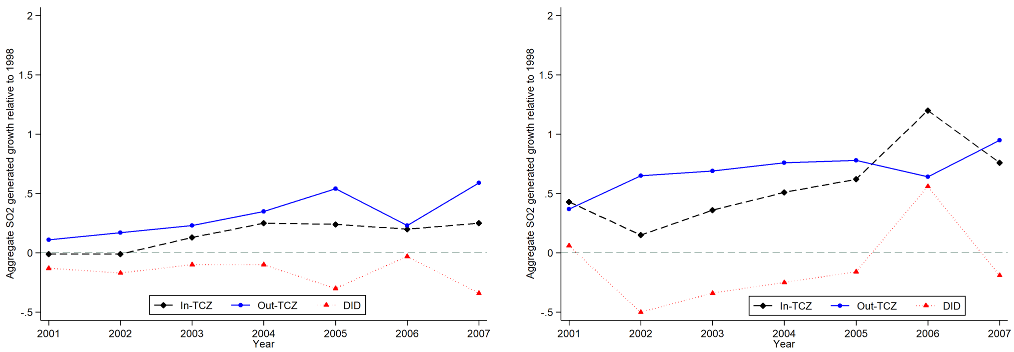
Note: The base year is 1998, i.e., $t_0 = 1998$. All changes are reported as log percentages (or log points), which be interpreted as percentage point changes.



(a) Within-firm effect

(b) Cross-firm effect

Figure 6.9: The decomposition of SO2 discharged amount for surviving firms contribution



(a) Within-firm effect

(b) Cross-firm effect

Figure 6.10: The decomposition of SO2 generated amount for surviving firms contribution

6.6 Robustness Check

In this section, I use firm-level waste gas discharged as the weight in the decomposition analysis. I get a robust result which is similar to the results in Table 6.5.

Consider first the case of SO2 discharged in the top panel of Table 6.7. Columns (2) to (4) report the underlying weighted average emissions changes for all three groups of firms in the TCZ area across all time spans. For the in-TCZ table, as shown in column (6), the growth of the weighted average SO2 discharged is negative in all given years, which indicates the reduced weighted average emissions caused by regulation over the years. The decomposition reports a positive contribution of entry and a negative contribution of exit. The contribution of net exit (combined contribution of entrants and exits, column (5) remains negative in any given year, which is attributed to the reduced total weighted average emissions in column (6). For the out-TCZ table (columns 7-11), the contributions of survivors remain negative but there is not a neat moving trend for net exit. Columns 12-16 of Table 6.5 are the DID framework decomposition for emissions variables proposed in this research. Similar to the basic result in Table 6.5, the difference between weighted average SO2 discharged growth for the in-TCZ and out-TCZ areas is primarily driven by the gap in surviving firms channel across the two groups rather than the net exit channel.

Turining to SO2 generated in the bottom panel of Table 6.7. As shown in column (6), the growth of weighted average SO2 generated is positive over the years. The decomposition reports a positive contribution of survivors and entrants and a negative contribution of exit. In the out-TCZ panel (columns 7-11), the positive contribution of survivors and net exit are the reasons for the increased weighted average SO2 generated shown in column (11), which is a similar pattern to the in-TCZ area. However, the contribution of net exit for the DID framework decompositions has been negative over the years. The reduced average SO2 generated is driven by the net exit effect difference between in-TCZ and out-TCZ groups.

Table 6.7: Robustness check using waste gas weight

	Aggregate Emission Change Relative to 1998														
	In-TCZ, $t1-t0$					Out-TCZ, $t1-t0$					DID				
Year ($t1$)	Surviving	Entering	Exiting	Net exit	Total	Surviving	Entering	Exiting	Net exit	Total	Surviving	Entering	Exiting	Net exit	Total
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
SO2 Discharged Amount—Output Share Weight															
2001	-0.36	15.42	-15.43	-0.01	-0.37	-0.47	15.16	-15.41	-0.25	-0.72	0.12	0.26	-0.03	0.23	0.35
2002	-0.68	15.44	-15.59	-0.15	-0.83	-0.47	15.28	-15.45	-0.16	-0.64	-0.20	0.15	-0.14	0.01	-0.19
2003	-0.51	15.58	-15.81	-0.23	-0.74	-0.46	15.36	-15.37	-0.02	-0.48	-0.05	0.22	-0.43	-0.21	-0.26
2004	-0.55	15.88	-15.89	-0.01	-0.56	-0.46	15.75	-15.11	0.64	0.18	-0.09	0.13	-0.78	-0.65	-0.74
2005	-0.72	16.17	-15.89	0.27	-0.44	-0.39	15.92	-15.63	0.29	-0.10	-0.32	0.24	-0.27	-0.02	-0.34
2006	-0.05	15.65	-16.58	-0.93	-0.98	-0.46	14.53	-16.15	-1.62	-2.08	0.41	1.12	-0.43	0.69	1.10
2007	0.13	15.35	-16.50	-1.15	-1.02	0.17	14.12	-15.51	-1.39	-1.22	-0.04	1.23	-0.99	0.24	0.20
SO2 generated Amount—Output Share Weight															
2001	0.07	15.84	-15.70	0.15	0.21	0.42	15.37	-15.31	0.05	0.47	-0.35	0.48	-0.38	0.09	-0.26
2002	0.09	15.93	-15.95	-0.02	0.07	0.13	15.48	-15.37	0.11	0.24	-0.04	0.45	-0.58	-0.13	-0.18
2003	0.01	16.02	-15.81	0.20	0.22	0.04	15.51	-15.10	0.40	0.44	-0.03	0.51	-0.71	-0.20	-0.23
2004	0.08	16.29	-15.89	0.40	0.48	0.08	15.92	-15.14	0.79	0.87	-0.01	0.37	-0.76	-0.39	-0.39
2005	0.15	16.53	-16.13	0.39	0.54	0.42	16.14	-15.48	0.67	1.08	-0.27	0.38	-0.66	-0.27	-0.54
2006	0.52	16.13	-16.29	-0.16	0.36	0.85	14.84	-15.56	-0.72	0.13	-0.34	1.29	-0.72	0.56	0.23
2007	0.79	16.57	-16.31	0.26	1.05	0.89	14.49	-15.64	-1.16	-0.27	-0.10	2.09	-0.67	1.42	1.32

Note: The base year is 1998, i.e., $t_0 = 1998$. All changes are reported as log percentages (or log points), which be interpreted as percentage point changes.

Table 6.8: Notations for decomposition

Notation	Description	Calculation
P_t	Aggregate productivity (Weighted average productivity) at period t	$P_t = \sum_i w_{i,t}p_{i,t}$
w_{it}	Market share (Wight) for firm i at period t, the ratio of firm i's output to sector's aggregate output.	$w_{it} = \frac{output_i t}{\sum_i output_i t}$
p_{it}	Firm i's productivity at Period t	—
ΔP	Aggregate productivity growth	$\Delta P = w_{i,t1}p_{i,t1} - w_{i,t0}p_{i,t0}$
$\overline{w}_t$	The mean market share	$\overline{w}_t = 1/n_t$
$\overline{p}_t$	The unweighted firm productivity mean	$\overline{p}_t = \frac{1}{n_t}\sum_{i=1}^{n_t} p_{it}$
Φ_t^A	The weighted average emission for firms in area A at period t	$\Phi_t^A = \sum_{i\in A} w_{it}\varphi_{it}$
A	A dummy variable to denote the in-TCZ area and out-TCZ area	$A \in \{in{-}TCZ, out{-}TCZ\}$
$\varphi_{i,t}$	The sulfur dioxide (SO_2) discharged/generated amount of firm i at period t.	—
$\overline{\varphi}_t$	The unweighted firm emission mean at period t	$\overline{\varphi}_t = \frac{1}{N_t}\sum_{i=1}^{N_t} \varphi_{it}$
t	Time period index denoting a year before/after the policy implementation. After the policy implementation, $t = 1$	$t \in (0, 1)$
n_t	The number of firms.	—

6.7 Conclusion

Inspired by existing literature relating to the productivity decomposition approach, in this research I propose an extension of the decomposition method, namely a new DID framework decomposition. The DID framework decomposition for firms' weighted aggregate emissions provides an accounting for the contributions of surviving firms, entering firms, and exiting firms to aggregate emissions change. It also breaks down the separate contributions of firm-level emissions growth and market share reallocations among surviving firms. I apply my proposed decomposition to the large measured decreases of SO2 emissions in China during the 2000-2010 period, accounting for the separate contributions of firm-level emissions changes, market share reallocations, entry, and exit. Using the DID framework decomposition, I explore the underlying causes of weighted average emissions changes and investigate how various decompositions of weighted average emissions can capture the changes' key microeconomic sources, i.e., the contributions of entry and exit, and track individual firms over time.

I obtain different findings with different metrics for emissions (SO2 discharged/generate First, when using SO2 discharged to denote firms' emissions, the DID framework decomposition implies a negative effect of the TCZ policy on weighted average emissions subject to the firms in the control group. As the time span increases, the gap widens between the in-TCZ area's emissions reduction and the out-TCZ area's emissions mitigation in the first five years of implementation. The difference between weighted average SO2 discharged growth for the in-TCZ area and the out-TCZ area is primarily driven by the gap in the surviving firms channel across the two groups rather than the net exit channel. For the in-TCZ group samples, before 2005 negative weighted average emission change is primarily driven by surviving firms rather than net exit. But as the time span increases, net exit contributes more to aggregate emissions reduction. The out-TCZ area did not experience a pattern as the in-TCZ area did, because of weak regulation but the total effect is negative. After decomposing the contribution of surviving firms into within-firm and cross-firm subcomponents, within- and cross-firm subcomponents both contribute to the reduction of weighted average emissions of surviving firms, while reduced firm emissions holding the firms' shares constant instead of market share reallocations are the key reason leading to the negative contribution of surviving firms.

Second, when using the amount of SO2 generated to denote firms' emissions, the DID framework decomposition also implies a negative effect of the TCZ policy on weighted average emissions compared with the firms in the control group. However, effective policy implementation is driven by the gap in the net exit channel between in-TCZ and out-TCZ groups. Whether we consider the in-TCZ group or the out-TCZ group, the positive contributions of survivors and net exit are the reasons for the increased weighted average SO2 generated. Both survivors and net exit contribute to the increased weighted average SO2 generated, and net exit contributes more than survivors in most years. These findings can not be explored through panel regression. By decomposing the contribution of surviving firms, I find that both in-TCZ and out-TCZ surviving firms' contributions can be decomposed into a positive within-firm subcomponent and a positive cross-firm subcomponent. The negative contribution of surviving firms in the DID frame decomposition is induced by lower within- and cross-firm subcomponents for the in-TCZ area than for the out-TCZ area.

Our findings highlight the negative impacts of the TCZ policy on firm emissions. Based on the evidence documented here, environmental policy can generate spillover effects on unregulated cities. It not only minimized the pollutants discharged by firms complying with the policy but also reduced the pollutants discharged by firms in neighbouring cities. Meanwhile, firms respond to the environmental policy by reducing discharged pollutants rather than generating less, which is the opposite finding against the panel regression result. They are prone to remove pollutants at the end of the production process by using additional devices but fail to reduce pollutants generated during the production process. The high net entry contribution implies China's polluting firms are becoming more environmentally efficient.

Chapter 7

Conclusion and Discussion

In rapidly developing countries like China, the effectiveness of environmental policies and their impact on firm behaviour has captured the attention of both scholars and policymakers. The debate about whether environmental regulation hiders firm performance remains controversial (Jaffe and Palmer, 1997; Copeland and Taylor, 2004; Porter, 1990; Porter and Linde, 1995). The negative side effects of environmental policies on firm performance has been widely investigated (Greenstone et al., 2012; Walker, 2011; Berman and Bui, 2001). Meanwhile, governments are more interested in avoiding trade-offs between improving environmental quality and sustaining economic growth. The result of this thesis helps to answer the questions about the impact of the TCZ policy on firm performance and emissions and the possibility of reducing aggregate emissions constraints with current technology.

In Chapter 4 (the first topic of the thesis), I investigated the impact of the TCZ policy on Chinese firms' emissions and performance. The result shows that the TCZ policy has averagely reduced the amount of SO2 discharged by 28.9% and reduced TFP levels by 35.7% for firms located in the TCZ area. Channel and heterogeneity analysis shows that "end of pipe" and "change in process" are two measures used for emissions abatement. Firms that only adopt "end of pipe" activities would face TFP loss as a result of the increase in production costs. The adoption of "change in process" activities can offset the TFP loss brought about by "end of pipe" activities because the TCZ policy has had an insignificant effect on TFP for firms taking both measures for abatement. The deleterious effect of "end of pipe" measures is in line with Neo-classical theory on environmental economics, while the influence of "change in process" measures also supports the Porter Hypothesis, the opposite of Neo-classical theory. The final effect of the TCZ policy on firm performance depends on the abatement measure adopted. Furthermore, I calculate the economic cost of this air pollution control policy. A 10% abatement in SO2 emissions can lead to a 0.42%-1.2% drop in the 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. High environmental quality improvement is accompanied by high economic cost, which is particularly salient for fast-growing economies such as China.

The result in Chapter 4 shows that China is facing a dilemma, namely a trade-off between improving environmental quality and sustaining economic growth. As firms could have different environmental efficiency even in the same sector, resource distortion is widely acknowledged as prevalent in China generating significant welfare loss (Hsieh and Klenow, 2009; Hovakimian, 2011; Ek and Wu, 2018; Ding et al., 2021). In Chapter 5 by reallocating production across firms subject to constant aggregate production, I try to find a way to reduce aggregate emissions, which helps to solve the trade-off dilemma.

In Chapter 5, I find that the TCZ policy has a significant impact on firms' marginal emissions of energy and its dispersion. Compared with firms without regulation, firms complying with the environmental policy on average experienced a 4% to 16% drop in the marginal emission of energy and an 8.6% to 15.7% rise in the marginal emission of energy dispersion. The drop in marginal emission of energy due to the environmental policy shows that firms' environmental efficiency could be improved by adopting an appropriate regulation policy. The increase of MEPE dispersion due to environmental regulation represents the magnitude of environmental efficiency differences across firms in the sector that could be aggravated by policy implementation. In this sense, the impact of environmental policy on MEPE dispersion represents increased environmental misallocation. As for why environmental regulation brings more environmental misallocation, my heterogeneity analysis indicates that environmental regulations have a more effective impact on big firms and private firms than on small firms and SOEs. Because of financial constraints and difference in bargaining power, big firms and private firms are more willing and able to improve their environmental efficiency. It is concluded that ownership and financial frictions are the key sources of resources distortion in China (Brandt et al., 2013; Wu, 2018). Ownership and financial friction could also result in variations in environmental efficiency among firms even within the same sector. Finally, aggregate emissions can be reduced by approximately 30% under better allocation conditions.

In Chapter 6, I proposed a DID framework decomposition for emissions growth. This chapter helps to make up for the missing information on entering firms and exiting firms in Chapters 4 and 5 which use panel regression analysis. I decompose the gap in the weighted average reduced amount of emissions between the TCZ area and non-TCZ areas into survivors, entry, and exit channels. The contribution of surviving firms is decomposed into the within-firm component and the cross-firm component.

I obtain different findings with different metrics for emissions (SO2 discharged and generated). First, when using SO2 discharged to denote firms' emissions, the DID framework decomposition implies a negative effect of the TCZ policy on weighted average emissions compared with the firms in the control group. The difference between weighted average SO2 discharged growth for the in-TCZ and out-TCZ areas is primarily driven by the gap in the surviving firms channel across the two groups rather than the net exit channel. For the in-TCZ group samples, before 2005 negative weighted average emissions change is primarily driven by surviving firms rather than by net exit. But with the increasing time span, net exit contributes more to aggregate emissions reduction. The out-TCZ area did not experience a pattern as the in-TCZ area did because of weak regulation but the total effect is negative.

After decomposing the contribution of surviving firms into within-firm and cross-firm subcomponents, within- and cross-firm subcomponents both contribute to the reduction of surviving firms' weighted average emissions, while reduced firm emissions holding the firms' shares constant instead of the market share reallocations are the key reason leading to the negative contribution of surviving firms.

When using SO2 generated to denote firms' emissions, the DID framework decomposition also implies a negative effect of the TCZ policy on weighted average emissions subject to the firms in the control group. However, effective policy implementation is driven by the gap in the net exit channel between in-TCZ and out-TCZ groups. Whether in the in-TCZ or out-TCZ group, the positive contributions of survivors and net exit are the reasons for the increased weighted average SO2 generated. Both survivors and net exit contribute to increased weighted average SO2 generated, and net exit contributes more than survivors in most years. These findings can not be explored with panel regression. By decomposing the contribution of surviving firms, I find that both in-TCZ and out-TCZ surviving firms' contributions can be decomposed into a positive within-firm subcomponent and a positive cross-firm subcomponent. The negative contribution of surviving firms in the DID frame decomposition is induced by the lower within- and cross-firm subcomponents for the in-TCZ area than for the out-TCZ area.

Overall, the thesis discusses the impact of environmental policy on firm emissions, firm performance, firm environmental efficiency, and environmental misallocation. The contribution of exiting firms and entering firms is investigated through the decomposition approach. The thesis contributes to the understanding of the effect of policy implementation. I highlight the tradeoff involved in environmental policy implementation and provide an approach to reducing aggregate emissions within the economy without output loss.

A policy implication of these findings is that overcoming the trade-off between productivity increase and increasing emissions is an important point that should be considered by policymakers. For developing countries, a stringent command-and-control environmental policy could hinder the development of the local economy. Air quality is positively correlated with human physical and mental health, while productivity is correlated with economic growth. They are key factors influencing human well-being. Thus, the trade-off has become particularly important in order to maximize the well-being of residents.

Another important practical implication is that we should pay more attention to breaking the link between "environmental bads" and "economic goods", which is a "decoupling" idea defined by the OECD in 2002. It is recommended that replace current dirty technologies with cleaner technologies through taxes and subsidies, which means reducing the dispersion of environmental efficiency between firms in this research. My proposed method helps to transition to a net-zero world. Approximately 76% of global emissions are covered by countries that have set net-zero targets, including China, the United States, and the European Union (Source: UNEP Emissions Gap Report 2022). The international cooperation on substitution-based decarbonisation can help reach the net zero target by 2050.

As environmental regulations become more prevalent and stringent, policymakers must carefully consider the potential impact on the economic performance of regulated firms. Striking the right balance between environmental conservation and economic growth is imperative. Policymakers should explore mechanisms that incentivize firms to adopt environmentally friendly practices without unduly burdening their financial performance. In addition to revealing the trade-off between firm emissions and performance under environmental policy, the study offers insights into the effectiveness of different environmental management strategies. Firms that only adopt the "end of pipe" approach will experience the trade-off, emphasizing the limitations of such reactive strategies. On the contrary, firms that take both "end of pipe" and "change in process" approaches will seem to avoid the trade-off. This implies that environmental policies should not only encourage emission reduction but also incentivize a holistic transformation in production processes. Policymakers are urged to support and promote eco-friendly technologies and sustainable practices that go beyond mere compliance.

Meanwhile, the findings of this research emphasise the important role of reducing the dispersion across firm environmental efficiency in achieving a meaningful reduction in aggregate emissions. Policymakers can draw crucial policy implications from these results to foster a more environmentally sustainable landscape. One key avenue for intervention lies in designing policies that incentivize the sharing of environmentally friendly technologies across firms. Creating platforms that facilitate knowledge exchange and collaboration could amplify the spillover effect, enabling more firms to adopt efficient environmental practices. Additionally, targeted measures to reduce misallocation of resources, such as providing support and guidance to less efficient firms, can contribute significantly to an overall improvement in environmental performance. Emphasizing the importance of environmental efficiency as a shared goal and fostering a culture of collaboration within industries can further enhance the impact of such policies. In essence, a concerted effort to minimize the variation in environmental efficiency among firms can pave the way for a collective reduction in emissions, aligning economic growth with sustainable environmental practices.

My study has several limitations. First, there is only two years pre-treatment period due to the data limitation. The data span starts from 1998 in the Annual Survey of Industrial Firms Database and the policy implementation year is 2000. The moving trend before policy implementation is unclear. Second, the best production for each firm is not provided in the research. I also do not prove the optimal environmental efficiency for each sector. Based on the existing literature, setting the firms in the U.S. as the frontier could be a possible solution for developing countries. Third, the causal relationship between environmental policy and firm environmental efficiency could be investigated. In Chapter 5, I employed the pooled-OLS approach in the specification, which fails to display the underlying causal relationship. My future research will try to fill those limitations and investigate the firm's technological improvement under environmental regulations, including R&D investment and green patent applications.

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